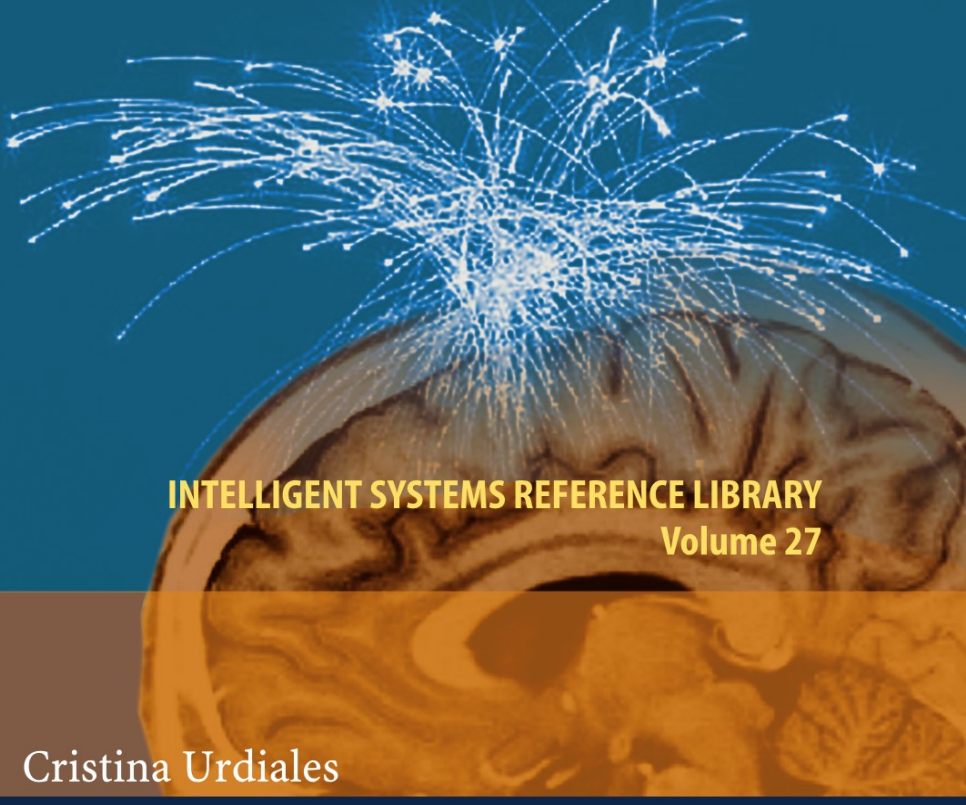

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Collaborative Assistive Robot for Mobility Enhancement (CARMEN)

The Bare Necessities: Assisted Wheelchair Navigation and Beyond

Springer

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The Bare Necessities: Assisted Wheelchair Navigation and Beyond

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An expert is a person who has made all the mistakes that can be made
in a very narrow field.
- Niels Bohr

Just keep swimming. Just keep swimming, swimming, swimming.
Dory - Finding Nemo

Foreword

Ops! I did it again!
If every journey starts with one step, mine usually do it with a slip, which is just the same, only fancier. In this case, I stomped into this awesome book that a friend gave me: "On Intelligence" [65]. I read and read and thought to myself, hey, this could be a nifty writing style for a dissertation! You can use an easy-going tone for a book and still be scientifically sound. Maybe I watched too many Mazinger shows or read too many Yoko Tsuno BDs as a kid and, surely, I think the best way to end up humanity would be to migrate Skynet to Windows Vista, but somehow I thought it could be fun. And that was it. On my behalf, I must say that I initially planned this work for someone else, but, hey, she ran faster than me. So here I was: I had faith, hope and SHARE-IT, even though hope overruled the other two through most of the project .
This may look like an exercise of self-indulgement, yet there was this group of people crazy enough to hit the road with me, even when I did not know where I was going. This one goes for all of you, buddies!
It was written in the Iliad: never trust Ulises. Anyway, if you do, yay!, you are in for the ride of your life.
To Roberta, who showed me that swearing sounds better in Italian. It's been great working with you, my friend.
To my three musketeers, Manolo, Peula and Jose Carlos, who always managed to bring back queen Anna's pearls in the proverbial nick of time.
To Paco Sandoval, a fellow, a friend and an inspiration.
To Huey, Dewey and Louie, aka Julian, Lucia and Clara, who always put a smile in my face, and to whomever comes next.
To all the oompa loompas of science and the Frikishare-IT crowd. Have you tried turning it off and on again? :P :D
And, last but never least, to mom, who has been my longest relationship and still has not tried to kill me ... much. Love ya, ol' girl!
It was worth the ride, guys!

Preface

In nowadays ageing society, many people require assistance for mobility. In some cases, assistive devices require a certain degree of autonomy when the person's disabilities difficult manual control. However, mobility platforms like wheelchairs are not supposed to overtake full control on human mobility, as clinicians report this leads to loss of residual capabilities and frustration. Furthermore, the level of control that a person can exert over a wheelchair may be indicative on his/her physical and/or cognitive condition. Consequently, it is important to rate the performance of wheelchair users with some accuracy to check their condition and evolution and also to evaluate the quality of different control strategies and environment configurations. This book presents a new method to support wheelchair based person-mobility through collaborative control. The amount of help provided to each person should be adapted to his/her condition through evaluation of his/her performance. To do that, we also present an overview of common metrics for wheelchair navigation and also we propose new ones to take into account new approaches to wheelchair control. We have tested presented metrics on a robotized Meyra wheelchair at Fondazione Santa Lucia (FSL), a hospital in Rome, with volunteer inpatients presenting different disabilities. Results obtained are coherent both from a quantitative and qualitative point of view, proving that the proposed metrics are adequate for wheelchair navigation evaluation.

Malaga Cristina Urdiales

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Chapter 1
On the Why of Robotic Assistive Devices

Good news, everyone! I've taught
the toaster to feel love!
- Professor Farnsworth, Futurama

1.1 Hephaestus and Everything after

Once upon a time, someone came up with the idea that, given some intelligence, machines could possibly make humans' life easier. These machines would be called robots and, somewhat surprisingly, they were not born in the mind of Asimov, but in classic Greek culture: according to Homer's Iliad, Hephaestus used robots to assist him in building Achilles' new armor (Book XVIII). Literature has always been ahead in these areas, yet the first real known robot was built somewhere around I century. Hero's steam-powered Automatic Theater [41] or Archytas' Dove -mentioned by Aulus Gellius, Noct. Att. L. 10- could be considered the first built robots in written history[1]. They favored common mechanisms employed in entertainment by the time, like steam engines, weights, pulls or hydraulics. The only surviving example is the *Antikythera* mechanism, an ancient mechanical analog computer presumedly coming from Rhodes, where they had apparently a tradition on mechanical engineering. Indeed, Pindar's seventh Olympic Ode goes like:

> The animated figures stand
> Adorning every public street
> And seem to breathe in stone, or
> move their marble feet.

Those first robots, known as automata were not truly such, in the sense that they blindly followed a tight sequence of actions, predetermined by their creators. In this sense, they were no more intelligent than, for example, the pencil used to write the Theory of Relativity. Even though the idea of what a robot should do -work we did

[1] References to some pretty ancient mechanical orchesta lead to think, though, that the first gadgets might well have had the usual "Made in China" sticker.

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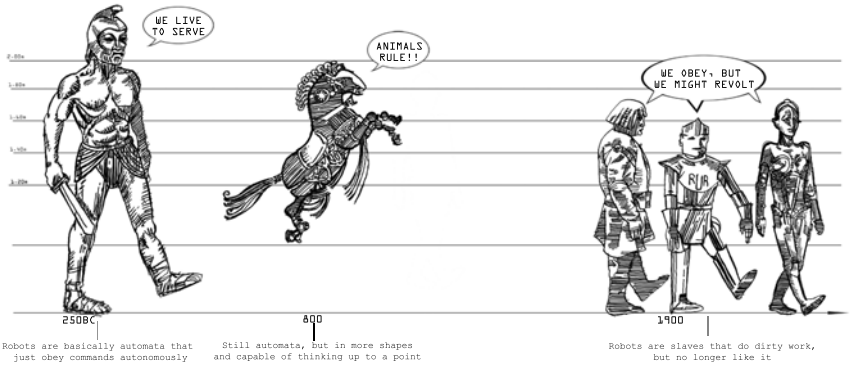

Fig. 1.1 The robot evolution in fiction (1500BC-1920AD)

not want to- was already there, technical knowledge to build it was not available. In order to make decisions, they would have required some sensing and processing skills, so that they could decide the most adequate thing to do, given the circumstances. On top of this, there was no real need for robot workers at the time, as human ones were fairly cheap or, unluckily for them, even came for free. Most automata were, in fact, moving sculptures.

Centuries would bring the basic technology required to build more complex mechanisms, plus precise knowledge on motion and articulations, particularly after Da Vinci decided to open up corpses for anatomical studies, if just to give some headaches to the Inquisition. Da Vinci himself designed an automaton resembling an armored knight. Again, most devices developed through the Renaissance and up to the Industrial Revolution were automata, mostly based on pegs and levels. The master piece of this wave would be the famous *Vaucanson's Digesting Duck* [190] which was reported to move, eat and defecate through mechanical combination of more than 400 pieces. However, less mechanically complex devices, actually closer to modern robotics, had been built before. Hydraulic *Al-Jazari's Peacock Fountain* (XII century), used a primitive sensor to trigger a small metallic figure carrying either soap or a towel when water was flushed [138]. This might look like an exercise in mechanics not very different from cuckoos or any other mechanized clocks (*Le Gardien du temps*, *Prague Astronomical clock*, etc), but it sets the basis of modern robotics: rather than a fixed sequence of actions, a given machine may act one way or another dependind on what is happening around at the moment. In the fountain case, the system actually decided what to bring to the user -soap or towel- depending on the amount of water on the basin. However, human workers were still cheaper than robots and jobs no person could do were too complex to achieve with robots. Indeed, even though mechanics could do the trick, machine processing capabilities were still an alien concept, so technology was not really ready yet.

Clearly, the next stage for robotic development would be processing and sensing skills. The XIX century brought Babbage's computation machines. Shortly later, *Jaquard's programmable looms* -even though not very robot-looking- were the first

reprogrammable machines, based on punched cards. The idea was, obviously, to obtain different patterns at wish without major changes in machinery and, indeed, this type of robots led the industrial application field for years and they are still under use in areas like automobile industry. At last, both technology and need where there, even though only affordable for large enterprises. It is interesting to note, though, that somewhere along the way the concept of sensors was dropped and replaced by fixed, *a priori* coding. Now, machines could change their behavior, but they needed someone to tell them what to do and, until new commands were available, they would do the same thing over and over. At this point, sensors came into play to give real time input to machines, so they could act one way or another without reprogramming.

Sensors may measure many different magnitudes, like thermal, electromagnetic, mechanical, chemical, optical radiation, ionising radiation, acoustic, motion, orientation and range data. Specifically, mechanical and range sensors have been widely used in robotics. The role of sensors in modern robotics is crucial, as they allow inner programs to fork to appropriate responses depending on dynamic, real time conditions. Basically, asking a robot to operate without sensors would be like asking someone to cross a highway blindfolded and ear-plugged. It could be feasible to just measure a priori how many cars are moving across at a given time frame and how fast they move, and to ask the person to just go for the opening and expect that everything will go as expected. Indeed, this type of robots thrive in industrial environments and most automata could just operate without sensors, even though some of them used primitive ones, like Heron's hydraulics. However, XX-XXIth century robots would bet on sensors for flexibility to adapt to a changing, usually unpredictable world.

It was the first half of the XXth century that brought everything that was required for modern robotics. The word robot (*robota*) was first used by czeck writer Karel Capek in his Rossum's Universal Robot (RUR), applied to humanoids that did the hard work according to a program in a very Golem-like way. *Metropolis* would

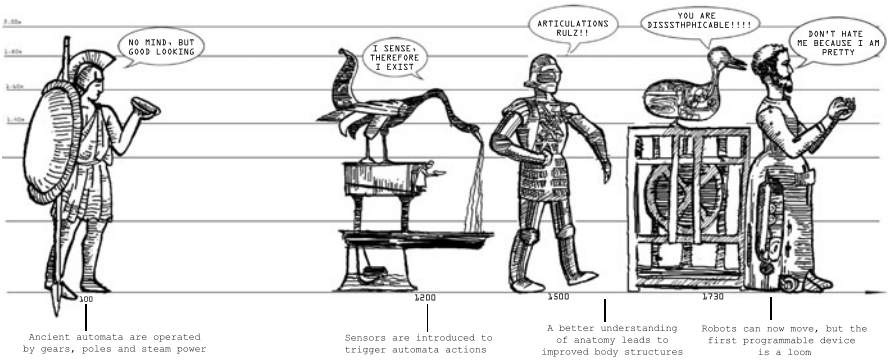

Fig. 1.2 The robot evolution in reality (250BC-1900AD)

introduce Maria Robota, a full metal android capable of thinking on her own, and, finally, Asimov would introduce *robotics* as a science in his short tale: *Runaroud* (1941). Obviously, these robots on paper were still impossible to build at the time, but the idea of using a robotic assistant capable of thinking was finally set upon a technological basis.

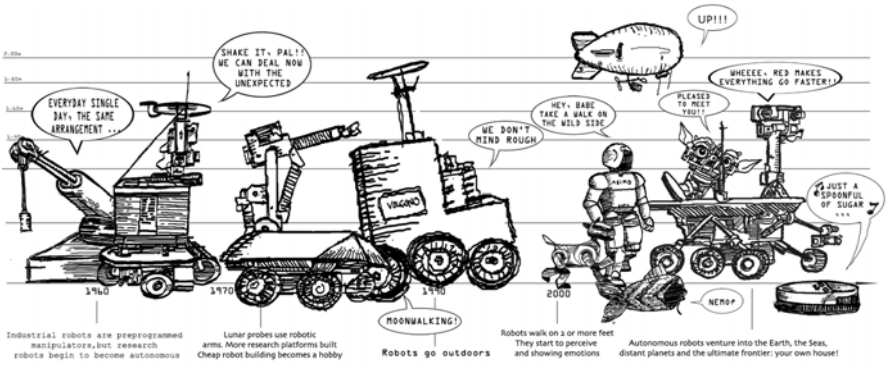

Fig. 1.3 The robot evolution in reality (1940AD-2010AD)

By the middle of the XXth century, technology was also there and, after two world wars provoked a shortage of workers both in Europe and America, there was also a real need to build such expensive devices. Industry was the first to give a shot to robots, and the only customers who could afford one at the time. Devon and Engleberger, two north American engineers, created the Unimates, originally used to move heavy stuff around in factories. Not too surprisingly, General Motors was the first large firm to introduce robots in their factories and they have thrived in the car industry ever since. These 50s devices fitted quite well the robot definition that the world used for more than 20 years, but, in fact, they lacked something important to fit what robots are supposed to be today: although they could change their activity in a very Jacquard's loom-like way, they did not make decisions. From this point of view, old robots were not smarter than our programmable kitchen robots, that may produce a milk shake or a quiche by simply turning a knob, but, obviously, do not decide what we will eat for lunch. In this sense, if a car factory changes a car model and is using a robot to do the painting, it can be easily reprogrammed to fit to the new height and length of the vehicle and not, for example, paint the windshield. However, some person would have to load a new set of instructions into the thing, as it would not be able to decide that, in fact, the car it is painting is not the same old one. Robots became, at this point, the swiss army-knife of industry. 1700 years might seem an awfully long time to move from automata to robots. However, if we consider that it took humans 3.9 million years to evolve from Australopitecus to Cromagnon, it is not so much. Should we consider evolution in terms of speed, in the 17 minutes it would take humanity to cover 35 km in a highway, robots would be back from a trip around the Earth.

The ability to adapt on their own to a potentially changing environment would be a key requirement for the next, big, robotic step: space, far and beyond. In this case, rather than a lack of human resources, robots were supposed to replace humans in hazardous situations. Indeed, Victor Scheinman managed to put a Vicarm robotic arm in several Viking probes to gather rocks and soils for research. In lunar missions, robotic teleoperation via a video link could do the trick to decide *where* and *how* to move. However, Mars missions would require more decision capability on the robot side, as delays in video transmission would make it unfeasible to actually tell the robot where to go before it was already stumbled into a deep crack or a cliff. Fortunately, Artificial Intelligence (AI) had already been established as a science on its own right in Dartmouth and computers were starting to reach acceptable dimensions for adaptive robots to be developed. The key idea was simple: given a set of sensors, their readings could be fed to a computer so that it might choose the most suitable line of actions for the input situation. In fact, much work was being conducted in research at the time, along with industrial applications.

Sensors were, as commented, of key importance and, while the first of these robots, turtle ELSIE, could only follow a light, its descendants incorporated as many of them as possible, like cameras, infrared, sonar, contact sensors, etc. Most of these robots, though, were not supposed to do anything more complex than navigate, which, in this context, means to move towards a goal in a safe way. However, they now decided how to reach it on their own. These research robots remodeled the classic definition of robot into "*a device capable of moving and making decisions on its own to achieve a certain task*".

Even though technology and need were already there, robots were still far from affordable and customers where mostly government, research centers or large industrial firms. In the first case, robots typically included rescue devices, planet rovers, deep sea or volcano explorers, radiation cleaners, etc. Industrial firms were basically concerned with robotic arms and heavy equipment transportation, which in a factory environment only requires the robot to be capable of following a line on the floor. Research produced very interesting prototypes, including humanoid robots like Asimo or HOAP, flying helicopters, scuba-bots, insectoids, swarm robots, etc. However, none of these prototypes was commercialized in a massive way.

It may be revealing to just observe robot evolution in time, both in reality and fiction. In fact, robots in fiction did not evolve much from a functional point of view until Asimov pointed out that they might have a soul. From the very start, they were designed as humanoids or, at least, animals, capable of reasoning up to a limit, yet devoid of free will. Indeed, all robots up to the XXth century, from Hephaestus' assistants to the Golem were just supposed to serve human kind, but they could reason on their own to do so. RUR changed this concept, as robots became a metaphor for opressed social layers in the middle of the Marxist Revolution, a trend that Metropolis was happy to follow. Asimov went one step further and, from the 60s on, robots started to have their own personalities. Still, they were mostly humanoids, until real robots started to be constructed and it became obvious that they would not be ironing our clothes anytime soon. Star Wars changed this view up to a point: aliens were no longer humanoids, so why should robots be? Instead, we could plug and play

R2D2 in our X-Wing or ride a legged ATAT to destroy the Alliance, leaving human shape for protocol droids like C3P0. The next 10 years would not change things much, except in terms of AI: machines would get fed up with human supremacy and revolt against their creators, that mostly wished they had never stopped finger-counting. The next big r-evolutionary step came with Battlestar Galactica (BSG), where robots had evolved so much that they became flesh and blood and the frontier between their kin and humans became so thin that noone was really certain about their nature anymore.

If we compare human history from, let's say, the Troy War in 1250BC till now with robot history, starting with ELSIE, via a simple linear approximation, each year in robotics is approximately equal to 48 in our time span. Thus, we can get some idea on the magnitude of progress in the field. For example, in the approximately 20 years that passed from ELSIE to commercial UNIMATES, we would have moved from the Bronze Age to the Rise of Rome, and then to its fall in the 9 years it took to build SHAKEY, the first navigating autonomous robot. In 9 years more, VICARM would have robot arms in the Viking probes, and Arthur, King of Britain, would have died in Camlam. Legged robots like Ghenghis would correspond to Marco Polo travels, and, curiously, the Age of Discovery, starting with Columbus arrival to America, roughly corresponds to Dante exploring Mt Erebus and Sojurner arrival to Mars. Kismet, the first social robot, would be somewhere around 1580, when Mary Queen of Scots and Elizabeth I fought over Britain sucession, and then multishaped robots adapted to air, sea and whatnot would appear by the dawn of Industrial Revolution. Both timelines would match back in 2010, with events so unbelievable as nanobots swimming in blood flow and a black president in the White House. Fiction robots moved faster: our Bronze Age models would be the outer space killing robots from the 50s, evolving into piloted mechas by the time Caesar ruled in Rome. Terminator would be searching for Sarah Connors by the time Angkor Wat started to be constructed and machines would have created the Matrix during the Age of Discovery. After the Industrial Revolution, it would become widely accepted that robots might actually have a soul and Pixar would give us Wall-e and EVA a few years

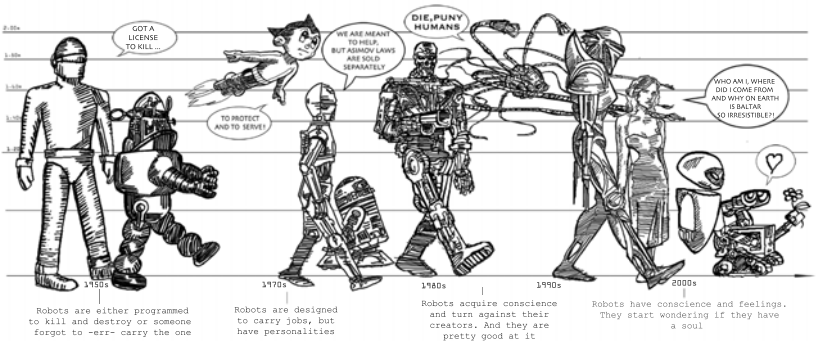

Fig. 1.4 The robot evolution in fiction (1920AD-2010AD)

ago. The movie would go back to inorganic multi-shaped robots, yet insists on how little separates artificial beings from human souls, not just in terms of intelligence, but also in terms of feelings.

1.2 History of the Bots

Robotics evolution has had its ups and downs along human history, yet it obviously shows patterns here and there. While people remained optimistic about the posibilities of creating artificial life even after we all read Frankenstein, most researchers in the field found it obvious that current hardware may create anything from a giant rubber skinned T-Rex to a swarm of mesh robots. However, software was a completely different thing. At most, we could create something that seemed intelligent to the casual observer, like Eliza [188], but, would robots ever become aware of themselves? Maybe the right term up to this point is that we can develop *smart* robots, get them to evolve and even to achieve new behaviors that would be, nevertheless, severely limited: smart robots may not be what one expects. As Hawkins concludes in [65], to pass the Turing Test, an intelligent machine would need to have most experiences and emotions of a real human and to live a human-like life, something difficult and, possibly, even pointless. In any case, it seems that the best we can get is, naturally, a function of available technology and computational power. However, is this search for the best possible robot necessarily the silver lining of robotics evolution?

Let's try an exercise of fancy graphical representation of a large number of multivariable vectors, in our case, robots in history, if only because we love Visual Complexity. We can assume that fictional robots can be included in our timeline. After all, what would robotics be without people like Asimov?

First, to represent robots, we need to quantify somehow its nature. How do we define a robot, though?. Smartness is not the universal answer: if you ask someone at random who is smarter, Spirit or stair-climbing P3, you might be surprised at how many people think that any 3 years old kid can do the last, yet she most likely will never travel to Mars. Indeed, if someone asked me if I'd rather have Kismet or Mazinger Z, hey, count me in for the big, dumb, fighting thing!

A major discussion in our labs -that was settled by sheer force of stubborness and endless changes after *everything* seemed to be already programmed- led us to characterize robots via four features: i) **smartness**, where 0 corresponds to teleoperated robots and 100 to human thinking[2]; ii) **adaptability**, where 0 corresponds to non-moving robots in predefined environments and 100 would be ... no, not an inhabited planet, but a metro station at rush hour!; iii) **biomimicry**, where 0 corresponds to robots that have no similarity whatsoever with a biological being and 100 corresponds to robot that look exactly like an animal -humans, of course, included-; iv) **manufacturing**, where 0 corresponds to robots whose creator had to model every little piece and 100 to commercial models. To avoid further confussion, we also

[2] This could be argued, sure, but let us assume that at the moment ANY human is smarter than your average bot.

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Id	Name	Year	Type	Goal	Adaptability	Artisan/ Manufactured	Biomimicry	Fict/ Real	Smartness	Relevancy
202 X	UBOT-5	2009	Wheeled	Assistance	100	60	65	100	70	4.60377e-05
198 X	i-Limb	2009	Bionic piece	Bionic hand, prosthetics	100	80	100	100	20	0.000145283
177 X	Fujitsu Teddy Bear	2009	Emotion robot	Social robot	100	80	80	100	70	0.000140566
137 X	Biped Pete Jr	2009	Humanoid	Entertainment	10	20	90	100	20	1.69811e-06
150 X	Hexbug (Innovation first)	2009	Animal Robot	Toy	100	100	80	100	25	1.32075e-06
176 X	Spider pill	2009	Microbot	Scanning of inner body	50	10	35	80	15	2.21698e-05
123 X	Land Walker (Sakakibara-Kikai)	2009	Cyborg	Entertainment	60	20	60	100	0	1.88679e-07
93 X	Alice (from Transformers: Revenge of the Fallen)	2009	Cyborg	War	70	50	100	0	40	5.66038e-07
178 X	SimMan 3G (Laerdal)	2008	Humanoid	Training for health professionals	0	60	100	100	0	9.43396e-08
108 X	PackBot (iRobot)	2008	Platform	Military	70	100	0	100	30	1.21698e-05
117 X	Robot Suit HAL (Cyberdine)	2008	Bionic piece	Enhancement of physical capabilities	100	15	90	100	10	0.000191509

Fig. 1.5 The robot evolution database

added a "reality" value that most of us thought should be a Boolean (0=fictional robot/1=real one), but finished as an integer ranging from 0 to 100 because someone thought -very loud- that it could be controversial not to have reality-challenged things.

Fixing a parameter value was also pretty tricky: if you ask 10 different people how smart a robot is, you get 10 different answers. This was solved quite democratically: we built a MySQL database (Fig.1.5) that can be modified via web and enabled a vote system where people rankings on the same robot would be averaged[3].

Now, any robot could be represented by a 5 feature vector in time but, unfortunately, we humans are not particularly apt at visually appreciating 6 dimensional spaces as such. Hence, we did a bit of a trick: we equaled the first four vector elements to C,M,Y and K components in the Cyan-Magenta-Yellow-Black (CMYK) color space. The fiction component was assigned to the *Alpha* channel, e.g. transparency, so that real robots seem more solid than fictional ones. Then, we drew a sphere for each robot, whose color and transparency was related to its nature. For example, we could state that a hobby tracer mesobot built by a student team is *(15,25,0,25)*, e.g. solid pale violet, if we assume that it is not biologically inspired, its environment will not change much, kids designed it using commercial motors and a microcontroller and it does not have a killing strategy capable of evolving

[3] And, in case of disagreement, us, all-mighty system administrators, could reset the robot to our favorite value in a really democratical way.

beyond human line-tracking imagination. An ancient automata would be instead completely yellow *(0,0,100,0)*, because it would be done from scratch, biologically inspired like your average kouros and mechanically preprogrammed to repeat the same set of actions over and over. If we do not want spheres to overlap, though, we need to distribute them in a cloud around the year they were created in. And, hey, here comes a new variable in play: size. If just for the word play, we decided that size would be importance: we Googled ("name of the robot" & "robot") and scaled items according to the number of results. Thus, Soujourner would be larger than, say, RUR, but significantly smaller than Wall-e.

If we check colors through the database (Fig.1.5), distribution is strongly discontinuous, and there is no noticeable trend, except at the beginning, where robots were all different shades of yellow: bright and solid for real devices and darker and more transparent, for imaginary ones. Indeed, a line is not the best dimension to show interdependencies, so we discussed once more and someone suggested a circle. If we place all robots in a circle, similar ones could arrange themselves into groups and see if there are interdependencies among them. This arrangement was performed via a electrostatic field set of equations, where balls attract or repel each other depending on their distance and color likeness:

$$\begin{aligned} fx &= dx \cdot [\frac{d \cdot cos(\frac{dx}{d})}{M_{atr}(i,j)} - \frac{M_{rep}(i,j) \cdot 10}{d^2}] \\ fy &= dy \cdot [\frac{d \cdot cos(\frac{dy}{d})}{M_{atr}(i,j)} - \frac{M_{rep}(i,j) \cdot 10}{d^2}] \end{aligned} \tag{1.1}$$

fx and fy being speed modification in that component, dx and dy being the distance between balls in that component, d being the distance between balls and M_{atr} and M_{rep} the attraction and repulsion matrices respectively. After fx and fy are available,

$$\begin{aligned} vx(i) &= vx(i) + fx \\ vy(i) &= vy(i) + fy \\ vx(j) &= vx(j) - fx \\ vy(j) &= vy(j) - fy \end{aligned} \tag{1.2}$$

Finally, all components are multiplied by friction F and the process finishes when average speed is lower than a threshold. Some heuristical parameter fixing work led to field convergency after a few iterations and, indeed, groups become now more clear. However, circles do not give sensation of time, so they do not represent trends. Instead, they rather represent types of robots that have consistently appeared again and again in human history, i.e. fictional thinking humanoids.

Naturally, a timeline needs to be represented in function of time. However, rather than using a lineal time scale, given the much larger concentration of events in the last 50 years, we can go for a log one, where older events are squeezed in a time slot that may go for centuries and still we may have the same space for a single,

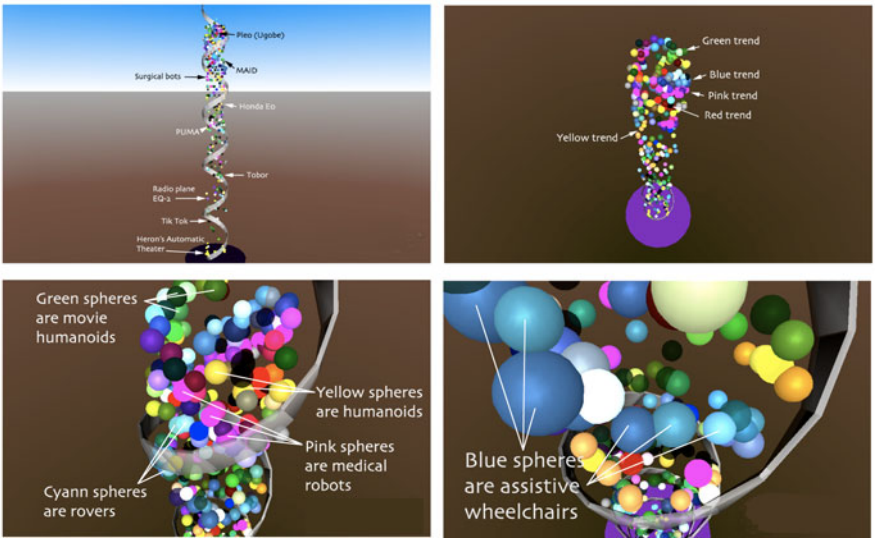

Fig. 1.6 The robot evolution helix

very busy year. Thus, if we just up the circle in 3D via OpenGL, not only we get a sense of time, but now the whole thing looks like a DNA helix[4]. This representation presents several interesting features. First, similar robots that are close in time conform groups of nodes on a side of the helix: the larger the cluster, the more important this robot tendency has been. Homogeneous groups at time origin extend to whole rings of the helix, ranging only from yellow to green, when real robots were all automata and fictional ones were humanoids. However, as soon as they diversify, there are different trends at all sides of the helix that may last for long periods of time -like fictional humanoids or robotic arms- or just be locally punctual, like flying robots before the XXth century. In any case, close clusters correspond to similar colors and, hence, robots, so transitions between them should be smooth unless something makes evolution jump abruptly. Such changes may be correlated -even with some delay- with important events in history, like marxism at the beginning of XXth century or massive commercialization of cheap computers in the 80s. After 2000, though, the helix is so packed with robots that it is not easy to detect trends anymore, yet, there are noticeable streaks of yellow, green, cyann, pink, red and blue, corresponding roughly to humanoids, both real and fictional, rovers, medical robots, toy robots and assistive devices (Fig 1.6).

Trends are a nice outcome of our helix, but we have still something up our sleeve: the distance matrix used in our field calculation. A distance matrix is crying out loud for a path planning algorithm and we are only happy to comply. Basically, if we calculate the path between any two robots using this distance, we are representing how the first robot evolved to turn into the second one, so we can, for example,

[4] Helix available via web using a 3DXML plugin: *http://www.grupoisis.uma.es/history*

see how many prototypes it took to go from ELSIE to Essex Robocarp. Initially, our matrix simply provides the distance between robots in terms of space over a plane, but we need to recall that we are adding a time dimension later. Hence, time is included in the original matrix for two different goals: first, the distance between any two robots grows with their separation in time; second, we give directions to the graph, meaning that moving ahead in time from one robot to another is significantly less costly than going back in time. This makes sense because we are looking for evolution, and moving back in time seems to be contrary to this idea. Yet, we do not forbid totally to move back in time while searching for a path because some robots might be dead-ends for a given type of evolution, meaning that it is impossible to move from them to a newer one that is closer to our destination. Think, for example, of gastrobots, which are pretty unique in their design. A jump back in time is usually related to finding a robot from which origin and destiny forked into different lines.

Naturally, we can turn on and off fictional robots to remove them from path calculation. In any case, we also increase the cost to move from a real robot to a fictional one or viceversa, meaning that, while fiction may be inspirational in the field, it does not provide the technology to move a step ahead. Finally, we also favor paths that go through well known robots via the relevance parameter that we extracted from Google. This adjustment returns paths full of robots we are familiar with rather than obscure prototypes we have never heard about.

When the distance matrix is arranged, we can search for paths of minimum gradient via a propagation minima (e.g. Fig.1.7). Thus, we get natural dead-ends in robot evolution, along with promising lines very alive. In brief, robots organize themselves into families of a sort. Also, if we are lucky, sharp discontinuities may correspond to inflection points in robot evolution... or to areas where we did not introduce enough robots, too. And, of course, we can search for the shortest path from Archytas' dove to Pleo and see what happens in the way.

1.3 The Trifecta of Technology, Cost and Need

If we observe living trends in recent robotics, there are three outstanding ones: space robots, domestic robots and assistive robots. Of course, there are many, highly innovative units ranging from robofishes and roboinsects to social robots that react to our emotions, but these are just prototypes and they are not really inserted in our society. This mostly happens because complex robots are somewhat an expensive gadget that people can not afford unless necessary. For example, nifty AIBO robodog from Sony, with its open OS and wide sensing capabilities, became so popular in education and research that Robocup included an Aibo category and universities like Carnagie Mellon had courses on the subject. However, when the last CEO arrived to Sony, the first thing he did was to close the robotic line, including also the very promising biped QRIO that would have been much cheaper than previous systems like HOAP. It turns out that Aibos where not really profitable as toys, so the money went otherwhere, mostly to audio and TV equipments.

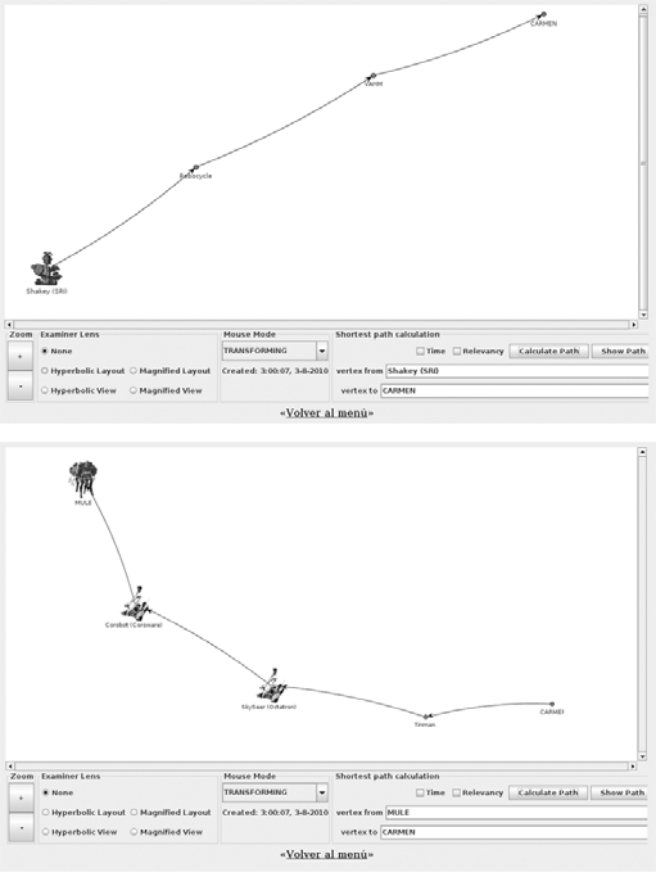

Fig. 1.7 Path calculation within the helix

Given this premise, it is easy to understand why the aforementioned lines have predominance over the rest. Space robots are goverment investment, expected to go ... well, where no man has gone before, meaning that they do things that people can't and, in any case, they are not supposed to be sold in your average Wallmart. The same could be applied to rescue robots or explosive defusing ones, where money is, by any means, justified. This is the feature that characterises a first category.

Domestic robots are a completely different issue, as the only healthy selling models have been Roomba, its family and its clones: vacuum cleaners and floor washing robots that can be purchased for 200-300 USD and are quite handy to avoid the broom in your daily routine. In this case, robots are not that necessary, anyone can in fact sweep the floor, but they are cheap and replace us in tasks we do most likely not want to do. In other words, cost is compensated by benefits. This would be the case for robot toys, also, but people is not willing to pay so much to keep children

entertained[5]. Hence, Aibos were discontinued, yet small, 10 USD creatures like Hexbugs are so appreciated by kids, and, lets face it, adults like us. Of course, need and cost are coupled in this area, so less popular, yet widely employed industrial robots are the big siblings of domestic robots and could be enclosed with them in a second category.

Assistive devices are a combination of the previous two categories. People need them for their daily living, so costs are acceptable, yet they can not afford a NASA prototype at home. However, either them or their country social services are willing to pay more than a few hundred bucks to ease their lives. Years ago, technology was either too expensive to bring these robots home or, simply, did not exist. However, assistive robotics, like eAssistance, has become fairly popular in developed countries. These robots are the focus of the current book.

1.3.1 Power in Numbers

Population today is progressively aging in developed countries. The increase in the proportion of older persons (60 years or older) is being accompanied by a decline in the proportion of the young (under age 15). Nowadays, the number of persons aged 60 years or older is estimated to be 629 million and expected to grow to almost 2 billion by 2050, when the population of older persons will be larger than the population of children (0-14 years) for the first time in human history [189]. Naturally, a longer life cycle also implies an increasing number of people affected by chronic diseases, such as heart disease, cancer and mental disorders. Chronic diseases may frequently lead to disability. It is estimated that the costs of health care could rise from 1.3 trillion to over 4 trillion dollars for these reasons [21]. Costs are particularly high if persons are not independent due to a disability.

Disability is a difficult concept to define, unless in a broad sense. It could be accepted that a person has a physical or cognitive disability when they *lose* the capacity to do some things on their own, meaning that their independence is threatened and that they require assistance in every day tasks. More specifically, disability implies not being able to carry out the so called basic Activities of Daily Living (ADL) such as bathing, eating, using the toilet and walking across a room, as well as shopping and meal preparation.

Under these circumstances, either home assistance has to be granted or the person needs to be institutionalized. In nursing facilities, though, costs are higher and the quality of life is often reduced [6]. Lack of human resources to assist elder people leads naturally to create systems to do it in an autonomous way (e.g. [25][27][129][181]). Studies on the use of assistive devices in a general population in Swedish descriptive cross-sectional cohort studies [69] reported that one-fifth at the age of 70 and almost half the population at the age of 76 had assistive devices, usually in connection with bathing and mobility. Another study of 85-year-olds in

[5] Kids, in these cases, are well known for ignoring a 300 USD toy and rather focus on, e.g. its box.

a general elderly population found that 77% of them had one or more assistive devices, also more frequently for bathing and mobility. The same pattern has been found in other general population studies, although the prevalence rates vary from 23 to 75% according to studied population, age group and type of assistive devices. To sum up, prevalence rates vary, but the use of assistive devices is very common among the elderly and their use increases with age. It is consequently of extreme importance to create a new generation of tools to assist people with disabilities, so that their independence and autonomy is improved. Specifically, it is stated by health professionals that mastering of mobility assistive device skills enhances a person's autonomy and participation in ADL [26]. Training these skills is also an important part of the rehabilitation process. Furthermore, assessment of wheelchair skill performance can provide valuable information about daily functioning and participation and even be used to check the progress of degenerative processes or rehabilitation therapy.

1.3.2 Two Is Company

Even though there have been proposals to build human-like robots to assist people, it is important to be realistic and to take into account what technology is offering at the moment: we are not getting any replicant at home to do the laundry for us anytime soon. As commented, most assistive devices nowadays focus on mobility and the most usual ones are wheelchairs and walkers. These devices range from manual to motorized ones and, lately, may present some degree of intelligence to assist people with special needs. In fact, both have been robotized to assist people with disabilities in navigation in houses, residences and hospital environments.

Hardware modifications to robotize an assistive device basically consist of adding input sensors and processing units to detect what the device should do, given the user's wishes and environment state and, then, to provide commands to the motors that can either replace or complement the user's input. Even though research in this kind of devices is strongly influenced by traditional navigation robots, it is necessary to note that assistive robotics differ from conventional ones in several basic aspects. Mainly, the goals of the robot architecture are continuously affected by the user's goals and/or needs and sometimes might be in direct conflict with the user's wishes. Consequently, optimization or intensive deliberation is not advisable in these cases, as robot decisions can not be imposed on assisted persons. Besides, robotic platforms in this case tend not to act completely, nor continuously autonomous. Instead, when the user performs an action, its outcome may be affected by the actions of the assistive agent. It is necessary to outline that human commands can not, in general, be neglected: in this particular field, even if we left ethical and/or moral considerations aside, machine actions that go against the user's wishes may cause him/her stress or/and discomfort.

1.3.3 All Help and No Play ...

Despite this sometimes complex coordination between people and devices with an opinion, robotic assistive hardware is usually beneficial. Due to physical, cognitive disabilities or both, in some cases persons can not benefit from assistive hardware. However, even though some persons might not be able to operate a standard assistive device like a power wheelchair, they may still exert some control on navigation and, consequently, gain some autonomy. Indeed, clinicians believe that nearly half of the patients that are unable to control a power wheelchair by conventional methods could benefit from this type of systems. Cases where this need becomes obvious include physical problems like tetraplegia, Parkinson or motor ischemia, as well as cognitive ones like Alzheimer, dementia, *etc*. In all these situations, persons could simply provide a general direction or a target and the mobile could navigate on its own, not paying attention to the person except to note a change of goals. Devices would choose trajectories, speed, safety constraints, etc and the user would feel like a person in a taxi: after an address is provided, it is simply a matter of waiting. This approach is perfectly valid for persons who can not exert further control over motion, like tetraplegics. However, there are many cases where they could operate devices in an acceptable way under some conditions and only require help in specific situations. An illustrative example of this is a person who moves well in a corridor but needs some help to cross a door or a narrow space, but there are more complex situations: some persons with specific disabilities might have an excellent control on the right side of physical space, but no perception on, for example, their left side. Furthermore, each case is different in its own way, so it is difficult to establish a set of categories *a priori*.

A typical solution to these situations would be to offer help either needed or not. However, specialists in rehabilitation have been reported that excessive assistance may lead to loss of residual capabilities [26], as no effort is required on the user's part to control mobility[6]. A second choice is to offer the user the possibility of choosing whether they want help or not. This solution might suit fine the corridor/door navigation example, even though it does not fit a rehabilitation approach. Unfortunately, more subtle cases are ill served by this choice, as the set of behaviors to be developed *a priori* would either need to be too wide or tailored to each specific user. Furthermore, in many cases the person could be unable to decide if he/she would need help or not to face a specific situation until it is too late. This would be like actively choosing whether ABS should be triggered or not just in the moment our car is about to run into a tree. Besides, too many control choices would turn into a very complex interface, like a VCR remote with dozens of choices where we stick just to the Play/Stop/Rew/Fw buttons. Alternatively, we could let machines decide on our behalf, but they might not be able to decide whether helping or not and how much help to offer unless several, problem related constraints are added.

[6] Loss of skills due to lack of practice is fairly common. Some birds in New Zealand, for example, lost their ability to fly in absence of natural predators. Most of them are currently close to extinction, after in the XIX*th* century those predators arrived to the island conveniently on boat.

These issues are not neglectable. On one hand, it would be economically unfeasible to manufacture a personalized device for each user depending on his/her condition and state, same as it would be to, for example, to produce a tailored car according to preferences, size, weight, and other specifics for each user. The "design for all" paradigm is not applicable here, either. Modern robotics, though, are all about learning and adaptation, so they could actually be applied to personalize the assistive device through use, taking a general design as a basis. One of these robotized devices would use a set of sensors to capture the user condition and wishes and then decide how much assistance must be provided at each occassion. This idea is not new; take, for example, software agents lurking in the web do personalize our access to sites depending on our preferences in exchange for cookies. The problem is, naturally, how to determine the correct amount of help required by a specific user and how to provide it. This book focuses on this specific area.

1.4 CARMEN in a Nutshell

The main goal of this book is to present *a system to give assistive devices, more specifically power wheelchairs, the ability to detect how much help a given user needs depending on his abilities and current condition and to provide the required help: not more, not less*. The concept behind our approach is to avoid loss of residual skills due to excessive help, but to provide, nevertheless, the required assistance to achieve mobility in everyday environments with a power wheelchair. This goal can be divided into several task-oriented targets: i) understanding clearly what technology can do and can not do, plus what has already been done in the subject; ii) estimating how much assistance persons do need at a certain time or situation; and iii) finding a way to provide the right amount of help in an adaptive, reliable way, yet preserving safety and comfort.

Collaborative Autonomous Robot for Mobility ENhancement (CARMEN) has been a living work well until this book has been finished, meaning that we kept a very active profile in tests with volunteers at Fondazione Santa Lucia (FSL), a rehabilitation hospital in Rome involved, like us, in FP6 EU project SHARE-IT [150]. Even though CARMEN was not planned as an outcome of the project, initial tests with the system were promising, so we kept polishing it until the end of SHARE-it in december 2009. We were extremely lucky to count on doctors and patients to work with. However, as soon as people got involved, rather than plan, we sort of reacted to the results of the latest tests in order to solve one problem or another. Hence, rather than organizing this book into conventional chapters roughly corresponding to the targets discussed above, it is organized into chapters that correspond to this evolution: *why* decisions were made and *what* was their outcome. Some parts have been somewhat reordered for the sake of readability, though.

First, existing assistive devices are presented to set the departure point of this work. Chapter 2 covers the best known and most influential examples of robotized wheelchairs and a discussion on their operating principles from a robotic point of view. In order to outline the differences between systems in a simpler way, it

reviews Human/computer interface (HCI)s and input sensors first. It also covers most common navigation architectures, referring analogous work in robotics to solve autonomous navigation. While describing autonomous wheelchairs, we pay special attention to how control is shared between human and machine. The most relevant approaches are briefed on a table for easier consultation.

Chapter 3 focuses on collaborative control. It presents a novel approach to solve the navigation problem. At this point, the target was estimating *how* much help a person needs and providing it, so that the user exerted as much control as possible in resulting motion, but, at the same time, safety was granted and required assistance was provided. This approach was first successfully tested using a Pioneer robot in a controlled artificial environments and worked well ... up to the point we moved to the hospital. All these experiments proved, in any case, that we needed some sound benchmarking procedure, as covered in chapter 4. In this case, we first cover state-of-the-art on how to measure performance in assisted navigation, with a special effort on creating some taxonomy to find which metrics fits better our specific problem. A chosen set of metrics was used in the next set of experiments, also presented in chapter 4, in FSL. In this case, we worked with CARMEN, several volunteering inpatients and the hospital staff. We found out, though, that our approach had a drawback: persons who realized that the wheelchair was affecting their commands tended to fight help and lost driving efficiency, most likely getting stressed as well. This fact led us to develop a new algorithm based on Case Based Reasoning (CBR) to let the wheelchair adapt to how a particular person drives. This algorithm is presented in chapter 5 and was tested in simulations using data gathered in previous real experiments. As a result, we also developed a system to emulate how a specific person would drive in different environments that would be useful to check new algorithms before real tests. Afterwards, the whole system was tested again, this time in Casa Agevole, also in FSL. Results were satisfactory and they are presented in chapter 6. However, there were still some issues that could be solved in a fairly neat way because we had worked with a hierarchical navigation architecture since the very beginning. Hence, since we still had time for one extra week of experiments, we added a modulation layer to the proposed collaborative control system, as presented in chapter 7. Results were the best achieved thus far.

Chapter 8 briefs all the knowledge we gained through this work and also what we propose to do from this point on. We have tried to keep in mind what users and caregivers suggested during our experiments and also to preserve as a guideline that users should receive only as much help as they need, despite the complexity of the underlying system.

We would like to outline that CARMEN was built from a commercial wheelchair donated by *SAUER Medica* and we tried to keep modifications to a minimum (see Annex A). Our goal was to build CARMEN via a set of add-ons that would be easy to extent to other power wheelchairs, so that people interested in our system could reuse whatever vehicle they had at home. The perfect outcome would have been a plug-in system, but we had to add some specific circuitry to the motory system to avoid power surge to fry our electronics and this task can only

be carried out by a technician. Nevertheless, CARMEN has minimal modifications and, indeed, they are easy to extent to other power wheelchairs. The whole architecture employed in CARMEN (Distributed Layered Architecture (DLA)) is General Public License (GPL) license and available on the web. Collaborative control will be also Open Software very soon and we expect hardware modifications -except the commercial motory circuitry, which is commercialized by ESCLAT SL- to be public as well, now that SHARE-it is over. Also, this work has been complemented with the blog Social Assistive Robots (http://socialassistiverobots.blogspot.com) to show multimedia files and related contents.

Chapter 2
A Dummy's Guide to Assistive Navigation Devices

Those parts of the system that you can hit
with a hammer are called hardware;
those program instructions that you can
only curse at are called software.
- R. P. Brennan, Levitating Trains and Kamikaze Genes ...

Mobility assistive devices can roughly be categorized into two types: walkers and wheelchairs. Walkers are used by persons who can walk with some assistance. They are meant to give physical support and improve equilibrium. From a practical point of view, walkers imply a highly collaborative profile: if the walker tries to move in a different way than the user or he/she is not expecting it, a fall could happen. Most works on walkers [68][183][29][55] focus, consequently, on kinematics and balance and force calculation. Wheelchairs, however, are meant for persons who can not move on their own and, hence, require a less collaborative profile in a physical sense. Most works on wheelchairs used to focus on navigation. In fact, robot navigation only requires human intervention to pinpoint a goal, as any mobile robot can nowadays do all the rest. However, persons like to take part in these tasks and, indeed, it seems beneficial to give them a good share of control to avoid loss of residual capabilities and/or improve the rehabilitation process. This chapter focuses on this second kind of devices.

Assisted wheelchair navigation is not a new idea. As soon as platform navigation was solved in robotics and power wheelchairs were affordable, researchers had the idea of combining robotics and chairs into assistive wheelchairs, that had some say in what persons did with them. **SEnsor Aided Intelligent Wheelchair NAvigation System (SENARIO)** [74], **Vehicule Autonome pour Handicapes Moteurs (VAHM)** [9], **Wheelesley**, **Sistema Integral de Ayuda a la MOvilidad (SIAMO)**, **Rolland**, **Navchair**, **Smartchair** or **Spherik** are all wheelchairs based on autonomous navigation systems[4][88][191].

Unfortunately, research found some resistance in real testing. Users with disabilities were only available in large numbers in hospitals and associations and

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 19–39.
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these places had extensive regulations to state the limits of trials, including Ethical Committees. Doctors are required to control tests at all times and evaluation of experiment results was far from simple. Indeed, most work on assistive navigation devices is still in the research stage, but there are some companies that manufacture such products. KIPR[1], for example, has designed a controller that can be attached to conventional power wheelchairs in its **Tin Man** series. The Swedish company Permobil[2] also has two optional controllers, Enhanced Steering Performance (ESP) and Intelligent Control System (ICS), which can be attached to their wheelchair models **C300, C400, C500** and **K300**. Applied AI Systems[3] manufactures **TAO-7**, mostly to researchers, though, for approximately 38000 USD. Active Media Robotics[4] has also announced development of its Independence-Enhancing Wheelchair (IEW) for a similar price: 37000 USD. Smile Rehab, Ltd manufactures simpler models, Smart Wheelchair and Smart Box, for 14000 and 5000 USD, respectively. Smart Box is just an add-on to a wheelchair, like Wheelchair Pathfinder, from Nurion Industries, also for 4500 USD.

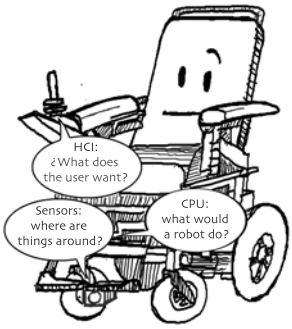

Fig. 2.1 Elements in an assistive wheelchair.

All commercial and research systems present differences, but they also share some common features: a set of sensors to perceive the environment, a HCI controller, one or more Central Processing Units (CPU) and a control software to decide what to do at a given circumstances (Fig. 2.1). This chapter basically goes through this common ground to state the different choices that robotic wheelchairs may offer. We separately cover the hardware and software modifications required in a conventional wheelchair to achieve an autonomous assistive device in the following sections.

2.1 The Art of Conversation

Autonomous wheelchair navigation operates on the same principles than mobile robotics does. Originally applied to sailing, navigation can be roughly defined as the ability to reach a destination in a safe way. This problem basically consists of answering three questions:

- Where am I
- Where are things with respect to me
- Where should I move.

[1] *http://www.kipr.org/*
[2] *http://www.permobil.com*
[3] *http://www.aai.ca/*
[4] *http://www.activrobots.com/*

These simple questions have relatively complex answers in robotics, that conform the fields of **Localization**, **Environment Modelling** and **Path Planning**, respectively, even though the first two have recently been combined into Simultaneous Localization and Mapping (SLAM) lately. In order to navigate, onboard sensors are used to detect things in the way and also to calculate the relative position of mobile, obstacles and target(s) in the environment. The CPU(s) and engines are in charge of all the rest. Unlike robots, wheelchairs tend to be assistive rather than to totally replace the user's commands. *Hence, the user's interface in these cases may be considered as an additional sensor representing the user's will.*

HCI may have a major impact on how technology is used. The key idea is that control should be as intuitive as possible or using the machine could become a problem in its own. Experience with new technology has shown that increased computerization does not guarantee improved human-machine system performance. On the contrary, poor use of technology can result in systems that are difficult to learn or to use and it even may lead to catastrophic errors [117]. This may occur because, while there are typically reductions in physical workload in these cases, mental workload has increased [187]. If edge technology interfaces are used, it is also necessary to take into account the Digital Divide: some persons are simply not ready to deal with new, strange looking gadgets. Basically, this means that complexity should be handled by the computerized device rather than by the person driving it. Unfortunately, persons with disabilities may present *mild* or even *severe* constraints to use physical devices, so interfaces may range from obvious to fairly complex input systems.

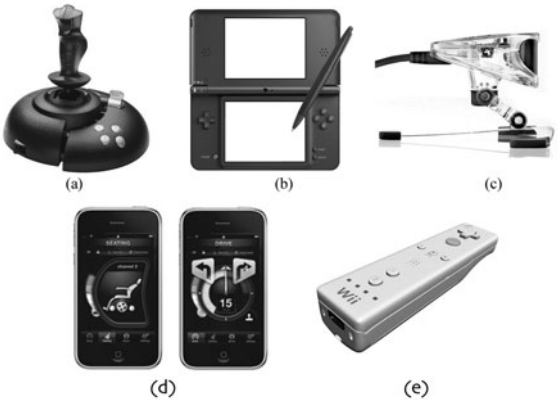

Fig. 2.2 Conventional controllers: a) MS Sidewinder FF Joystick; b) NDSi XL Touchscreen; c) TrackIR3 Pro; d) Dynamic Control iPhone App; e) WiiMote.

Most people are used to either steering wheels or handlebars to operate mobiles, usually depending on whether they have two wheels or more. Indeed, experience shows that vehicles like quads, that present a handlebar interface but, indeed, behave more like cars, might be tricky to drive at first, specially for bike users. Both interfaces, however, are somewhat uncomfortable and too big for wheelchairs. Hence, the most frequent user interfaces in wheelchairs are joysticks, which simply allow the user to direct the mobile towards a chosen direction.

Joysticks are cheap, compact and fairly intuitive, but they only provide direction information and speed is usually prequantified. In order to grant safety, force

feedback joysticks [45, 10] have also been used. These joysticks make it difficult to move towards obstacles, as they include motors to present some resistance depending on how close things are with respect to the mobile platform (Fig. 2.2a). They could also favor one or another direction in a similar way if the CPU wants to suggest some particular track. The main advantage of these devices is that HCI becomes bidirectional, meaning that the person might indeed be able to realize that his/her commands are not adequate and correct them on his/her own. Some experiments try to achieve this effect by providing either color lights [28] or sounds, but both techniques are more intrusive than haptic joysticks. In some cases, though, users might be unable to use a joystick, either due to cognitive or physical disabilities. This requires a different approach to navigation control.

Motion based joysticks like Nintendo WiiMote (Fig. 2.2e) have been used to control wheelchairs when physical disabilities make it difficult to deal with fixed joysticks [42]. These joysticks are unattached to the vehicle and, hence, can be carried in the user's preferred position. If persons can not physically use a joystick at all, some systems rely on touch screens that present a map of the environment (Fig.2.2b-d). In this case, a goal can be fixed by simply touching the desired goal [37][71][151][107]. From this point on, autonomous navigation techniques borrowed from classic robotic mobile platforms may take over to calculate and follow a path to the goal.

Fig. 2.3 Modular voice control systems for wheelchair.

There are different types of touch screens, both integrated in computers, like UltraMobile or Tablet PC, or external, either connected to a conventional PC like CINTIQ tablets or attached to a different device like iPad, iPhone, Nintendo DSi XL (Figs. 2.2b and d), etc that can connect to the PC via WiFi with costs ranging from thousands to a hundred EUR. These interfaces are fairly intuitive and easy to use, but their main drawback is that, after a destination is set, users are not supposed to do much but being transported to the goal. At best, depending on their capabilities, they can be asked to draw on the screen a preferred path (e.g. [24]) or steer right of left sometimes or, if the user is feeling like it to maneouvre the wheelchair via simple commands like "go ahead" "turn left" "turn right", etc[5].

In some cases, persons can not move at all and, hence, setting the goal via a pointing device is not possible either. Voice interfaces have been used in these situations [5], so that persons may actually tell the robot where they want to go. These devices, like joysticks, are commercially available (Fig.2.3) and, after adjusted to a given user, fairly reliable, particularly after mobile phones have included voice

[5] Dynamic Control reports they will release and iPhone app for wheelchair touch control for iPhone. Everything is better with iPhone xD.

recognition in their operating systems.[6] Technically, they are not so different from touch screens from a qualitative point of view, as, after all, the system just receives a destination. At some point, it was even believed that persons could simply control the chair via voice commands, in terms of *left*, *right*, *slow down*, *stop*, etc. Unfortunately, it has proven to be almost impossible to make frequent small adjustments to a wheelchair's velocity via voice [154]. Furthermore, a failure to recognize a voice command could cause the user to be unable to travel safely and stress tends to do that, specially if users have some disability related speech difficulty. Instead, some systems decided to make adjustments on line to modify a wheelchair trajectory, previously chosen via conventional path planning instead [132].

Some persons, though, have strong speech impairments and, consequently, can not use voice control as such. Voice in these cases can be complemented or replaced by other physical interfaces, controlled by head, feet, chin, shoulder switches, etc, which are fairly common, yet quite expensive in the field of assistive technologies. These interfaces are not as comfortable as the aforementioned ones but, in some cases, there may be no other choice for the user to exert some control on mobility. While it might be tempting to just intuitively choose one of these, given a particular case, it is extremely important to take into account ergonomics and medical factors. For example, some headtrackers might not be advisable for people with spinal cord injury, as they imply significant neck motion.

In more critical situations, even simpler, specifically designed interfaces can be used (Fig. 2.4). After studying the needs of a patient stricked by Amyotrophic Lateral Sclerosis (ALS), the Telethesis project [125], decided to use an *on/off* switch to choose an option in a screen that is continuously renovated. If mobility is completely out of question, more invasive interfaces are still an option. Eye tracking, for example, tries to estimate where the person is looking in order to move in that direction. Some eye tracking mechanisms are based on capturing video of the person's face to check for the position of the cornea, either with natural light or structured illumination [43]. Other systems, like EagleEyes, rely on electrodes to measure the Electro-Oculographic Potential (EOG), which corresponds to the angle of the eyes in the head [191, 186]. Electromiographic sensors use probes to capture muscular activity.

In extreme, technology has recently made it possible to actually control systems with the brain. This field, widely known as Brain Computer Interface (BCI), is extensive, but has offered irregular results. However, there have been successful experiments in the wheelchair field lately, most related to Electro-EncephaloGraphy (EEG), with some work on magneto-encephalography, near-infrared spectroscopy, and functional magnetic resonance imaging as well. EEG is a favorite because it is non-invasive and fairly comfortable to use. The main problem of EEG, though, is that it provides a large amount of data with a very poor signal to noise ratio, meaning that it is actually as difficult to extract patterns from captured signals as to find

[6] Leading companies in the voice recognition field include Microsoft Corporation (Microsoft Voice Command), Nuance Communications (Nuance Voice Control), Vito Technology (VITO Voice2Go), Speereo Software (Speereo Voice Translator) or MyCaption for BlackBerry, to name just a few.

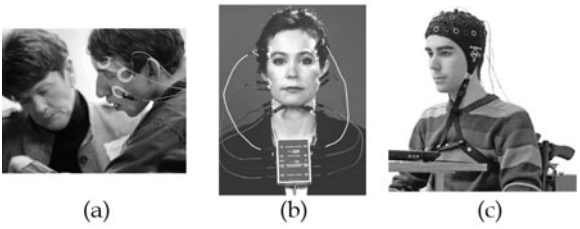

Fig. 2.4 Advanced controllers: a) Eagle Eyes system; b) electromyography; c) BCI.

the proverbial needle in a haystack. Consequently, rather than looking for very precise commands, researchers mostly quantify a reduced number of bins -sometimes labeled as *mental states*- to choose among a limited number of options [103]. A typical example is trying to move a square in a screen in any of the four dominant sides -right, left, up or down-. These commands could be translated into motion directives to the wheelchair. However, in order to fit clearly in one of these bins, the user must keep a state of continuous awareness to adequately maneuver the wheelchair. Think, for example, about juggling with several balls while following a lively conversation at the same time. Obviously, fine control here is analogous to voice-based fine control, only harder, something that could lead to excessive mental load and exhaustion. Assuming that a person can not be concentrated 24/7, some researchers found a different technique that might do the trick: rather than clustering existing signals, it is also possible to provoke a strong one and detect it. The chosen one is usually the P300 evoked potential. This natural, involuntary response of the brain to infrequent stimuli is coherent to an oddball paradigm, where a random sequence of stimuli is presented, only one of which interests the subject. Around 300ms after the target flashes, there is a positive potential peak in the EEG signal, which can be reliably detected and related to the interesting stimulus. The P300-based BCI requires no user training and only a few minutes to calibrate the detection algorithm param and has been successfully used to control a wheelchair [132].

Finally, it is interesting to note that some companies are manufacturing multimodal interfaces that combine several of the aforementioned systems, like Dufco 3420-3470. Table 2.1 briefs all commented HCI systems[7].

2.2 Tools of the Trade

Once we have told the machine what we want to do, it is up to it to actually obey or not. There are some guidelines, specially in fields related to human health, that must be respected at all times, as Asimov stated in his first law. Hence, even if someone wants to crash at full speed against a wall using a power wheelchair, the system might not allow him/her to do so. In a similar way, a path via a stair might be forbidden by a planning system.

[7] Manufacturers and prices were checked during december 2008-january 2009 and may have suffered some changes at the moment.

Table 2.1 Wheelchair HCI commercial systems

Type	Physical Skills required	Invasiveness	Control type	Manufacturers	Price range (2008/09)
Conventional joystick	Arm/hand motion	None	Command oriented	Everest & Jennings, Hoveround, Sunrise Medical	75-150 USD
Force feedback joystick	Arm/hand motion	None	Command oriented	Logitech, MS Sidewinder, Saitek	40-150 USD
Touch screen	Pointing	None	Goal oriented	CINTIQ, TERN, Honeywell, JUNG	350-1500 USD
Switches	Button pressing	None	Command oriented	ASL,	2800 USD
Voice recognition	Speaking	Low	Goal/command oriented	Kempf, Dragon NaturallySpeaking, IBM Viavoice	500-1600 USD
Head tracker	Head motion	Low-medium	Command oriented	APT Tech. Inc, Peachtree, Magitek	990 USD
Head mouse	Head motion	Low-medium	Command oriented	Smartnav, Tracker-Pro, EagleEyes	500-900 USD
Chin sensor	Head motion	Medium	Command oriented	Dynamic DX	1200 USD
Tongue switch	Tongue motion	Medium	Command oriented	Prentke Romich, Enabling devices, Newabilities Systems	100-200 USD
Breath actuator (sip & puff)	Blowing/suckling	Medium	Command oriented	Sunrise Medical, Dynamics DX, PG Omni+	1700 USD
Eye tracker	Eye motion	Low	Command oriented	ASL, Eyelink	45000 USD
EOG	Eye motion	Low-medium	Command/goal oriented	Adinstruments Inc, Biocontrol Systems	1000 USD
Electromyography	None	High	Command oriented	Cadwell, Micromed, Nihon Kohden, Oxford Ins. Med.	275 USD (per sensor)
BCI	None	Medium	Command oriented	Cyberlink/Brainfingers, Emotiv	2100-3500 USD

Depending on the chosen HCI, orders given to a wheelchair may be of two different types (See table 2.1): punctual commands -like *turn right* or *stop*- or global goals -like *reach the kitchen* or *bring me to the bathroom*. In the first case, they can be sent to the motors in a fairly straight way. In the second, they need to go through the robotic planning system to be transformed into simple commands. This second case, indeed, includes the first one and is solved via traditional robotic control architectures. Indeed, assistive power wheelchairs were originally conceived like autonomous robots that, after receiving a goal, could drive the user to his/her destination without any other human intervention. Autonomous mobiles can do that by using on-board sensors to detect how far are nearby obstacles, so that they can be avoided, and reasoning about the environment to reach their target. These issues are covered in the following subsections.

2.2.1 Sense and Sensibility

Traditionally, wheelchairs relied on range sensors to navigate (Fig. 2.5). These sensors -in decreasing order of cost, weight and range- include laser, sonar, infrared and bumpers, although cameras have been also used to measure distance either in pairs (stereovision and divergence) or via optical flow. Most range sensors basically use the Time of Flight (TOF) of an echo signal to offer their distance to the closest

obstacle in the direction of the sensor, but many of these can be rotated like a sonar in a submarine to cover a wider range of detection. Others, like cameras, provide information on a wider area, but this information is typically more complex to process. In a dynamic, potentially unstructured environment, a quick response time might be the difference between safety and collision, so in many cases, when video cameras are used, they are combined with other range sensors to achieve faster responses [99]. Furthermore, visual information is so rich that video processing has only been solved when some constraints can be applied. These restrictions usually imply some knowledge about the operation environment and a heavy specific problem-solving orientation.

Simpler range sensors also present their own drawbacks. Sonar sensors, for example, have an uncertainty angle that, in models like Polaroid, may be up to 22.5^o. Consequently, when obstacles are at a significant distance, say 4-5 m., we know how far they are, but not exactly where. Newer sensors have reduced the uncertainty angle (Table 2.2), but also the range and precision of the measurement.

Table 2.2 Commercial sonars characteristics

Company	Distance range (m.)	Uncertainty angle(°)	resolution (mm.)
Polaroid Corporation	0.26-10.7	<20	3
Siemens	0.1-6	5	10
Massa	0.1-2.5	8	100
MaxSonar-EZ1	0-6.25	10	25.4

Infrarred sensors are sensitive to natural light and their output may change sharply when there is a significant illumination change, like whenever someone is stepping in front of a window. switches on a light or opens a door. Lasers can not detect glass doors and deal poorly with black surfaces. Furthermore, all three of these sensors only detect obstacles in their own plane, so irregular objects like a table might be completely missed. Recently, though, laser sensors have become smaller, cheaper and stronger, so they have been particularly favored by the wheelchair industry[8]. An ultra low cost (30 USD) laser rangefinder was proposed in [80] and it is the main sensor of the commercial Neato XV-11 robot vacuum cleaner. Even buying the whole robot is cheaper than one of the traditional rangefinders.

We can mix together different kind of sensors to compensate each one weak points. This is the case of the Microsoft's Kinect game controller. It contains a RGB camera, a 3D infrared depth sensor[9], a multi-array microphone and a tilt sensor, all built on a motorized pivot. This sensor provides gesture, face and voice recognition at the same time, just for 150 USD. Six months after Kinect release, willow Garage offered a low-cost development robot -turtlebot- based on it.

[8] A classic SICK LMS 291-S05 laser weights 4.5 kg. and is 156 x 155 x 210 mm., whereas a modern Hokuyo URG-04LX weights 160 g. and is just 50 x 50 x 70 mm.

[9] Developed by Primesense for this purpose.

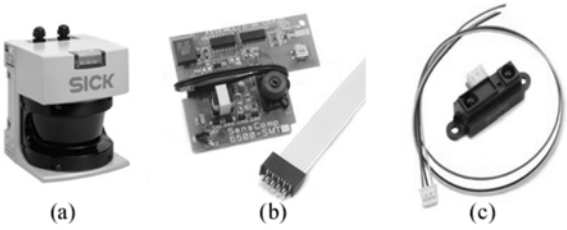

Fig. 2.5 Range sensors: a) SICK laser; b) Polaroid sonar; c) SHARP Infrared.

In any case, since all sensors have advantages and drawbacks, it is usual to work with several ones or, at least, to statistically combine the readings of a single one in time and space to obtain more reliable knowledge on the environment. If these readings are combined in a short time span within the surroundings of the robot, range sensor readings can be used to avoid close obstacles by heading it in a free direction. Readings can also be combined into a wider model of the environment to predict more efficient and safer trajectories to the goal, to combine several goals or to coordinate different mobiles [163]. In order to build global models of the environment, though, it is important to know the position of the mobile within the environment with some accuracy. Otherwise, it would be like asking directions to someone who is actually lost.

2.2.2 The X Marks the Spot

The easiest solution to the localization problem is to use dead reckoning: if we know how fast and how long we have been moving, we can estimate approximately how far we are from our original position. Alternatively, we can measure the number and length of our steps or the number of wheel turns of our vehicle to do the same. Indeed, boats used to proceed like that: their speed and direction was estimated in terms of how long a knot in a rope dropped from the bow of the vessel took to reach its back side[10] and new locations were estimated in terms of how long that speed was kept. Naturally, odometry can only work for a time, because errors tend to accumulate in an unbounded way. If no external reference is used to correct the position from time to time, after a while the vehicle is lost. One could try, for example, to precalculate the path to a spot 10m away and then try to walk there blindfolded. Chances are one would most likely end fairly far from the desired destination, specially if turns are involved, or, at worst, stuck into an unexpected obstacle. In order to avoid this problem, we could just open the eyes that, in the robot case, means we can combine different information sources using methods like Kalman filters [44] or Montecarlo techniques [99] to remove or, at least, reduce uncertainty.

Things are easier if we know the location of at least two relevant features in the environment that we can perceive at a given location. For example, boats originally relied

[10] In fact, the idea was to sing a song and write down in the bitacora in which word it had stopped. One can only hope that a crew was able to keep the rythm.

on the position of the stars and nowadays they use Global Positioning System (GPS) satellites to triangulate where they are. Mobile robots can do the same if external beacons are available (GPS, ultrasounds, wireless beacons, *etc*). Of course, active beacons might not be available; GPS, for example, can not be used indoors. If this is the case, robots can refer to known features in the environment -natural or artificial landmarks- to estimate where they are, in the same way we could check a metro station we are watching in a map to decide where we are at the moment. In these cases, cameras are typically used not as range sensors, but to detect the expected landmarks within the field of view [38][182]. A very special case among these ones is omnicameras, whose optics have been designed so that all points in the world are projected through a single center of projection. Hence, they capture 360° fields of view in a single frame and usually extract fairly reliable landmarks from the picture [99].

If cameras are not available or do not want to be used, geometric landmarks can also be detected. These landmarks are significant, distinct locations that can be detected by means of range sensors, like a corridor with two open doors at each side. This would be equivalent to try to check where we are by touching the walls if the lights go out. However, similar landmarks may exist in different areas of the environment, so it is necessary to disambiguate perceptions by keeping some track of the mobile position on accumulating several landmarks in a row via a statistic method like, say, Markov Models [1][52].

In absence of a model of the environment, it is necessary to correct the position, store detected landmarks and build a new model, all at the same time. Think, for example, of trying to draw a map of a city we have never been in by marking every distinctive building we see and trying to guess the distance and relative position between each two of them. This problem is known as SLAM. SLAM conforms a quite complex, complete field of research and it is out of the scope of this book.

2.2.3 My Map of the World

Once a mobile knows, at least approximately, where it is, it can build a map of its environment to make more efficient plans or, if available, use one available a priori. Most maps used by humans tend to be geometric, even though space seems to be understood in a different way in our heads [83]. Geometric maps have a scale and represent space in absolute terms, meaning that if we know our position in the map, we can actually calculate the physical distance to our goal even if we have never been there. In a geometrical map, everything is located with respect to a prefixed coordinate system, like the typical 0 km in capital cities. GPS maps, for example, are geometric ones.

A very common range-based geometrical map approach in mobile systems is to use occupancy grids [110]. Grids are built by dividing the environment into cells and statistically modeling the range sensor readings into a function. When a sensor detects an obstacle in a given area, we increase the probability of occupancy of all cells at the obstacle position and decrease the value of the rest of the cells within

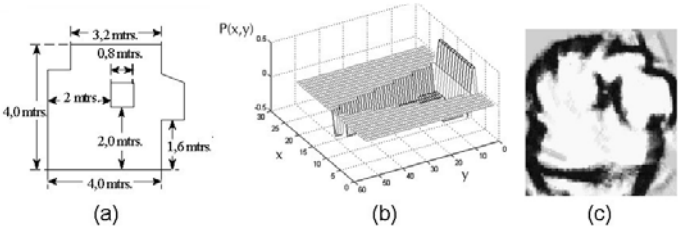

Fig. 2.6 Occupancy grids: a) room; b) local sonar grid; c) global sonar grid.

the detection range. Cells outside this range are not modified. Readings may be combined either in space to produce local grids or in time and space to produce global grids. There are several variations to this kind of spatial model, like fitting lines to walls and other relevant geometric features or representing point landmarks, but most of them require localization to be reliable in order to produce suitable representations [87].

As commented, humans seem to understand space differently. First, we do not store spatial knowledge into a single map, but into disconnected components, with little or no relation between them. Second, knowledge of routes and such may be represented asymmetrically, so that a route can be followed in one direction but not in the other [83]. In this sense, there are more compact models of the environment for robots as well, known as topological maps [100]. Topological maps represent significant locations as nodes, which are connected if there is a path free of obstacles between them. Topological maps are not so localization-dependent. Thus, space becomes a graph. Arc weights are related to the difficulty of travelling between the nodes they connect, in terms of distance, slope, obstacle density, *etc*. Nodes are inserted in these graphs via different criteria, like detecting a new distinctive input sensor instance, travelling a certain distance, discovering a specific environment structure (corner, corridor, door ...), *etc*. A typical representation of this kind are Visibility Graphs, where each node or vertex in the graph represents a point location, and each edge represents a visible connection between them [134]. Yet, there are many different approaches, like Roadmaps, where graphs are built by approximating allowed movement in the environment [89].

Topological maps seem to be more similar to human perception of space. However, when a new node is inserted into the graph, it is not obvious to know if it corresponds to a previously inserted one, due to the lack of geometrical data. Hence, they may require heavy post-processing a posteriori for dissambiguation. Furthermore, unvisited places are never included in the representation, so it is not possible to produce paths through unexplored places. To avoid this drawback, many researchers rely on topological-metrical representations, like the Semantic-Hierarchy [84], Voronoi diagrams [160], pyramids [166] and others [163] (e.g. Fig. 2.7). Top-down approaches like the Spatial Semantical Hierarchy rely on annotating topological maps with metrical information for later dissambiguation. Bottom-up

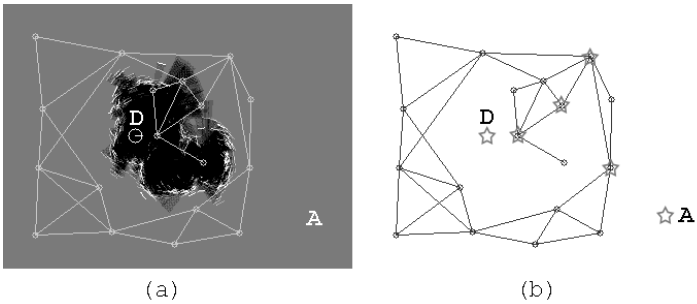

Fig. 2.7 Hybrid maps: a) geometrical map (occupancy grid); b) corresponding topological map (hybrid pyramid).

approaches like Voronoi diagrams rely instead of extracting a graph from a metrical representation via a partition algorithm. Since metric maps do include unexplored space, these approaches represent unexplored areas and, hence, allow survey navigation.

It is important to note that models of the environment are not necessarily required. Indeed, after a given sensory input is available, some processing control architectures provide suitable commands to the motors even when no space representation is available. The different approaches to this problem are described in next section.

2.2.4 Ghost in the Machine

After a robot has every tool it needs to navigate, it still requires the algorithms to do so. As programs required to work a robot became progressively more complex, systems went naturally modular. However, modules need to communicate in an organized way. Decomposition into modules and interaction among them in a robotic system is what we call its architecture. Indeed, architectures are defined by their *structure*, which is the number and nature of the modules they are composed of, and their *style*, which comprises the communication mechanism employed in their interaction [31]. Recent *styles* offer not only communication mechanisms but also abstraction layers from physical devices. The Carnegie Mellon Robot Navigation Toolkit (CARMEN)[11], Player/Stage Project[12] or the Robot Operating System (ROS)[13] offer an homogeneous communication primitives over a wide range of robots and sensors. Even though every architecture has its own particularities and, most of the times, it is heavily grounded on the problem to solve, there are general guidelines to develop one.

Early control architectures were based on the so called deliberative processing, according to the traditional Sense-Plan-Act (SPA) scheme: given a model of the

[11] http://carmen.sourceforge.net/
[12] http://playerstage.sourceforge.net/
[13] http://www.ros.org/wiki/

environment, SPA relies on classic path planning processing algorithms to calculate a safe path to the goal (Fig. 2.8 a). Only after a plan is available, the robot is able to act, always accordingly to this plan. This is basically what one does when driving by car to a new place: first, we get a road map; then, it is consulted to check for the best path to destination in terms of proximity, road quality, etc; finally, we drive though the chosen roads and check from time to time that we are in the right way. Naturally, if we get lost, it is time to stop and ask for directions to get to our original track or, if this option is unfeasible, to check where we are at the moment and look for a new path. SPA architectures would do the same, should the robot get lost from its original route: consult the model, find a new path and get moving.

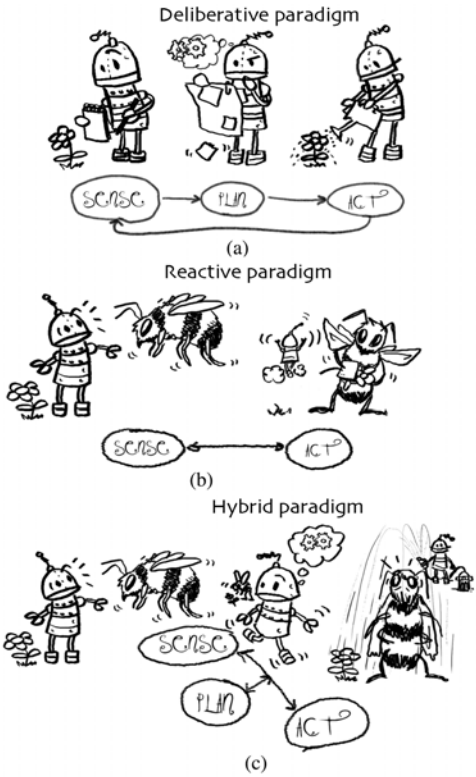

Fig. 2.8 Control architectures: a) SPA; b) reactive; c) hybrid.

In order to model the environment, any commented representation (metrical, topological or hybrid) can be used. The main features of SPA schemes are:

- a top-down hierarchical structure with well-defined functions for each level;
- predictable and deterministic control flow; and
- strong dependence on representations of the environment.

Due to these features, though, SPA control, unfortunately, presents serious drawbacks:

- all modules had to be fully functional to perform a basic test;
- a single failure provokes a collapse in global functioning;
- it has poor flexibility; and
- it can not act rapidly because information is linearly processed by every module.

One could assume that as long as a computer is fast enough to handle input data as it comes, SPA is adequate but, still, in dynamic environments responses may not be valid if the model does not adapt rapidly to changes.

In order to solve SPA drawbacks, reactive architectures like the subsumption architecture [13] tried to emulate simple low level animal behaviors to work in highly dynamic unpredictable environments. Going back to the road trip example, in this case we just get general directions and rely on road signs to move on rather than precalculating our way in a map. In most cases, it will take us longer and we might get lost once or twice, but, if there is a path to our destination, we may find it. And then, again, we might not.

The subsumption architecture is also hierarchical, but in a bottom-up way. Simple behaviors are the result of coupling sensor readings and actions. The combination of several basic behaviors running concurrently produces a complex one, known as emergent behaviors (Fig. 2.8 b). Reactive schemes

- can easily deal with several sensors and goals;
- are quite robust against sensor errors and noise; and
- may adapt to changes in hardware or tasks.

The main problem of reactive architectures is that resulting global behaviors are unpredictable and, hence, not necessarily efficient. Furthermore, reactive systems may be sensitive to local traps, as they do not have a time horizon to look for.

A later development, hybrid schemes, consisted of combining both reactive and deliberative paradigms to achieve the best possible performance (Fig 2.8 c). The hybrid style facilitates the design of efficient low level control connected to high level reasoning. Hybrid architectures typically consist of a Reactive System, a Control System and a Deliberative System for high level planning [179]. One of the best known hybrid schemes is the 3 Tiered (Three Tier (3T)) architecture [81](Fig 2.9). Three-layer architectures organize algorithms according to whether they contain: i) no state (reactive behaviors); ii) state memories about the past (sequencer); or iii) state predictions about the future (deliberative algorithms). These layers are known as skill layer, sequencing layer, and planning layer. The sequencer basically supervises behavior triggering and cooperation to achieve higher level plans, as provided by the Deliberator. The skill layer is in charge of everything else. Most current hybrid architectures are derived from a 3T scheme (*e.g.* [128][165]).

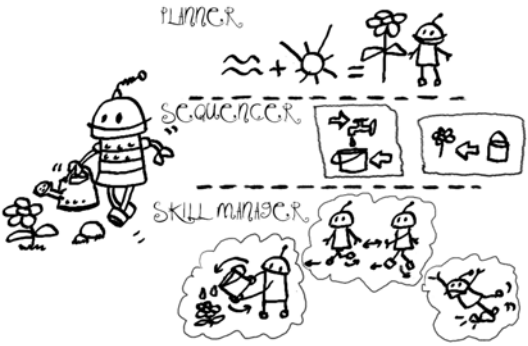

Fig. 2.9 The 3T control architecture.

2.3 Guys and Cogs

Since assistive wheelchair systems are fairly recent, most follow a hybrid scheme, where part of the system is deliberative, part is reactive and a middle one is in charge or coordinating them both, usually in a 3T like way. Indeed, autonomous wheelchairs were originally designed to behave like autonomous robots. Soon, however, it was decided that people should have as much control as possible over the wheelchair, unless there was collision risk. The main difference between existing assistive navigation approaches is, in fact, usually based on *how* control is handled from human to machine and viceversa: persons and robot control architectures are making decisions all the time, but it is necessary to decide who makes the smartest move at each situation. This is, in fact, one of the main differences between a robot wheelchair and a conventional robot, but, in fact, other robotics systems also operate like this. For example, rescue robots, exploration rovers and surgery ones are teleoperated up to a point, yet they have some autonomy to correct potential human errors or in case the wireless connection to the robot is delayed or lost. Adjustable Autonomy focuses on transferring decisions from a person one or several robot and viceversa in an adaptable, smart way without overly burdening humans [144].

Adjustable Autonomy (AA) can be applied to different fields. In the most general case, agents embedded in large organizations do not only interact with one or several persons, but also with other agents as well in what we call teamworking in the field. Most works in this complex case are related to *software* agents, associated to different persons or processes, and have mostly focused on coordination [144][26], but there are also works on teams of robots [61], which are easier to handle than people and, hence, conform a particular case of the general problem. If we simplify it even more, we may limit interaction to a single agent and a single person, where research is usually related to cost based decision theory [46]. The agent may, of course, be *physical*: typical situations include robots in a hazardous environment that need to be remotely controlled, like space or rescue missions [39][114][15]. Wheelchair assisted navigation falls within this category as well, which is widely known in the field as

shared control [79] [3] [15] [67]. There are different shared control approaches depending on *how much* autonomy is given to the user.

In safeguard navigation mode, wheelchairs are totally controlled by humans but, in some cases, the robot makes some decisions to avoid imminent danger, e.g when communication interruption and delays are frequent [81] [111] or when human control is not adequate [121] [119] [102]. Under these circumstances, either the vehicle stops or a reactive algorithm, most frequently a Dynamic Window Approach (DWA) based algorithm [54] [104], is used to avoid the upcoming danger, like in the ABS car braking system.

In other cases, control may go from person to machine and viceversa according to different criteria, usually either because the user decides so -think, for example, on automatic pilot landing- or because the machine detects a given situation -e.g. moving in a car washing tunnel-. These shared control approaches rely on using a basic set of primitive actions like `AvoidObstacle`, `FollowWall` and `PassDoorway` to assist the person in difficult maneouvres [15] [23] [67] [104] [131] [153].

In extreme, the user might just point a destination and the robot would be in charge of getting there [9] [32] [54] [116] [152]. These systems work like an autonomous robot, only in most these cases, the user may override automatic control and take over at wish [104].

The key concept in shared control is, in any case, how to detect exactly when to switch control from person to robot and viceversa. In safeguarded operation, there is a safety threshold, usually expressed in terms of obstacle proximity. In other modalities, it is up to the user to choose whether to activate a given behavior or not. The rest of the approaches trigger one or several behaviors after a given sensory instance is detected, overriding human control. In any case, it can be observed that all shared control approaches share a common feature: control is either in the hands of the user or exerted by the robot, but not by both at the same time.

The first autonomous wheelchairs, like Mr Ed [23], offered a basic set of primitives like `AvoidObstacle`, `FollowWall` and `PassDoorway`. These primitives were used to assist the driver in difficult maneuvers. This technique is mostly based on the subsumption architecture (Fig. 2.10): detected events trigger one or several behaviors, that are chosen either automatically or by the user and merged into an emergent behavior that is finally executed.

MAID (Mobile Aid for Elderly and Disabled people), NavChair [153], TinMan [104], Smartchair [131] also follow this shared control approach. The main difference among them is how behaviors are implemented. MAID, for example, relies on

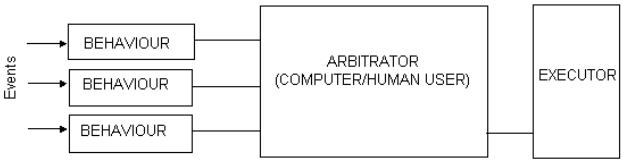

Fig. 2.10 Subsumption based architecture for full/shared control.

an occupancy grid to model free space. A prediction algorithm is used to avoid collisions with mobile obstacles using the Velocity Obstacle Approach (VOA) [155]. NavChair uses a modification of the Vector Field Histogram (VFH) [8], also based on an occupancy grid limited to an active window in front of the mobile (Fig 2.11). Each cell applies a virtual repulsive force towards the vehicle, proportional to its occupancy probability and inversely proportional to the power of 2 of its distance to the vehicle. The resultant repulsive force vector and a constant-magnitude virtual attractive force are combined into a resulting force vector, which is used to steer the wheelchair.

It is necessary to note that all these behaviors present the common feature of handling only local models of the environment, as expected from reactive systems. In these cases, the user is in charge of determining a global course of action and, hence, no global model of the environment is required. It is nevertheless interesting to observe that most modern systems also provide a fully autonomous mode, usually built by adding a deliberative layer to the underlying system, where the user simply provides a destination [152][32][116]. SENARIO [74], for example, also uses a variation of the VFH called the Active Kinematics Histogram (AKH), where kinematics are specifically regarded, but this local navigation layer is controlled by a high level planner based on a topological representation of the environment. This planner takes into account several risk assessments and even the user condition. Navchair [153] also uses VFH, but includes a new method called Stimulus Response Modeling (SRM). The system qualitatively monitors changes in the user's behavior and adapts in real-time, so that mode changes are intuitive to the user.

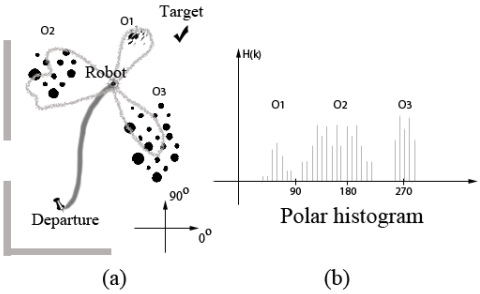

Fig. 2.11 VFH: a) geometric environment and obstacle distribution; b)polar histogram.

In some cases, it is the wheelchair who decides when to override the human and select a behavior on its own for safety reasons, either by probabilistic reasoning [153] or by suppression mechanisms [59]. VAHM [9] relies on a subsumption like architecture, where free space is represented by a set of rectangles and obstacles are defined by their boundaries. Using this model, an A* algorithm is applied to obtain a trajectory free of obstacles to the goal. At any point, the user may override automatic control and take over. Wheelesley [191] also relies on the subsumption architecture, where the deliberative level is controlled by the user via a EagleEyes interface and

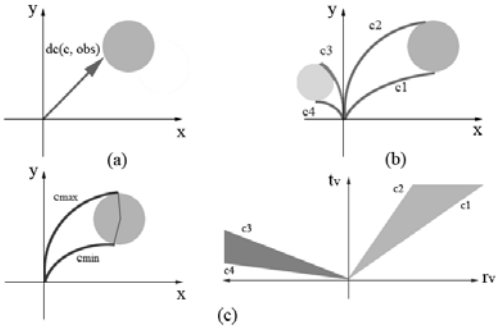

Fig. 2.12 DWA: a) obstacle distance calculation; b)tangent for obstacle and maximum and minimum curvatures c_i; c) curvature interval constraints and distances d_i within intervals.

the reactive one is a simple obstacle avoidance module. The method in [60] models the environment by means of Kuiper's Spatial Semantic Hierarchy (SSH) [84]. While high level planning is performed at topological level, where the environment is represented by a reduced set of nodes, relevant data like distances, directions, shapes, etc is preserved at geometric level.

TAO [59] uses two Charge-Coupled Device (CCD) cameras to detect the depth and size of free space in front of the robot but also to detect visual landmarks. These landmarks are stored into a topological map and the robot can reach a destination by travelling from one to another.

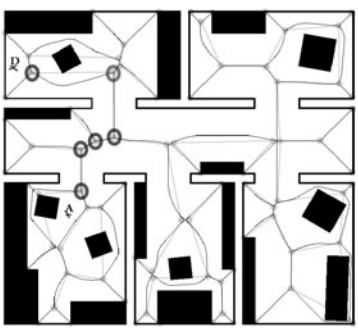

Fig. 2.13 A* based Path planning at topological level via a Voronoi topology of a geometric map.

Rolland III [99] uses a DWA based reactive algorithm [51] to solve local navigation. DWA operates in the so called velocity space, by assuming that the wheelchair always travels along a curve, whose curvature is the ratio among translation and rotation speeds. Each point in velocity space corresponds to movements of constant curvature in Cartesian space. This algorithm evaluates a cost function which minimises the distance to the goal and the length of the path to execute and maximises the distance to the obstacles along the selected path at the same time. Roughly speaking, the objective function should prefer higher speeds and curvatures that travel longer before hitting obstacles, and should try to orient the robot to head in the desired goal direction (Fig. 2.12.a-b). Geometrically, each curvature interval defines a pair of lines in velocity space, with the distance value between the lines being constant (Fig. 2.12.c). In this case, unlike in the original DWA, paths are composed of clothoids and circular arc segments to preserve curvature.

SENARIO allows the user to select desired paths from a topological diagram and, then, the system follows it. Deliberative navigation requires, as commented before, a fairly global model of the environment to reason about it according to the SPA paradigm. In this case, this model is a laser based occupancy grid from which a Voronoi diagram, a fairly common tool in robotics to reduce a path planning instance [20], is extracted (Fig. 2.13).

Similarly, SIAMO [101] relies on modelling the environment by means of Visibility Graphs processed by an A* algorithm. Paths are designed via interaction of two modules: a Potential Fields based one and a Reactive one. Resulting paths are tracked via a fuzzy control strategy.

2.4 All Together Now

In brief, after evaluating all commented systems, it can be concluded that in most cases research on robotic wheelchairs focuses either on: i) interfaces to support different types of disability; or ii) in control architectures mostly based on previous robotic research. In the second case, wheelchairs usually rely on the hybrid control paradigm, simplified in extreme to a reactive layer that is frequently designed according to the subsumption principles. Specifically, in this work we use our DLA, a GPL layered, 3T based structure where modules can be spread over one or several machines in a transparent way via shared memory/sockets communication mechanisms. This architecture is very intuitive, efficient and reliable and it has been fully described in [123].

Regarding style, most assistive wheelchairs work in shared control mode and efforts mostly focus on switching from human to machine control and viceversa. The main problem with shared control is that either person or machine are in charge of motion at a given circumstance. Hence, persons who have trouble with a skill, like crossing a door or turning a corner, never get to practice it, so they will never get a chance for rehabilitation via this assistive technology. Also, it is almost impossible to personalize offered behaviors to each individual, so they may require extra help at some situations and less in another ones. It would be desirable to develop intelligent modules capable of adapting to the specifics of each user and to the evolution of his/her condition. Next chapter focuses on this very idea.

All details on the presented evaluation of wheelchair assistive devices are briefed in table 2.3.

Table 2.3 Assistive wheelchair systems

Name	HCI	Hardware	Control type	Capabilities	Control algorithm
Mr Ed [23]	Joystick	2 bumper, 8 infrared, 2 sonar	Control switch	Avoid obstacle, pursue mobile	Subsumption like
MAID [129]			Shared control	Avoid obstacle, deliberative navigation	VOA
Navchair [153]	Joystick, voice control	12 sonar sensors	autonomous[1], shared control[2]	autonomous mode[1], follow wall[1], pass doorway[1]	VFH, SRM
TAO [59]	Keypad, joystick	2 CCD cameras, 2 processors, infrared and bumpers	Autonomous[1] Shared[2]	Autonomous navigation[1], Collision avoidance[2], Corridor navigation [2]	SLAM, topological navigation, purely reactive obstacle avoidance
Tinman [104]	Buttons, joystick	infrared, sonar and bumper	Switch[1] Safeguarded operation [2]	Turn[1], forwards[1] Collision avoidance [2]	Subsumption like architecture
VAHM [9]	joystick	infrared, sonar and bumper, IR beacons	Autonomous[1], Switching [2]	Autonomous navigation (user override)[1], wall following, door crossing [2]	3T, hybrid maps
Smartchair [131]	virtual interface, camera and projector	omnidirectional camera, laser, infrared	Switching	Avoid obstacle, follow wall, pass doorway	Subsumption like architecture
SOS [143]	Joystick, video captured arm gestures	Stereo omnidirectional system (SOS)	Safeguarded	collision avoidance	Reactive video based obstacle avoidance
SENARIO [74]	Joystick, arm gestures, voice	13 sonar, infrared, SICK laser	Autonomous[1], Safeguarded[2]	Preprogrammed topological navigation[1], collision avoidance [2]	AKH
SIAMO [101]	Joystick			collision avoidance	Potential Fields Approach (PFA) (reactive), Visibility Graphs (deliberative)
Wheelesly [191]	Joystick, buttons, eyetracker	Notebook (control) and Powerbook (interface) infrared, Hall, sonar, camera, indoors/outdoors light detector	Autonomous	Autonomous navigation	Sumsumption like
SENA [49]	Joystick, voice control	SICK laser, infrared and sonar, CCD camera	Autonomous and Shared navigation (ACHRIN)	Driver assisted autonomous motion	Top-down hierarchical planning
Parikh's wheelchair [122]	Virtual keyboard and display	SICK laser, infrared, omnidirectional camera	Autonomous, safeguarded	Avoid obstacle, autonomous navigation, deliberative navigation	Top-down hierarchical planning
Taha's wheelchair [159]	Joystick	SICK laser	Autonomous, safeguarded	Autonomous navigation (user intention prediction), deliberative navigation	Top-down hierarchical planning

Continued on next page

Name	HCI	Hardware	Control type	Capabilities	Control algorithm
Rolland [99]	Joystick	2 SICK lasers	Autonomous[1], Switch[2]	Autonomous navigation[1], turn-in-place[2], wall following[2], trajectory playback[2]	DWA (reactive), Generalized Voronoi diagram (deliberative)
Zeng's wheelchair [195]	Joystick	Barcode scanner, proximity sensor	Autonomous navigation, shared control	Avoid obstacle	Elastic Path Controller (EPC)
Xeno [136]	Head-movement interface	2 SICK laser	Shared control	Avoid obstacle	Deliberative navigation
Sevillano's wheelchair [149]	Joystick	External cameras, wireless sensor network (WSN)	Shared control	Autonomous navigation, Avoid obstacle, pass doorway	Virtual Potential Field (VPF) (Reactive), top-down hierarchical planning
Ju's wheelchair [72]	Joystick, facial recognition, head-movement interface	2 ultrasonic and 8 infrared sensors	Autonomous navigation, shared control	Avoid obstacle	
Trieu's wheelchair [162]	Head-movement interface	SICK laser	Shared control	Avoid obstacle, follow corridor and wall, pass doorway	Subsumption like architecture
Carlson's wheelchair [19]	Joystick, joy-pad	Laser, sonar, camera	Shared control	Avoid obstacle	Forward models based obstacle avoidance
Lopes' wheelchair [96]	Simulated Brain computer interface	Simulated laser	Shared control	Avoid obstacle, deliberative navigation	Vector Field Histogram+ (VFH+) (Reactive), A* (Deliberative)
IntellWheels [133]	Facial recognition, head-movement and voice interface, keyboard, joy-pad and joystick	Sonar, camera	Autonomous navigation, switching	Follow wall, pass doorway, wander, go to bedroom...	Deliberative navigation
Minguez's wheelchair [108]	Tactile screen and voice interface	SICK laser	Autonomous navigation	Avoid obstacle, turn	D* Lite planner (Deliberative), deliberative navigation

Chapter 3
From Shared Control to Collaborative Navigation

A little misunderstanding?
Galileo and the Pope
had a little misunderstanding...
- Sheldon, The Big Bang Theory

Situations where machines and persons cooperate to achieve a common goal fall within the field of shared control [3][15][79][67]. As commented, it is medically advisable to give people just the amount of help needed, and not to provide too much, so that persons keep active and practise their skills. This approach avoids, at least partially, loss of residual capabilities and minimizes stress and frustration. Shared control, in extreme, leads to human control -if the robotic wheelchair provides no assistance at all- or to conventional robot autonomous navigation, if the user only provides a destination. Ideally, though, the contribution of person and machine to control should be adjusted depending on the environment, input instance and user's state and condition.

After reviewing assistive wheelchairs in section 2.3, we observed that most approaches to shared control rely on handling control from human to machine in a more or less pre-established way. This kind of control is indeed shared, but navigation is not really cooperative in the same sense that a relay race globally depends on the speed of all racers, but collaboration is more obvious in, for example, a team row race. At this point, it seems that users might benefit from continuous contribution to control. Furthermore, there are no approaches yet in this sense that we know of, so it seems interesting to take a step in this direction.

This chapter presents a new proposal to shared control that is based on a purely reactive navigation scheme to combine user and robot inputs as seamlessly as possible. The key idea here is to rate user's performance with respect to the machine's to calculate how much help to provide at each time instant. We define collaborative control as a specific type of shared control where there are no sharp control switches between person and machine. Furthermore, humans always retain some control and are rewarded with more when they perform better, yet receive more assistance when needed.

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 41–66.
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3.1 Got Help?

Any wheelchair can be controlled via different HCI devices, depending on the user condition (see table 2.1), e.g. joysticks, pads, voice, etc [37] [71][151] [152]. Similarly, robots may produce motion commands via different navigation approaches, like PFA, AKH, VFH, etc (see chapter 2). In any case, we can assume without loss of generalization that motion can be punctually reduced, in extreme, to a vector. In essence, shared control consists of deciding which vector to use at a given situation: human's or robot's.

These vectors might be similar or not: if situations are locally evaluated, the number of choices to solve them is limited [106], so it stands to reason that both robot and human would act similarly. Persons with disabilities, though, could be unable to produce a given input command or to decide what to do at a given time instant. Besides, some situations might be solved in different ways due to driving habits or to global plans that can not be locally evaluated. If vectors are similar, it does not matter much whether we favour robot or person to decide what to do. However, when vectors are very different, it is necessary to choose one carefully, specially because we do not want to impose on the user, unless necessary.

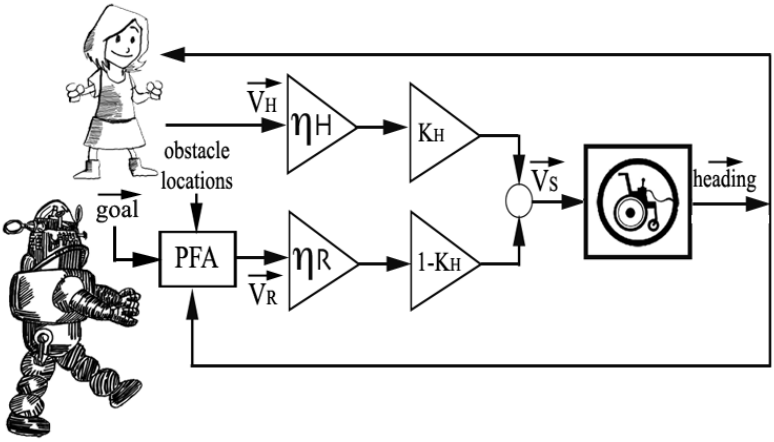


Fig. 3.1 Proposed collaborative control paradigm

There are several criteria we could use to decide which vector to use at a time in shared control mode. Optimally, the decision should be related to the person's condition. However, we already explained how difficult it is to measure the disability degree of a person with accuracy. In fact, disability would probably not affect equally every skill of a person, but rather reflect on partial aspects of driving. Furthermore, the same person may drive better or worse due to random circumstances, like tiredness or stress or just a simple cold. This leads to major subjectiveness in scoring how well a person can do, not to mention it requires continuous monitorization. It is far easier to go for a more objective criterium and simply measure *how*

well they are doing, rather than *how well they could*. Indeed, it has been stated that user's performance may provide insightful information about a person's condition [28], so we are going to evaluate that performance to estimate who has more weight in control (Fig.3.1).

3.1.1 And the Winner Is ...

There are many ways to calculate motion efficiency: shortest paths, smoother trajectories, energy consumption ... However, it is not simple to choose a winning combination. For a start, precision should not be an issue, unless we want robots to be in complete control. In fact, we should stick to features related to safety and comfort, so that the user does everything he/she can. Also, evaluated factors should be local, as we do not know a priori where the user might want to go. Furthermore, if we want to stick to hybrid architecture schemes, as most systems do, these factors should be local in an absolute sense, because assistance should start at reactive level and only reach the deliberative layer if the user has cognitive impairments and does not know where to go.

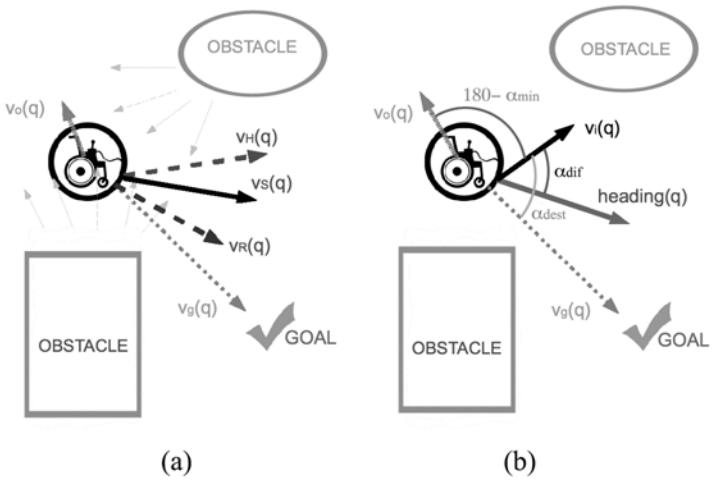


Fig. 3.2 a) Local efficiency factors for an agent i; b) vectors involved in motion command calculation.

At reactive level, global factors like trajectory length or completion time can not be used because, in fact, the trajectory is not over yet and long time memory should not be used. Consequently, efficiency η has to be measure in a punctual way. In fact, when someone asks us how he/she drives, the things we can recall better is how abrupt they are in their maneouvres and how close they got to other cars or people rather than, for example, how much fuel did they save. Initially, we identified two local factors related to these issues that have an impact on η: smoothness (η_{sm})

and safety (η_{sf}). Some rather funny experiments, though, taught us that getting to a goal within the current century was also a plus, so we added a third local factor to actually get somewhere within a reasonable time span; directness (η_{dr}).

Smoothness reflects how sharp direction changes are undesirable for driving, at least if we plan to keep on driving in a future. Safety reflects that it is better to keep away from obstacles, specially because mobile ones tend to be terribly interested in coming in our direction. Directness tries to reflect that keeping directions in average leads to shorter paths. All these factors range from 0 to 1 and our efficiency η is the average of all three. It needs to be noted that since human, robot and collaborative control commands are usually different, their respective efficiencies are different as well and calculated separately (η_H, η_R and η_C, respectively). Fig. 3.2 a shows how these factors are calculated at location q and they are calculated as follows.

Smoothness (η_{sm}) is locally evaluated as the angle between the current direction of the wheelchair and the new motion vector. This factor is included because non-holonomic mobiles can not change directions abruptly due to their kinematics. Hence, it is better to change heading as little as possible to avoid slippage and oscillations (Fig. 3.2 b). Given C_{sm}, a constant to fix how efficiency is affected by direction changes, and α_{dif}, the angle between the current direction and the command vector, η_{sm} will be:

$$\eta_{sm} = e^{-C_{sm} \cdot |\alpha_{dif}|} \tag{3.1}$$

Safety (η_{sf}) depends on the distribution of the closest obstacles at each instant with respect to the proposed command. The closer the wheelchair gets to obstacles, the less safe the trajectory is. In our implementation, the obstacle distribution is obtained from the addition of all PFA repulsion forces at the evaluated location. Assuming that C_{sf} is a constant and that α_{min} is complementary to the angle conformed by the input command and $V_o(q)$ -meaning that we want the robot to keep away from nearby obstacles- (Fig. 3.2 a), η_{sf} will be:

$$\eta_{sf} = 1 - e^{-C_{sf} \cdot |\alpha_{min} - \alpha_{dif}|} \tag{3.2}$$

The third factor, directness (η_{dr}) is locally measured in terms of the angle formed by the input command and the direction towards the next target, should there be any. Partial targets come from a deliberative path planner, as presented in [126], and correspond to the points of maximum curvature of the path it returns. This strategy means that a robot could move between partial goals safely and with minor curvature changes if no unexpected obstacles appear in the way. From the wheelchair's point of view, a partial goal would be the place of choice to change directions if there is a global plan. Otherwise, the target is calculated by averaging the wheelchair heading within a shifting time window whose size is inverse to the average curvature of the path within the window. This means that if the user is turning consistently, the window becomes small and directness may be high even though heading is changing. However, if we sway the wheelchair with no clear purpose, heading becomes inconsistent and directness decreases. In this sense, when there are no deliberative goals to reach, we just reward the skill of keeping directions.

Let C_{dr} be a constant and α_{dest} the angle between the robot heading and the direction towards the next partial goal (Fig. 3.2 b). Hence, η_{dr} is calculated as:

$$\eta_{dr} = e^{-C_{dr} \cdot |\alpha_{dest} - \alpha_{dif}|} \tag{3.3}$$

As commented, efficiency η is obtained by averaging the three aforementioned factors. Since each of the factors ranges from 0 to 1, they have equal weight in the global efficiency calculation.

$$\eta = \frac{\eta_{sm} + \eta_{sf} + \eta_{dr}}{3} \tag{3.4}$$

C_{sf}, C_{sm} and C_{dr} are set depending on how sensitive we want these three factors to be to small heading variations. In our tests, we kept them equal to a fixed value, high enough that minor heading variations are neglectable.

It needs to be noted that keeping all local efficiencies equal to 1 is not always possible. Some factors may be opposite in presence of obstacles, like keeping far from them and trying to turn as little as possible. Also, the layout of the environment may make it necessary not to head towards the goal all the time. Finally, in order to move through narrow places like doors, η_{sf} might be low sometimes. Eq. 3.4 is basically used to decide who makes the smartest move at each point, human or wheelchair, so they get awarded in terms of control.

3.1.2 A Wink and a Smile

Once η_R and η_H have been calculated, we could simply give control to the most efficient agent at each time instant or favour the person unless η_H drops under a threshold. However, any criteria to switch from one vector to another, while coherent with the shared control paradigm, present several drawbacks. The most important one is that control switches provoke jerky movements and are very noticeable to drivers, who would rather prefer to stay in control as much as possible and tend to overcompensate the machine. Also, in some situations where η_R and η_H are too similar, control may oscillate from one to another too fast or reach local minima. However, the worst is that maneouvres that persons can not do well will always be performed by the robot, so they will not improve with practise and users might even lose residual skills. Let's imagine, for example, that we are playing tennis doubles with a newbie. Ideally, we would go for balls in the left side of the court and our friend would be in charge of the right one. However, one could assume that a new player might have trouble with left shots, so we could ask him to just go for the drives and leave the rest of the court for us. However, our pal would never improve if we do not let him practise anything but the drive, plus we would be in deep trouble if our rivals make us run from one side to another. Of couse, it would be optimal if we just filled in for the most complicated balls and let him do as much as possible so

he/she can improve, but that would mean that we would be playing both at the same time, covering for each other rather than watching how each one plays by turn.

In fact, this is exactly our proposal: rather than switching control from user to robot or viceversa, we want them both to have a say in what the vehicle does at all times. To do so, it is necessary to combine their motion vectors into a single command to the motors. Our goal here is to establish a new paradigm for shared control that we will call collaborative control from now on. Its main difference to previous shared control schemes is that both person and robot have a say in whatever the vehicle does. We have specifically chosen to do this via a reactive navigation scheme because, after all, we want an emergent behavior to return from the combination of two uncorrelated, separate ones. As commented, reactive navigation is particularly adequate to deal with several sensors and goals in a simple way, so they fit perfectly to easily combine human and robot commands and goals [141][170]. The resulting system, though, is not completely reactive, as humans tend to have a deliberative agenda that they decompose naturally into joystick commands. Human influence on a reactive layer may be of help to gain global efficiency via prediction and to avoid local traps. Should the person present a cognitive disability that prevents him/her from making deliberative plans, a deliberative layer can be also added to the robot in a hybrid way. However, we have initially programmed the robot to operate only on a reactive layer [168], that can be easily hybridized later.

The proposed approach to collaborative control is quite simple: basically, human and robot produce their respective motion commands and we calculate their efficiency: η_H and η_R. The combined command to the motor will be the lineal combination of both vectors weighted by their efficiencies. Thus, the person's contribution to control will be higher or lower depending on his/her performance all the time (Fig. 3.2.b):

$$\mathbf{v}_S = \eta_R \cdot \mathbf{v}_R + \eta_H \cdot \mathbf{v}_H \tag{3.5}$$

Collaborative motion efficiency is defined as η_C. It must be noted that η_C is not equal to η_R nor equal to η_H. Since shared commands linearly combine both robot and human ones, η_C will tend to average η_R and η_H. It is fairly easy to weight these factors using biometrics or medical constraints as well [48][47], but in this case only the presented reactive factors are taken into account. Fig. 3.2.b shows how human and robot commands ($\mathbf{v}_H$ and $\mathbf{v}_R$) are combined into an emerging collaborative control command ($\mathbf{v}_S$) at location q. $\mathbf{v}_S$ is not just the average of $\mathbf{v}_H$ and $\mathbf{v}_R$. These commands are weighted by their respective efficiencies: η_H and η_R.

The proposed approach has several advantages: i) it tends to preserve curvature and to grant safety, as most PFA-based algorithms; ii) humans are in control all the time and they do not perceive sharp control swaps; and iii) humans provide deliberation to avoid local traps. Furthermore, the proposed reactive scheme is fully compatible with higher level navigation layers to achieve a hybrid shared navigation system, if necessary.

3.1.3 Eppur Si Muove

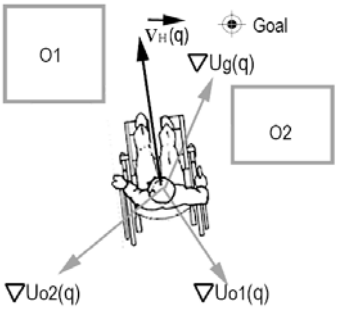


Fig. 3.3 Forces involved in collaborative control calculation at location q

Now that we have human commands and the tool to combine them with the robot output, it is necessary to choose a control algorithm for the robot, so it can provide its own vectors. Since the system is working at reactive level, it seems only fair to use a purely reactive navigation algorithm for the robot too, even though it is not strictly necessary. In our case, we go for the basics and use a pure PFA [75] for the robot for several reasons explained below. PFA is one of the best known paradigms for reactive control, based on electrostatics. It basically relies on modeling obstacles as repulsors and goals as attractors to create a vector field that returns a motion vector at each point. PFA provides a simple and efficient tool for autonomous motion that preserves smooth trajectories and works in a fast, computationally unexpensive way. Furthermore, it allows intuitive combination of several goals, which are simply included as other attractors in the field. The easiest PFA formulation simply goes like:

$$U(q) = U_g(q) + \sum U_o(q) \tag{3.6}$$

where attraction $U_g(q)$ and repulsion $U_o(q)$ are calculated as:

$$U_g(q) = k_{att} d(q, goal)^2 \tag{3.7}$$

$$U_o(q) = k_{rep} \cdot \frac{1}{d(q, obstacle)^2} \tag{3.8}$$

being k_{att} and k_{rep} constants to tune how fast we approach to the goal and how close we get to obstacles, respectively. Finally, the resulting motion vector $\mathbf{v}_R$ is equal to ∇U. All described forces, including the joystick command $\mathbf{v}_H$, are presented in Fig. 3.3.

In its simplest version, PFA has been reported to present some problems due to its purely reactive nature: i) oscillations when obstacles are too close; ii) sensibility to local traps; and iii) refusal to move safely through narrow corridors. Many of these problems may be solved by empowered versions of the purely reactive algorithm if the application domain is somewhat restricted. In fact, many assistive wheelchairs use evolved versions of PFA, mainly the *Dynamic Window Approach* (DWA) or the *Vector Field Histogram* (VFH) (table 2.3). However, we decided to use the basic PFA for a very simple reason: *to prevent the robot from having more weight than the human in the emerging motion all the time*. If the wheelchair moves too efficiently and people present physical and/or cognitive disabilities, emerging

commands are bound to be very similar to the robot ones and not to take much into account the human at all. Since our test environments include corridors, doors and narrow spaces, there will be situations that robot control will not handle well and this may evidence the importance of the person in the overall response.

The proposed approach has also been chosen because human commands can easily be added to the system equations as a second vector. Thus, it keeps all the advantages of the original one: it tends to preserve curvature and safety, as most PFA-based algorithms. Besides, it also has several extras. The most important one is that humans are in control all the time and they do not perceive sharp control switches, as there is none. Also, in absence of cognitive disabilities, humans provide deliberation to avoid local traps, as they are an uncorrelated source of commands to the system. Should this not be enough, the proposed reactive scheme is fully compatible with higher level navigation layers because it has been based on a 3T like hybrid navigation paradigm.

3.2 The *I* in Team

Fig. 3.4 Environment and robots used in experiments.

Whenever a mobile robot is going to be tested, but very particularly when someone is going to ride it, it is compulsory to check that it will not crash into whatever obstacles it may find. Laboratory tests, while not conclusive, are often enlightening and, if persons are involved in the process, in most cases, compulsory. Thus, even though the proposed scheme seemed to be fairly consistent from a computational point of view, our first tests with collaborative control were not run on a wheelchair, but with a remotely controlled Pioneer AT instead (Fig. 3.4). This robot is equipped with 8 frontal sonar sensors to get distances to surrounding obstacles. While navigating, the robot builds an occupancy grid [110] to show where obstacles are: free space is printed in black, obstacles in white and unexplored areas are presented in gray, meaning that the probability of occupation of the corresponding cells is equal to 0, 1 or 0.5, respectively. The path followed by the robot is printed in white on evidence grids. These grids, though, are simply used to graphically represent the environment from the robot point of view, but they are not used for planning at all, as our control system operates just reactively. Tests were performed using a Logitech *WingMan Attack 2* joystick to send commands to the robot from a point with direct visibility.

3.2.1 Who Is Who: A User Study

In our first experiments, as most researchers do, we basically used what we had at hand at our labs: undergraduate and PhD students, only we added some assistant professors to the lot so they would feel safer. The users' age, thus, ranged from 23 to 35 years old and had no reported disabilities. Obviously, this experiment was far from our target population (see Annex B), but one does with what one has and it was decided that it could do for an initial approach.

Tests were limited to thirteen volunteers, but prior research on collaborative control indicates that a small number of users is sufficient [50]. The sample space included people familiar and unfamiliar with robots, but just two of the volunteers actually knew about the underlying control scheme in the robot. We also made a point of having a significant group of people not yielding a driving license. Similarly, we included left handed people in the experiment. Finally, as people guided the robot using a joystick, we included individuals familiar and unfamiliar with video games as well to check if familiarity with HCI had some influence on performance. We asked all individuals to fill the questionnaire in table B.1 (Annex B), which took into account everything we could think of at the moment, which, afterwards, would unfortunately prove to be very little, but set some ideas in motion.

Users' features are presented in Table 3.1, based on data extracted from the questionnaires. It can be observed that the sample space consists of 5 men and 8 women -one man and one woman were left handed-. As commented, we purposely introduced 5 people without car driving license. It is also significant that 9 people never or rarely play video games. Finally, there were 8 people with none or little relation to robotics, as we were looking for.

Table 3.1 User descriptors.

Gender	Man	5
	Women	8
Car driving license	Yes	8
	No	5
Pulse	Not too bad	5
	Good	8
Wearing glasses	Yes	7
	No	6
Playing video games	Never	3
	Rarely	6
	Weekly	3
	Almost daily	1
Relation to robotics	None	7
	Little	1
	Enough	1
	A lot	4

3.2.2 The Name of the Game

After volunteers actually volunteered, experiments still needed to be clearly defined. During these experiments we wanted to test several things:

- if results using collaborative control were better than those using either human or robot guided trajectories alone;
- if humans managed to learn faster how to control the robot via collaborative control; and
- if they felt comfortable with this control mode.

Efficiency enhancement was easy to calculate in a quantitative way, whereas the user's opinion could just be asked. Learning, however, was a tricky thing to evaluate, but results would give some ideas afterwards.

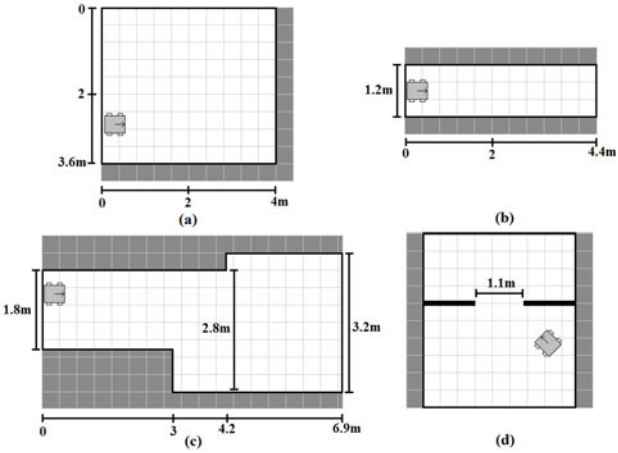


Fig. 3.5 Real environments configurations: (a) Follow wall; (b) Narrow corridor; (c) Double narrow corridor; (d) Pass door.

Volunteers were asked to drive the robot through four different environment layouts, just following qualitative guidelines, as no marks were placed anywhere during experiments. At this point, it was decided to go for the basics and cover the most usual behaviors in indoor navigation, mainly corridor and wall following and door crossing. These behaviors are well known and widely implemented through different methods, so they would do for the sake of comparison. Specifically, the proposed test environments are presented in Fig. 3.5 and, from now on, will be referred as Follow Wall (FW), Narrow corridor (NC), Double narrow corridor (DNC) and Pass door (PD). Naturally, real driving faces more complex situations than these ones, but most complex tasks in indoor navigation can be decomposed into simple tasks like wall following, corridor following or door crossing [112] [130] [94], which are exactly the behaviors implemented in our system.

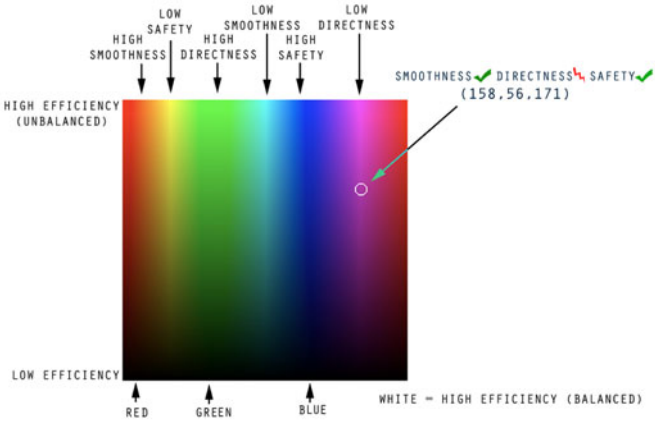


Fig. 3.6 RGB space for efficiencies.

All volunteers performed each test five times, resulting in 20 trajectories, in no particular order. We did not set the same order for all because we wanted to test if drivers starting with more complex trajectories outperformed the ones starting with easier ones or, on the contrary, they did worse. Volunteers were not informed about shared control: they were simply asked to follow guidelines like *cross that door* or *move in parallel to that wall*, as if all control was theirs. However, at some point of the tests most of them realized they were having some help with their runs.

3.2.3 All the Colors of the Rainbow

At this point, it became obvious that we would need some technique to present, at the same time, the robot 2D trajectory on the floor, global efficiency η at each point and, also, the three partial efficiencies we deal with in order to know why things happened. Fortunately, there are several color spaces with three components which, combined, give an emergent color, as we did in section 1.2 with the CMYK space. Thus, we use a graphical shortcut to easily represent global and local efficiencies at the same time over the trajectory. Graphically, each local efficiency factor is assigned to an Red-Green-Blue (RGB) color channel: red for smoothness, η_{sm}, green for directness, η_{dr}, and blue for safety, η_{sf}. Then, a 3D plot is used, where the XY plane represents the floor where the chair moves, and the Z axis corresponds to η. When the trajectory is deployed on the floor plane, it is easy to determine how good balanced local efficiency factors are on the point color. After getting used to it, this representation is quite useful, as it provides all required information at a glance. For example, a pure color area, e.g. blue, means that only the related efficiency factor, in this case safety, is preserved, whereas mixed colors, e.g. pink, mean that only the green component, i.e. directness, is low (e.g. Fig. 3.6). Bright colors mean that local efficiency values are high, whereas dark ones mean that they are low (Fig. 3.6).

3.2.4 It, Robot

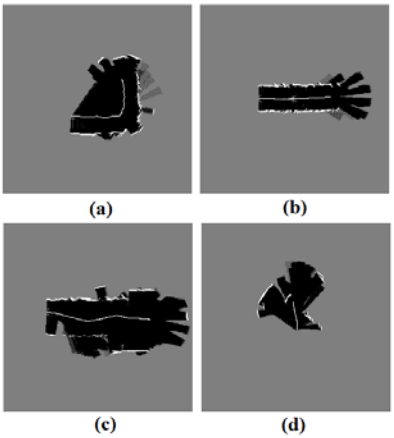


Fig. 3.7 Robot paths in environment: a) FW; b) NC; c) DNC; d) PD.

Even at this initial stage of experimentation, it became obvious that a baseline was necessary to compare results with. In this case, we chose the robot stand-alone performance as a golden standard. The requested trajectories for FW, NC, DNC and PD environments -as performed by the robot alone- are shown in Fig.3.7. As commented, the trace of the robot is overplaced in white to the evidence grid. Naturally, performance of the robot is affected by all typical problems in PFA, namely oscillations and refusal to move close to obstacles. Local minima, though, was avoided via a deliberative layer, which is described in [165].

Figs. 3.8 and 3.9 show the robot behaviour in its four trajectories in autonomous navigation mode. As commented, it may be appreciated that trajectories present typical PFA oscillations. It can also be observed in Figs. 3.8.c, 3.8.d, 3.9.c and 3.9.d that, in general, the global efficiency of the reactive control, η_R, is quite high. To be precise, average efficiencies are 74.13%, 91.90%, 80.84% and 58.84% for FW, NC, DNC and PD tests, respectively (Table 3.2). It is expectable, though, that efficiency factors depending on oscillations, like smoothness and directness to goal, punctually decrease when the agent moves close to obstacles (Figs. 3.8.c and 3.9.d). Instead, safety should be adequate depending on thresholds used by these behaviors. Its value, η_{sf}, is above 75% for all the tests, as the robot tries to avoid obstacles while moving.

Table 3.2 Statistical results of robot performance.

Test	FW	NC	DNC	PD
Average Efficiency (%)	74.13	91.90	80.84	58.84
Average η_{sm} (%)	63.44	97.24	73.69	64.54
Average η_{dr} (%)	63.57	88.59	72.02	34.84
Average η_{sf} (%)	94.83	90.00	96.84	77.09
Variance Efficiency (%)	21.89	2,79	11,81	9,01
Sum Curvature Function (°)	101.15	1.68	-1.22	2.64
Variance Curvature Function (°)	5.89	0.56	8.98	7.02

Average efficiencies presented in Table 3.2 rate the robot performance along its whole trajectory. As commented, there are situations with lower efficiency than the average. One of such situations happens in the FW test. Global efficiency decreases in average lower than 50% while turning in the corner, Zone A in Figs. 3.8.a, 3.8.c

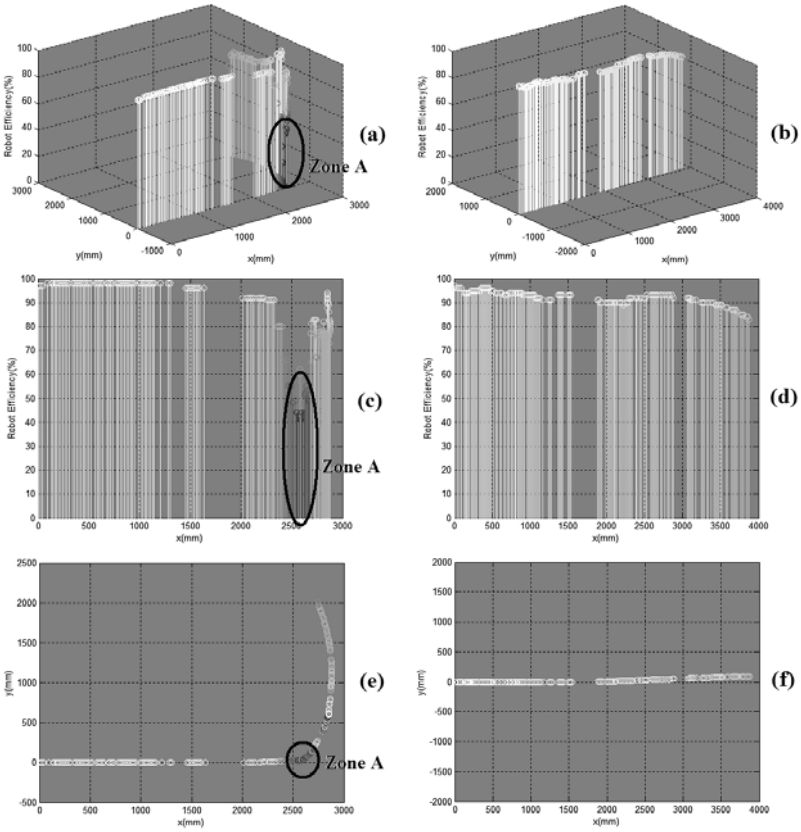


Fig. 3.8 Robot performance in FW and NC test environments: a) 3-D representation of robot efficiency in FW; b) 3-D representation of robot efficiency in NC; c) XZ projection of robot efficiency in (a); d) XZ projection of robot efficiency in (b); (e) XY projection of robot efficiency in (a); f) XY projection of robot efficiency in (b).

and 3.8.e. It belongs to a safe trajectory where smoothness and directness to goal have a low contribution to global efficiency. In fact, average smoothness and trajectory length are below 25% while average safety factor is above 95%. Table 3.2 presents, as well, the sum and the variance of the curvature function obtained from the trajectory performed by the robot alone. These values evaluate global factors on how good a given trajectory is from a qualitative point of view, no sharp turns and conservation of trajectory. For a given trajectory $y = f(x)$, its curvature function ρ is defined by:

$$\rho = \frac{\frac{d^2y}{dx^2}}{\left[1 + \left(\frac{dy}{dx}\right)^2\right]^{3/2}} \tag{3.9}$$

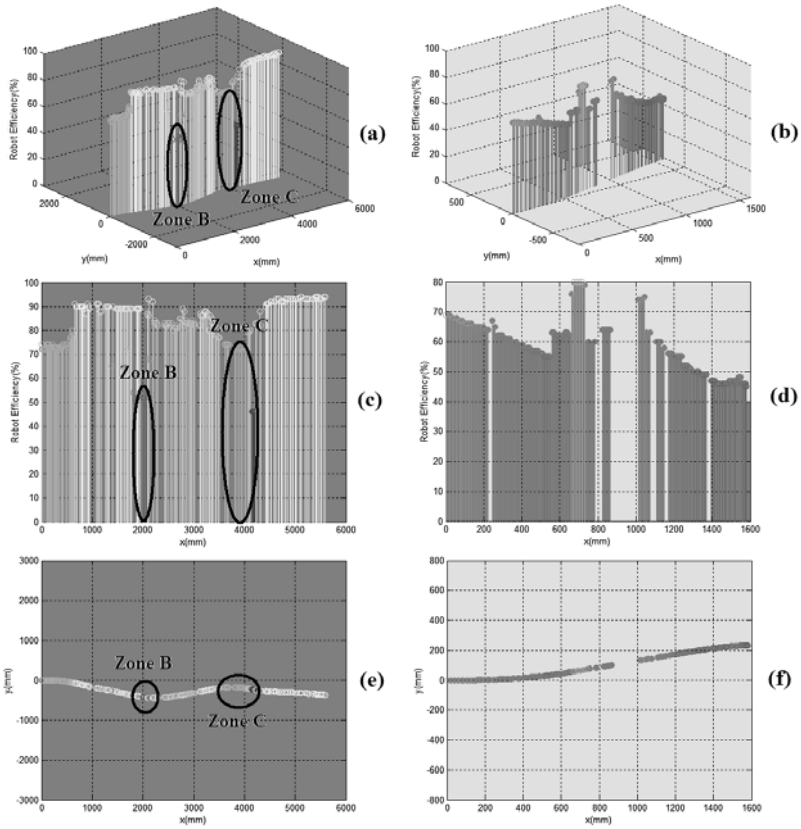


Fig. 3.9 Robot performance in DNC and PD test environments: a) 3-D representation of robot efficiency in DNC; b) 3D representation of robot efficiency in PD; (c) XZ projection of robot efficiency in (a); d) XZ projection of robot efficiency in (b); e) XY projection of robot efficiency in (a); f) XY projection of robot efficiency in (b).

being calculated as in [127]. Due to the turn in the corner (Fig. 3.8 e), the sum of the curvature function should be of 90°in the FW test. Actually, it is close to 100°, since the mobile robot oscillates after the turn, because the robot behavior, in this experiment, is based on a Potential Fields Approach. Furthermore, oscillations can also be observed in the DNC test (Fig. 3.7 c), while the robot tries to center in the corridor. These oscillations are concerned with two zones of the trajectory, Zone B and Zone C in Figs. 3.9 a, 3.9 c and 3.9 e. In both cases, global efficiency is less than 68%, that is, significantly lower than the average (80.84%). If we inspect the three factors involved, in both cases: i) trajectory is safe since average safety factor is above 91%; and ii) average smoothness and trajectory length are below 60%.

3.2.5 It ... Lives?

Whenever experiments with people were performed, collaborative control was compared to human and robotic control at each instant. Tables 3.3, 3.4 and 3.5 brief the results of collaborative performance for the 13 users. The average along the five trials is presented for each user and each experiment.

A first interesting fact is that all people involved in robotics performed similarly in all four experiments. In average, they achieved 79%, 91%, 79% and 66% collaborative efficiency in the FW, NC, DNC and PD tests, respectively. These individuals registered some differences, though, in control smoothness. We evaluated the curvature variation at each point, calculated simply as the difference between the current heading of the robot and the one commanded by the user. All users performed similarly in this aspect in NC, where the trajectory was supposed to be a straight line. There was not much variation either in their performance to move through the door (PD). However, we registered significant differences in their performance in the FW and DNC experiments, mostly because they had more freedom to decide when to start to turn the corner in FW or to correct the trajectory in DNC. It is necessary to note that, thus far, curvature was local, so it only measures reactiveness to perceived errors in desired trajectories, namely jerkiness.

Averages were good, but tended to compensate differences in the long term, specially regarding oscillations. Hence, in order to evaluate real differences in global decisions, the variance in the curvature of the complete trajectory was also measured. This factor depends on medium term guiding, meaning that the human decides to start turning earlier or later depending on his/her global perception of the environment to avoid sharp movements. These decisions are mostly influenced by the way people drive and all subjects in this case not only had a driving license, but also knew well how to drive the robot. We compared this global curvature changes to the reactive trajectories and found out that, in all cases, global smoothness is better in the aforementioned humans than in the autonomous control for the FW experiment. This was only expectable, as this environment is prone to oscillations. In the corridor tests, though, emergent curvature variations were similar to the robot or, in some cases, slightly worse, meaning that humans tried to correct their curvature all the time to keep in the middle of the corridor, whereas the system managed to reach equilibrium and not oscillate. It is interesting to note, as well, that drivers performing worse than the autonomous control system in this respect had less jerky trajectories, meaning that they kept their heading as much as possible, but had to smoothly correct it all the time. Humans outperforming the machine in these cases tended to turn sharp when needed, but did not correct their trajectories the rest of the time. Nevertheless, in this group of drivers the average collaborative efficiency of the human was better or similar to the robot in all cases. The only explanation we found to this driving likeness was that, knowing about how the robot operates, drivers suspected what it would do and purposefully or not, tried to compensate for the robot weaknesses only when necessary. Fig. 3.10 compares such a situation with an user involved in robotics and an user non-involved in it. Figs. 3.10.a and 3.10.b show the 3-D representation of η_C along the path and the trajectory, respectively,

Table 3.3 Statistical results of collaborative control performance for users 1-5.

Test	FW	NC	DNC	PD
User 1				
Average Efficiency (%)	77.93	91.53	80.51	65.18
Average η_{sm} *(%)*	68.23	92.93	74.54	54.86
Average η_{dr} *(%)*	70.01	92.26	71.00	59.06
Average η_{sf} *(%)*	95.94	88.37	95.85	81.96
Variance Efficiency (%)	15.27	3.88	12.22	7.04
Sum Curvature Function (°)	99.56	-0.13	3.32	-30.23
Variance Curvature Function (°)	5.13	0.62	8.11	8.49
User 2				
Average Efficiency (%)	80.19	91.85	77.93	66.24
Average η_{sm} *(%)*	68.49	95.33	72.31	58.24
Average η_{dr} *(%)*	77.27	92.12	65.05	58.47
Average η_{sf} *(%)*	95.10	89.17	96.25	82.32
Variance Efficiency (%)	14.70	4.82	11.23	6.94
Sum Curvature Function (°)	103.65	1.50	6.55	-27.03
Variance Curvature Function (°)	5.25	0.52	10.07	7.61
User 3				
Average Efficiency (%)	78.62	90.77	79.91	63.87
Average η_{sm} *(%)*	68.64	91.16	75.54	51.53
Average η_{dr} *(%)*	71.61	90.41	67.35	57.11
Average η_{sf} *(%)*	96.05	90.59	96.66	82.98
Variance Efficiency (%)	15.17	4.63	11.10	9.20
Sum Curvature Function (°)	100.18	3.53	5.68	-39.05
Variance Curvature Function (°)	6.77	1.08	6.89	8.88
User 4				
Average Efficiency (%)	80.86	93.81	88.37	65.41
Average η_{sm} *(%)*	70.53	96.69	85.70	63.12
Average η_{dr} *(%)*	73.85	94.48	83.09	52.11
Average η_{sf} *(%)*	98.15	90.28	96.13	80.96
Variance Efficiency (%)	16.62	2.04	6.74	5.57
Sum Curvature Function (°)	103.93	1.01	-0.67	-31.21
Variance Curvature Function (°)	6.08	0.25	4.96	9.21
User 5				
Average Efficiency (%)	75.19	90.12	77.21	61.66
Average η_{sm} *(%)*	63.50	92.00	68.23	46.65
Average η_{dr} *(%)*	64.51	87.97	66.43	51.79
Average η_{sf} *(%)*	97.75	90.28	96.87	86.61
Variance Efficiency (%)	17.25	5.65	12.13	11.18
Sum Curvature Function (°)	102.23	1.97	4.93	-31.05
Variance Curvature Function (°)	6.56	1.37	8.39	12.35

Table 3.4 Statistical results of collaborative control performance for users 6-9.

Test	FW	NC	DNC	PD
User 6				
Average Efficiency (%)	80.61	89.14	72.96	58.74
Average η_{sm} *(%)*	70.48	90.80	61.63	45.26
Average η_{dr} *(%)*	75.08	87.93	60.71	49.45
Average η_{sf} *(%)*	96.42	88.83	96.35	81.45
Variance Efficiency (%)	15.84	8.21	16.16	9.90
Sum Curvature Function (°)	97.47	4.36	3.64	-24.75
Variance Curvature Function (°)	5.96	2.24	8.16	10.63
User 7				
Average Efficiency (%)	71.28	92.29	79.41	61.34
Average η_{sm} *(%)*	65.91	96.28	73.51	50.39
Average η_{dr} *(%)*	61.03	89.33	69.37	50.08
Average η_{sf} *(%)*	87.15	90.72	95.36	83.75
Variance Efficiency (%)	16.48	4.06	11.67	8.40
Sum Curvature Function (°)	105.27	0.52	5.00	-25.74
Variance Curvature Function (°)	8.65	1.84	9.34	11.87
User 8				
Average Efficiency (%)	79.77	92.63	77.40	65.18
Average η_{sm} *(%)*	66.95	95.62	67.60	53.17
Average η_{dr} *(%)*	74.50	93.87	67.27	61.57
Average η_{sf} *(%)*	97.63	88.35	96.66	80.93
Variance Efficiency (%)	16.14	2.21	13.34	8.45
Sum Curvature Function (°)	97.50	3.71	2.67	-37.46
Variance Curvature Function (°)	5.61	0.61	9.41	10.92
User 9				
Average Efficiency (%)	79.25	91.29	78.04	66.43
Average η_{sm} *(%)*	66.85	92.38	69.29	53.32
Average η_{dr} *(%)*	72.41	91.21	67.94	57.07
Average η_{sf} *(%)*	98.34	89.90	96.90	88.86
Variance Efficiency (%)	15.42	8.30	11.56	8.21
Sum Curvature Function (°)	94.22	1.35	5.18	-34.12
Variance Curvature Function (°)	5.04	0.38	9.07	9.59

in the DNC test for an user involved in robotics. Figs. 3.10 c and 3.10 d present the same graphics for an user non-involved in robotics.

The person involved in robotics turned sharp at the beginning of the trial to centre the robot in the corridor. Once the robot was centered, this trajectory was not corrected, since the user applied her experience in the field to compensate only when necessary.

The user non-involved in robotics tried to centre the robot in the corridor in a smoother way. However, the user had to correct the trajectory, since he had not taken into account the robot kinematics. Average collaborative efficiency for the user involved in robotics was 80.4%, similar to the robot alone (80.84%), while the

Table 3.5 Statistical results of collaborative control performance for users 10-13.

Test	FW	NC	DNC	PD
User 10				
Average Efficiency (%)	75.45	88.33	79.62	68.71
Average η_{sm} *(%)*	64.34	89.25	73.22	60.43
Average η_{dr} *(%)*	64.48	88.01	68.77	59.11
Average η_{sf} *(%)*	97.60	87.89	96.71	86.55
Variance Efficiency (%)	18.33	14.83	12.79	6.96
Sum Curvature Function (°)	95.92	1.68	3.78	-30.63
Variance Curvature Function (°)	5.79	0.55	8.40	8.53
User 11				
Average Efficiency (%)	78.33	91.46	76.67	56.88
Average η_{sm} *(%)*	67.11	93.22	66.92	43.53
Average η_{dr} *(%)*	71.11	96.76	65.85	43.13
Average η_{sf} *(%)*	96.76	89.21	97.04	83.79
Variance Efficiency (%)	14.70	4.61	13.04	9.06
Sum Curvature Function (°)	100.96	2.14	7.47	-9.26
Variance Curvature Function (°)	9.13	0.57	9.16	11.77
User 12				
Average Efficiency (%)	79.06	89.45	76.54	71.58
Average η_{sm} *(%)*	70.15	90.79	66.27	62.28
Average η_{dr} *(%)*	70.82	86.95	66.69	66.71
Average η_{sf} *(%)*	96.47	90.03	96.65	85.92
Variance Efficiency (%)	18.06	6.64	12.41	9.35
Sum Curvature Function (°)	100.37	1.85	4.65	-12.75
Variance Curvature Function (°)	7.03	0.63	9.78	6.21
User 13				
Average Efficiency (%)	80.57	92.87	78.58	61.46
Average η_{sm} *(%)*	70.38	95.09	70.39	46.11
Average η_{dr} *(%)*	74.48	93.34	68.95	50.78
Average η_{sf} *(%)*	97.35	89.71	96.39	87.29
Variance Efficiency (%)	16.68	3.41	12.10	11.25
Sum Curvature Function (°)	96.26	1.92	3.90	-26.72
Variance Curvature Function (°)	6.02	0.50	10.67	11.25

same average collaborative efficiency was slightly worse for the user non-involved in robotics (77.5%). The non too large difference is justified by a larger amount of assistance provided by collaborative control, as expected. Collaboration is even noticeable for users with experience in robotics, because sometimes they overestimated their skills and needed correction.

It must be noted that efficiency is better at the beginning of the trajectory in Fig. 3.10.a (Zone D), than in Fig. 3.10.c (Zone E). Furthermore, the average efficiency in this area is 75.1% for the user involved in robotics, while it is only 66.7% for the non-involved one. Even more, the efficiency yields a smoothness (η_{sm}) of 67.9% and 49.5%, respectively. Thus, the person who knows about the performance of the

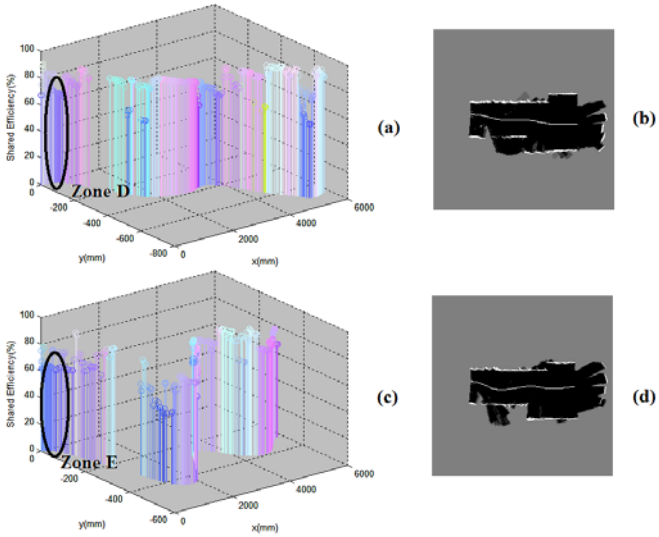


Fig. 3.10 Person involved in robotics: a) 3-D representation of collaborative efficiency in DNC; b) trajectory. Person non-involved in robotics: c) 3-D representation of collaborative efficiency in DNC; (d) trajectory.

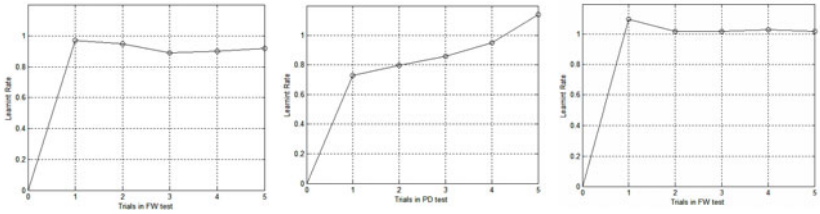
robot alone leads to a smoother trajectory even when he/she has turned sharp at the beginning. On the other hand, the user non-involved in robotics tries to drive through a smooth path. However, control applied by the robot decreases the efficiency at the beginning, with a lower smooth factor.

To evaluate the learning process during a test, we define Learning Rate (LR). It defines the relation between average efficiencies of human motion commands and robot motion commands through the whole trajectory, to estimate the percentage of control exerted by both the human and the robot:

$$LR = \frac{Average(\eta_H)}{Average(\eta_R)} \tag{3.10}$$

Fig. 3.11a shows the learning rate of an user involved in robotics along the five trials of the FW test. LR ranges from 0.89 to 0.97. The highest learning rate occurs at the first trial. Furthermore, there are not significant differences among the five trials since LR presents a nearly constant value. Such a situation points out that the user knows how the robot operates from the first to the last trial. Thus, as expected, the learning process is not noticeable, since the user takes into account collaborative performance from the beginning.

On a second instance, we also observed that people not having a driving license and not fond of video games who were not related to robots either tended to perform better than the rest, specially regarding adaptation, presenting a neat learning curve. We believe that they were more careful in their driving and, even though they



(a) FW test. **(b)** PD test. **(c)** NC test.

Fig. 3.11 Learning rate in: (a) FW, (b) PD and (c) NC tests

typically drove slower, they made sure to keep to the premises of the experiment as tight as possible. In average, this group of people achieved a 80%, 90%, 79% and 65% collaborative efficiency for the FW, NC, DNC and PD tests, respectively. These results may seem to be very similar to the experienced group of users, but there is a significant difference in their learning curves.

Also, in one of the individuals, the average collaborative efficiency of the human was above the machine all the time (80.8%, 93.8%, 88.4% and 65.4% in the FW, NC, DNC and PD tests, respectively). In no other case we detected something like this. The rest of the individuals did in this respect very much like the rest, averaging above the machine in the FW and PD experiments and slightly worse in the corridors as usual. Although users felt comfortable with the system, some of them qualitatively realized that the machine exerted a certain degree of control over the global performance in the FW and PD tests, but did not feel this control in the NC and DNC experiments.

Fig. 3.12 shows a trial in the FW test where the user feels the machine is partially controlling the system. When this user was performing the FW experiment, he noticed the robot was partially controlling the movement. This situation happened while turning in the corner (Zone F) in Fig. 3.12a. In this test, the user was not experienced with the system, since it tried to approach too much to the wall before turning (Fig. 3.12b), with an average joystick command efficiency of less than 38%. In such a context, the robot performs its behavior on its own, following the wall at a predefined distance, with an average reactive efficiency of 50%. Hence, collaborative efficiency is about 44%, where reactive commands have a higher weight. Although the robot moves far enough from obstacles, the user does not perform the task correctly, because he/she should have moved the robot not so close to the wall, but have driven the agent at a larger predefined distance. Furthermore, the users feel the system is helping them specially in the FW and PD tests, while actually this help is larger while centering in a corridor (NC and DNC tests).

Thirdly, we compared the performance of people used to video games not having a driving license and viceversa and concluded that video gamers performed slightly better in average, specifically because global curvature was better preserved by this group. We believe that this is mostly influenced by the robot interface -a joystick- and because people were not actually mounted on the robot, but guiding it from a

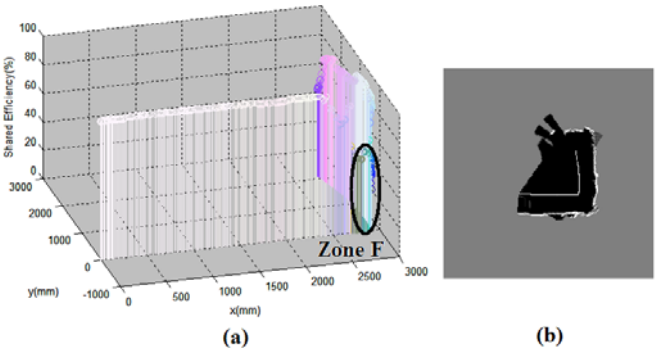


Fig. 3.12 User perceives machine assistance: a) 3-D representation of collaborative efficiency in FW test; b) trajectory.

distance. In order to extract a more reliable conclusion to this respect, we would need to perform a similar experiment on a robotized car or wheelchair and/or to change the interface to a driving wheel.

Regarding the order of the different experiments, the most obvious observation was that people starting with simpler experiments like FW or NC performed better in the hardest one (PD) in terms of curvature and efficiency from the very first try than those starting with DNC or PD. In this sense, Fig. 3.11b shows the learning process of an user in the PD test. This user started with the simplest experiments (FW, then NC), followed by the DNC test. The last experiment was the hardest one (PD). Fig. 3.11b graphically represent the learning rate of the user along the five trials of this PD test.

It can be appreciated in Fig. 3.11b that the first trial LR is 0.73, rising as the user performs more trials till a LR of 1.14 in the fifth trial. It must be noted that LR increases from first to last trial, meaning that the user is learning. Indeed, in the last trial the user is even more efficient than the robot (LR=1.14). Hence, the user exerts more control of the mobile than the robot, thanks to the learning process the human has experienced from the first trial in the FW test to the last trial in the PD experiment.

When a user starts with one of the simplest experiments (FW and NC tests), the situation is different. Fig. 3.11c shows the learning process in the NC test for an user starting with the hardest experiment (PD test), followed by the FW and DNC tests. LR ranges from 1.02 to 1.10. The largest LR (1.10) occurs at the first trial, yielding a constant rate along the last four trials. It must be pointed out that i) the user exerts more control of the mobile than the robot in the five trials of the experiment; and ii) the learning process does not exist in this trial, since LR yields an approximately constant value. Due to the previous learning process while performing the most difficult tests, the user has learnt about the peculiarities of the robot and the collaborative control. Thus, in this test, the user has a higher percentage of control in the system than the robot.

Finally, we did not observe major differences from an efficiency point of view between left and right handed people that participate in the experiments, except in the FW tests, which seemed to be easier for right handed people. Fig. 3.13 presents the trajectory followed in the FW test for a left handed (Fig. 3.13a) and a right handed (Fig. 3.13b) user. Since the joystick is adapted for right handed people, Fig. 3.13a shows the problems that left handed people are faced up to in the FW test. Firstly, they have difficulties to maintain the robot parallel to the right wall, whereas right handed people do not face this problem. Secondly, the left turn in the corner is not performed as correctly for left handed people than it is realized for right handed people. And finally, as presented in the trajectory of Fig. 3.13a, they do not move the robot at a predefined distance, while right handed people do, even after turning in the corner (Fig. 3.13b). From a subjective point of view, left handed people seemed to be forced through the FW test. However, all of right handed people seemed to be comfortable while doing this test. Furthermore, left handed people qualitatively stated their problems in this tests, but none of the right handed people expressed any difficulty.

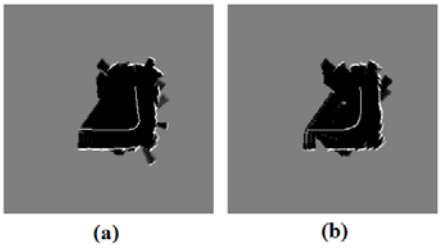


Fig. 3.13 Trajectory followed by the mobile robot in the FW test: (a) left handed user; (b) right handed user.

Although combination of both human and robot control commands is a positive feature in our collaborative control system, there are situations where this approach could not be valid because of an impending danger. Such a situation appeared when an user moved to close to the wall while turning in the FW test. However, the system can deal with this problem. The user qualitatively said that the robot did not pay attention to his/her joystick orders. This was true since he/she was not performing correctly the task in this test, highly decreasing his/her efficiency at this point of the trajectory. Thus, collaborative control gives more control to the robot commands that human ones. Since robot commands provides a safe behavior due to repulsion forces, the impending danger situation is overcome.

During the experiments some failures where observed. When the robot performed the four trajectories alone, it did not become stuck, even in the PD test where it oscillated in front of the door. When experiments with users were performed, some failures occurred in collaborative control mode. All of these situations appeared in the PD test. Actually, there were 7 collisions, all of them by users unfamiliar with robots. If we remember that tests were performed by thirteen users and that each test was carried out five times, 7 failures means just a 10% in the PD test and a 2.7% for the whole four tests. It must be pointed out that failures were made by 6 users. This implies that all of them made one failure and one user made two failures. It must also be noticed that all of the one-failure users' failed in the first trial of the test, while the two-failure user consecutively failed in the first two trials. Failures are due to their lack of experience in robotics. However, those users learnt how to

perform the task in the PD test after their failures. Furthermore, if the robot tends to collide because of the user's driving, in general, trajectories are corrected by the system, allowing the user to have more time to react to that situation.

3.3 Innocent Bystanders

At this point, it seemed that we had a solid new approach to shared control and that it was actually safe to test it with disabled persons. As commented, the key idea of the proposal was to measure η_H and η_R at each time instant and use them to weight human and robot commands and add them into a single motor one, which tends to be more similar to the most efficient one, but does not neglect the other. Punctually, this might not seem much, but continuous combination of these commands returns an emergent behavior that does not match exactly the robot nor human standalone performance, but tends to combine their advantages in a seamless way. All in all, results had been quite successful. Even though users were not informed about the existence of collaborative robot, their efficiencies improved with assistance and their overall performance tended to equalize with respect to each other, despite their backgrounds. At some point, they eventually realized they shared control with the machine, but most were not able to say exactly when they had more help.

Of course, this new system had only been tested with our 13 volunteers, which, as varied as we tried to get them, were fairly young and healthy. Furthermore, rather than a wheelchair, we had just used a teleoperated Pioneer AT robot in the four different scenarios presented. The next step was, of course, to move to persons with disabilities. We had the most important thing: doctors in FSL, would work with us and provide volunteers. We just had to fit the hospital protocol, but this is easier said than done.

The first question any hospital would make to an experiment proposal turned out to be: is your wheelchair standard-compliant? In fact, we did not have a wheelchair yet, and robotized commercial models were a bit expensive and had to be imported. Building one from scratch was out of the question, so the most obvious solution was to just modify a commercial power wheelchair. Thus, it would be standard-compliant from a mechanical point of view. Indeed, we just redirected the wheelchair joystick commands to an industrial PC and then back into the motory system of a Meyra Runner wheelchair[1] and added a Hokuyo laser to sense the environment, that was also fed to the onboard PC. Our algorithms would simply modify the input to the motors in collaborative control mode, as we did with the Pioneer robot. Adding encoders to the wheels was a bit trickier, as voltage peaks during motor operation tended to fry all circuitry. However, we managed to purchase a commercial system from ESCLATEC that fixed the problem for us. We will refer to this wheelchair from now on as CARMEN (Fig. 3.14).

Now, we had a wheelchair we could happily test with people, but there was a new objection yet: are your experiments ethical? This question, in fact, can not be answered lightly. For a start, research activities supported by the Framework

[1] This wheelchair was donated by Sauer Medica. See further detail in Annex A.

Fig. 3.14 CARMEN: modified Meyra wheelchair

Programme should respect fundamental ethical principles including the *Charter of Fundamental Rights of the European Union* and the opinions of the European Group on Ethics (EGE) in Science and New Technologies. This problem was already addressed in 2002 by the Science and Society Action Plan of the European Commission:

> The rapid pace of scientific and technological progress can give rise to serious ethical questions of concern to all Europeans. These questions may also have potential implications for future generations.

For a start, we learnt that explicit informed consent is required whenever research involves volunteers in interviews, behavioural observation, invasive and non-invasive experimentation, and accessing personal data records. Information should be clear enough on the purpose, procedures and outcomes of the research to let the individual make a voluntary informed decision about whether or not to participate in the research, and alternatives, risks, and benefits needed to be stated in a way they understand. Also, every person has the right to withdraw consent at any time and, if requested, associated data has to be destroyed. Furthermore, special consideration must be given when volunteers have reduced autonomy or are vulnerable, as was our case. FSL staff decided which users had a cognitive disability severe enough so that their informed consent had to be signed by family. Regarding privacy, research volunteers have the right to remain anonymous and we had to comply Data Protection legislation, plus we had to be careful with the manner in which research outcomes would be reported.

Still, this was only the beginning. Apparently, any experiment has to explicitly address ethical concerns in three aspects[137]: i) the research; ii) its conduct (volunteers in tests); and iii) its outcomes (final users). While we had already taken care of the first aspect, the conduct of research had to issue i) collection of evidence from target group; ii) testing protocols; and iii) definition of quality of life; and the outcome of research includes i) right to privacy and autonomy with respect to tracking and monitoring; ii) handling of associated medical data; and iii) potential misuse of application.

At the time, we had no previous experience with Ethical issues, but, fortunately, FSL has an Ethical Committee that helped us around. We only needed to deal with the research conduct, so we were asked to write down a test proposal and submit it to the Ethical Committee for approval. This document needed to be validated by the medical staff first and it was stated that the following sections had to be included:

- Experiment Definition
- Goals
- Experimental Design
- Description of the System
- Variables
- Experimental Unit
- Expected Results

This may look easy enough to write, but it must be noticed that every aspect of the experiment needs to be specified a priori, including the number and type of persons to work with and every algorithm involved in the process. After the document is approved by the Ethical Committee, no changes can be made, so any unexpected situation during tests would imply to start the whole process again. Despite the obvious loss of time, this may seem just like a minor drawback for engineers, but it requires doctors to run anew all volunteer protocols, because their condition changes in time. This implies getting new consents and running a new set of tests/questionnaires to quantify their degree of disability and their state. Furthermore, if it takes too long to get approval for these new patients, they are likely to leave the hospital and, hence, tests must be run again. For these reasons, it was decided to work with inpatients, who are expected to stay in the hospital for a while, but, in any case, sending back a proposal to the Ethical Committee takes too long to work with the same persons, so, basically, everything needs to be taken into account a priori.

Tests, of course, have to be set during the person's day schedule and, hence, fit their routine. A doctor must be present during the whole duration of the experiment and, consequently, can not do any other work at the time. Consequently, experiments must be well timed to avoid inpatients getting excessively tired nor to abuse too much of the medical staff. Again, as the whole process may take more than a day, it is advisable to work with inpatients rather than with non resident ones. All in all, we felt like we were in one of those TV interviews that takes the whole morning to film for a 20 seconds time slot in the news.

After realizing how much it would take to repeat a test for any missing data, we decided that it would be better safe than sorry: we needed to know *a priori*

how much information was to be extracted from the experiments as exhaustively as possible. As non-experts in this particular field, our best choice was to check what others look for so that we would not forget anything. Next chapter focuses precisely on this: the preliminary study on metrics to apply to the experiments and the tests themselves.

Chapter 4
Bigger, Faster, Better, More!

I know, I know. It's a Russian thing.
When we're about to do something stupid,
we like to catalog the full extent
of our stupidity for future reference.
- S. Ivanova, Babylon-5

And just when everything seems to be going so well, someone always asks, -*so, what is so special about your system?*-. For scientists, a simple *it works* does not seem enough, so -sooner or later- everyone stomps into the field of metrics . Inventing some metrics of your own, while obviously appealing, will just not do. Since words might do you no good either, this is the point where standards come handy. The key idea here is that we are good as long as our system behaves better than previous, similar ones in at least a few in quantifiable aspects.

When one starts to look for standard standards in the wheelchair navigation field, bad news come first: there seems to be no established way to measure wheelchair performance -specially regarding power wheelchair navigation and, more specifically, shared control-. Fortunately, there is a large number of proposals that more or less agree in terms of parameters of interest for assisted navigation (e.g. [185]).

Assisted wheelchair navigation is a field where many other fields converge, from cognitive sciences to medicine, and all the way through engineering. Consequently, trying to fit all related metrics into the same bin would be like trying to explain feelings with differential equations. Instead of doing so, we propose a tentative distinction between different categories, that might be more or less correlated, but are easier to explain in separate subsections: i) *user's condition*; ii) *obstacle courses*; iii-iv) task and psych metrics [24]; and v) usability.

4.1 How Am I Driving?

Metrics conform a field of study on their own. It includes the measurement of knowledge, abilities, attitudes, and personality traits. The field is primarily concerned with the study of measurement instruments such as questionnaires and tests: it

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 67–92.
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involves two major research tasks: i) the construction of instruments and procedures for measurement; and ii) the development and refinement of theoretical approaches to measurement. No established metric taxonomy has been found on wheelchairs so far, but, as commented, there are several solid proposals in some specific areas to benchmarking and evaluation in the field [172]. This section covers the different areas where these metrics exist.

4.1.1 Is There a Doctor in the House?

First things first, before making anyone drive a prototype, it is important to know about his/her condition. Of course, the doctor is the main source of information, but in order to process results afterwards, some index is always useful. The goal is to obtain a quantified estimation of a disability aspect.

The first problem to measure disability is to know exactly what disability is[1]. Disability is technically defined as a lack of ability relative to a personal or group standard or norm. It may involve physical, sensory, cognitive or intellectual impairment, mental disorder and/or various types of chronic disease. Disability involves an adaptive process, which depends on a host of psychosocial and environmental factors [118]. Operatively we can define this complex state as Function disability (FD): the result of the interaction of different individual components of compromised functions. Physical, emotional, and cognitive aspects usually interact to produce a comprehensive disability which is more than the simple addition of the single impairments, affecting the inpatient's global function and his self-dependency [70].

In order to simplify, we can define disability as the degree of difficulty or inability to independently perform basic ADLs [139][90] or other tasks essential for independent living without assistance[2]. We need to remember, though, that disability is not an attribute that is clearly present or absent, but rather a matter of degree.

One of the best ways to obtain global information about patient needs is represented by the multi-dimensional approach and, in particular, in case of elderly patients the most common approach is the Comprehensive Geriatric Assessment (CGA). The CGA is a multidimensional process designed to assess an elderly person's functional ability, physical health, cognitive and mental health, and socio-environmental situation. The multidimensional process differs from a standard medical evaluation by:

- including non-medical domains,
- emphasizing functional ability and quality of life, and
- relying on interdisciplinary teams

All this information is gathered by the MultiDimensional Evaluation (MDE), based on a set of standardized evaluation scales (see Annex B) largely accepted and used

[1] This subsection has been written in cooperation with PhD MD Roberta Annicchiaricco, from FSL. Without her work and supervision, the medical part of this work would have been impossible.

[2] This definition suits the medical model in International Classification of Functioning, Disability and Health (ICF), produced by the World Health Organization (WHO), 2001.

by international teams for clinical, care, and research purposes. It includes different disability scales to evaluate the cognitive and physical state and condition of individuals.

The Mini-Mental State Examination (MMSE) or Folstein test [33] is a brief 30-point questionnaire test that provides a quantitative measure of cognitive status in adults. Any score over 27 (out of **30**) is effectively normal, event though it changes depending on age and education. Below this, **20-26** indicates mild dementia; **10-19** moderate dementia, and **below 10** severe dementia. It can be used to screen for cognitive impairment, to estimate the severity of cognitive impairment at a given point in time, to follow the course of cognitive changes in a individual over time, and to document an individual's response to treatment. In the time span of about 10 minutes, it samples various functions, including arithmetic, memory and orientation.

Instrumental Activities of Daily Living (IADL), also called Lawton's scale, was developed by Lawton and Brody [90] and it is based on a questionnaire to evaluate the capacity of the subject to perform daily tasks ruled by cognitive functions (judgement, language, orientation, calculation, memory, planning). Thus, IADL measures the degree of autonomy of an elderly individual. This test appears complementary to MMSE, that rather evaluates cognitive functions. For example, a subject with memory disorders or difficulty of calculating shows a reduced score. Although the complete questionnaire is interesting, 4 tests are particularly important since they are well correlated with cognitive functions evaluated by the MMSE test. They include the ability to : i) use telephone; ii) use transportation; iii) take medication; and iv) handle finances. For example, using a telephone under his own initiative is related to the intention and planning of a task (to look up the name of somebody in a phone book) and to the comprehension of language (to have a conversation). On the other hand, to be limited to a small number of well known phone numbers or to answer the telephone without calling implies automatic mechanisms. An evaluation of these 4 activities allows early detection of cognitive deterioration, several years (approximately 3 to 5) before a dementia is diagnosed. Detection of an alteration of at least one of these 4 activities calls for a more precise neurological assessment.

The Geriatric Depression Scale (GDS), first created by Yesavage *et al.* [194] is a self-report inventory, constructed to assess depression and general well-being in the elderly. It is a brief questionnaire in which participants are asked to respond yes/no to 30 questions in reference to how they felt on the day of administration. Scores of **0 - 9** are considered normal, **10 - 19** indicate mild depression and **20 - 30** indicate severe depression. The items of this scale have content that is primarily focused on symptoms consistent with a clinical diagnosis of depression, and is sensitive to mild to moderate changes in mood.

The Barthel Index [98] consists of 10 items that measure a person's daily functioning, specifically ADL and mobility. Items can be divided into a group that is related to self-care (feeding, grooming, bathing, dressing, bowel and bladder care, and toilet use) and a group related to mobility (ambulation, transfers, and stair climbing). The maximum score is **100** if 5-point increments are used, indicating that the patient is fully independent in physical functioning. The lowest score is **0**, representing a totally dependent bedridden state.

The Modified Cumulative Illness Rating Scale (CIRS) [16] is designed to measure the chronic medical illness burden in the elderly persons. This is a 13-category scale measuring elderly persons' cardiovascular and respiratory system, gastrointestinal system, genitourinary system, musculo-skeletal-integumentary system, neuro-psychiatric system, and general system. CIRS is meant to provide a comprehensive recording of all comorbid diseases of a patient. It classifies comorbidities by 14 organ systems affected and rates them according to their severity from **0** to **4**. Within each category, when two diseases are present, the disease with the higher score is counted. A score of 0 represents "no problem", 1="current mild or past significant problem", 2="moderate disability requiring first-line treatment", 3="uncontrollable chronic problems or significant disability" and 4="end-organ failure requiring immediate treatment".

The SF-36 is a multi-purpose[3], short-form health survey with only 36 questions. It yields an 8-scale profile of functional health and well-being scores as well as Psychometrically-based physical and mental health summary measures and a preference-based health utility index. It is a generic measure, as opposed to one that targets a specific age, disease, or treatment group. Accordingly, the SF-36 has proven useful in surveys of general and specific populations, comparing the relative burden of diseases, and in differentiating the health benefits produced by a wide range of different treatments.

The Digit Cancellation Test [156] is used to measure sustained attention and visual scanning. It relies on evaluating time required to cross out a target number randomly interspersed in rows of other numbers. Using Conner's Continuous Performance Test and the Digit Cancellation Test, persons have been assessed for focused and shifted attention, short and long term memory and speed of learning, processing and intelligence.

Finally, apraxia is a neurological disorder characterized by loss of the ability to execute or carry out learned purposeful movements, despite having the desire to and the physical ability to perform the movements. It scores from **0** (worse result) to **10**.

4.1.2 Test Courses

Some of the best known benchmarking procedures in wheelchair skill tests are related to predefined obstacle courses. Kilkens et al. [77] present a review of a wide array of wheelchair skill tests, aimed to assess the ability to propel and maneuver a wheelchair under standardized and/or simulated conditions of daily living. The skills included in the 24 tests in order of frequency were:

- Wheelchair propulsion, assessed in terms of period of time, a fixed distance or longest distance possible.
- Transfer from and to the wheelchair, usually examining the performance in different transfers.
- Negotiation of kerbs, with kerb's height ranging from 0.025 to 0.15m, and some requiring ascending and descending the kerb.

[3] http://www.sf-36.org/

- Ascending slopes, defined in terms of inclination (ranging from 1 to 11 degrees) and length (ranging from 3 to 21m).
- Traversing tracks, *i.e.* slalom, figure of eight and obstacle course.
- Sprinting over a fixed distance (ranging from 6.5 to 30m).
- Performing a wheelie was also a skill included in few of the tests assessed.
- Half of the tests included other specific wheelchair skills, *e.g.* managing brakes, negotiating doors or loading the wheelchair into a car.

In eight of these tests, wheelchair skills were a part of a broader measure of ADL skills like eating, bed mobility skills and washing hands. Ideally, tests have to be as efficient and as short as possible, and should not require much space or special equipment. The *Valutazione Funzionale Mielolesi (VFM)*[18] or the *Tufts Assessment of Motor Performance (TAMP)* [57] take like 1 hour to complete, while the *Wheelchair Skills Test (WST)* [78] needs only 30 min.

The most common outcome of the different tests is *task performance time*. *Physical strain*, *Independence in performance* (from other assistive devices or persons), *distance covered in propulsion*, *endurance* or other subjective ratings like perceived difficulty were also used in the different tests. Kilkens [77] argues that tests should have preferably an uncomplicated scoring system that is convenient to use and can be easily analyzed. It is important to note that these metrics can be applied mostly to obstacle courses but usually not to daily living, as they are measured over a given time and trajectory.

The choice of an outcome measure also depends on the goals of the study. Measurements like physical strain, time or distance provide information of practicability of manual wheelchair mobility in daily life. On the other hand, a scale of independence performing wheelchair tasks describes the level of independent mobility in daily life. However, some parameters might be interdependent, like physical strain and performance time (e.g. more time of performance, means less physical strain), obfuscating the interpretation of the results. If several parameters are used, the overall score of the test can not be a straight sum of all the results if those parameters are not measuring the same phenomenon.

It is interesting to note that, in some cases, if persons driving the wheelchair present a high disability index, tests may simply consist of tracing a straight line in a corridor free of obstacles or crossing a door [28]. These tests have been used to relate the degree of disability to success in simple tasks like these ones.

The main problem with most of these courses is that they require a large space and investment to build structures just according to specifications. Furthermore, they are used to measure skills in controlled situations, rather than in everyday living. Still, they are widely used because they provide a benchmark to test most wheelchairs models.

4.1.3 Task Metrics

Task metrics include all quantitative measures that can be objectively related to the user's performance with the wheelchair while performing a given task. Most of them

can be extended from one task to another, and, hence, obtained through a *test course*. However, some can also be applied to long term use of the wheelchair. The most common and simplest metric concerning navigation is *task success*, meaning that the preset goal has been achieved. Usually, in test courses a maximum time to reach this goal is preset. In some cases, also, collisions during the course are allowed, if they have been evaluated as *safe*, but counted to evaluate a so called *degree of success*. Consequently, other popular metrics include *task completion time*, *number of collisions* and *Distance travelled* [120][192].

It is important to note that these metrics are task-dependent in the sense that, for example, the time required to complete a straight line painted on a floor in a corridor without obstacles can not be compared with the time required to find the way out of a labyrinth of narrow corridors. It is also important to notice that results depends heavily on HCI: a wheelchair controlled with a joystick can not be compared with, for example, a wheelchair controlled by voice. In most cases, it is not as interesting to measure how fast or how efficiently a given user may guide his/her wheelchair as to check if the value of these parameters decreases through use, meaning that the person actually learns to drive the wheelchair through practice. These results can, in fact, be plotted into a *learning curve*, where parameter evolution through different consecutive tests may be represented (e.g. [169]).

When paths consist of following a line drawn on the floor, a typical task metric is *deviation with respect to the canon trajectory*. Such a deviation can be measured straightly or, more often, quantified into a few bins as *ok*, *acceptable* and *wrong* [28]. However, this procedure in a general situation is not adequate, as most people are more concerned about not leaving that line than about general driving performance.

In some cases, specially when collaborative control is required and, hence, we need to check *how* the driver is doing at a given time instant, it is necessary to use local metrics instead of global ones. These local metrics rank performance at a given time instant, instead of after a whole test is finished. At a local level, driving efficiency η can basically be measured in terms of safety, directness and smoothness [167], as described in the previous chapter.

All global parameters can be locally represented by their maximum/minimum, average and deviation to provide a good insight about general driving in general. Also, local parameters averaged through a whole trajectory yield global information instead of local one. Similarly, the sum of these parameters up to a point of a trajectory provides information about how well the user is doing so far.

The aforementioned metrics are usually employed in static environments, where the test course is basically fixed. In real environments, though, obstacles might be relocated, other mobiles may unexpectedly appear behind any corner, or people could just move around. In dynamic environments, four difference metrics have been established: T_s, D_s, T_c and D_c, which correspond to *Time* and *Distance to Stop*, when the obstacle is not hit and *Time* and *Distance to Collision*, otherwise, all referred to the instant the obstacle is detected by the wheelchair [120]. Similarly, other authors measure the so called *obstacle clearance*, defined as the distance when an obstacle is avoided [85].

4.1.4 Psych Metrics

Psych metrics are related to the user's (mental) state rather than to his/her performance. From this point of view, psych metrics could be estimated via biometric sensors [176]. Typical metrics related to stress include a combination *heart rate*, *sweat*, *breathing* or even *facial gestures*. The main problem with psych metrics is that the measures they are based on change from individual to individual depending on age, gender, weight and physical condition and may even change for the same individual during a time span, so it is difficult to establish standards, even though there are accepted margins in the field [93]. For example, a healthy heart rate for a male between 20 and 29 years old may change from 60 to 84 beats per minute (bpm), whereas it usually changes from 70 to 94 bpm for females of the same age. After 60 years old, these rate goes up to 68 to 90 bpm for males and 78 to 106 bpm for females, even though it still depends on many factors.

Besides, the biometrics approach may be correct from a test course point of view, but in everyday situations biometrics sensors should be reduced to a minimum to reduce invasiveness and user's discomfort. There are currently multiparametric wearable sensors that might be up to match these expectations [113], but indirect methods to evaluate the user's state have been developed before.

While task metrics were mostly grounded with the on-going task, psych metrics are typically related to the user interface. For this reason, one of the first psych metrics in the field was the *interaction number*, or number of times that the user interacts with the interface [120]. When interaction was not easy to measure externally, some authors used the *amount of information exchanged* between user and machine instead. These values were reported to measure the usability of the system and they were originally used in teleoperation of mobiles for collaborative control navigation. Usability has been also measured as the number of error situations [120].

In many cases, it is interesting to measure workload instead of usability. This parameter is more coupled with the user's condition than with interface adequacy, even though it is correlated to several factors. Mental workload has been defined as the interaction between the demands of a task that individuals experience and their ability to cope with these demands. Some authors [22] [76] consider workload to be related with a very simple parameter: Joystick Variation, which measures a change higher than 10% in the position of the joystick. It is important to note, though, that in users operating a wheelchair, this variation may be also related to spasmodic joystick movements (e.g. Parkinson).

A popular psych metric is the well-known Intervention Level, defined as the portion of time that the user moves a joystick [24]. Intervention level was originally conceived for teleoperation of mobile agents, so it was desirable to keep it as low as possible, i.e. the teleoperator only needed to be aware of important decisions and was free to even control several mobiles at a time. However, in collaborative control, a high intervention profile may be desirable, as activity avoids loss of residual skills. In other cases, though, it is preferred instead to keep this parameter as low as possible, meaning that the user mostly agrees with the machine [24]. In order to take into account this duality, Intervention Level may be evaluated along with another

index, Disagreement, that represents the difference between human and wheelchair command vectors. Disagreement can be measured in terms of angles between them: a zero Disagreement means that the mobile and the human totally agree. A high Disagreement is expected to be related with effort and frustration.

Similarly, for persons with disabilities, it is also important to take Inconsistency into account, defined as the variation of the user output when facing similar situations. The goal of this index is to check if a person has a well defined course of action or, otherwise, tends to be erratic in his/her decisions. A low Inconsistency is expected to be related to users with good cognitive capabilities, whereas a high one is related to random courses. Thus, Inconsistency gives some idea about the cognitive driving capabilities of the user on-line and, in combination with Disagreement, provides information about the degree of comfort of the user with the wheelchair motion.

4.1.5 Usability

It has been reported that subjective ratings may come closest to tapping the essence of mental workload and provide the most generally valid, sensitive and practically useful indicators. Consequently, some effort has been dedicated to develop tests and questionnaires to rank activity from the user's qualitative point of view. Practitioners have developed their own clinical rating scales [135], but there is a lack of standardization in the field that may result in no replicability of experiments. There are, though, some well-known questionnaires which have been frequently used [56].

In order to measure workload, the NASA proposed the well known Task Load Index (TLX) [64]. TLX was developed under the assumption that workload emerges from the interaction between the requirements of a task, the circumstances under which it is performed, and the skills, behaviors, and perceptions of the operator rather than from interaction with an interface alone. TLX is generic for any task but can be applied to supervised navigation and, in our case, collaborative control. TLX consists of different component scales. An average of these scales, weighted to reflect the contribution of each factor to the workload of a specific activity from the perspective of the rather, is proposed as an integrated measure of overall workload. The most salient factors in TLX include overall workload (low-high), task difficulty (low-high), time pressure (none-rushed), performance (failure-perfect), mental/sensory effort (none-impossible), physical effort (none-impossible), frustration level (fulfilled-exasperated), stress level (relaxed-tense), fatigue (exhausted-alert), activity type (skill based/rule based/knowledge based). These factors are ranged within a 12 cm line which is later numbered from 0 to 100 and subjectively marked by each user.

There are more specific questionnaires for assistive systems, though. One of the best known ones is Psychosocial Impact of Assistive Devices Scale (PIADS)[4] [73][148], which is available free of charge for its use in clinical, research or educational projects. PIADS can be filled in 5 to 10 m and includes ratings for self-esteem,

[4] *http://www.piads.ca/*

well-being, quality of life, embarrassment, eagerness to try new things and up to 26 other subjective factors scoring from [-3, 3]. PIADS is reported to be very sensitive to differences among device options (*e.g.*, tilt, recline) within a device category (*e.g.*, powered wheelchairs).

The The Matching Person and Technology (MPT) [58] sheet[5] is also a well-known tool to assess how assistive technology is perceived from the user's point of view. MPT starts with an evaluation on people's condition regarding hearing, sight, mobility and communication skills and then moves to ADL like writing, reading, domestic tasks, *etc*. It also includes a section for cognition/learning. All these factors are evaluated regarding previously used technology, currently used technology and required technology. After this, MPT moves to the person's opinion on technology, experience with it, frequent activity and such, which are labelled as positive/indifferent/negative. There is a large part of the questionnaire that must be filled not by the user, but by the person supervising the process, instead.

Functioning everyday with a wheelchair (FEW) [105][6] is meant to be a dynamic indicator or profile of perceived user function related to wheelchair/scooter use. FEW was developed by a team of clinical researchers at the University of Pittsburgh due to the lack of available outcome measures related to functioning with a wheelchair. FEW is mostly concerned with the size, fit, postural support and functional features of wheelchairs (or scooters) and provides 10 assessments that the user may score into 6 bins ranging from *Completely agree* to *Completely Disagree*, plus one for *Does not Apply*.

Another similar questionnaire is Quebec User Evaluation of Satisfaction with assistive Technology (QUEST) [35]. QUEST focuses on the satisfaction of the user with the provided assistive technology and/or services. It tests psychometric properties with respect to test-retest stability, alternate-form equivalence, internal consistency, factorial composition and nomological validity. QUEST presents 12 items that score from 1 (not satisfied at all) to 5 (very satisfied), going from physical considerations, like weight or dimensions of the device, to service delivery or repair and servicing. It also includes subjective considerations about the ease of use or effectiveness.

In brief, it can be observed that TLX is related to human/computer interfaces for shared operation, whereas the rest of the questionnaires relate to assistive technologies specifically. Indeed, FEW is the only test which has been solely designed for wheelchair (or scooter) navigation. All of them, though, have been applied to this purpose.

4.1.6 Make Your Choice!

So, after much reading, it became clear that there are many different types of metrics applied to mobility assistance. Indeed, one of the main challenges in this study turned out to be to bring together all this extensive body of work into a taxonomy,

[5] *http://members.aol.com/IMPT97/MPT.html*
[6] *http://www.few.pitt.edu/*

as involved fields of research are often not related and some indexes could belong to different categories. Fields of application roughly include:

- machine teleoperation;
- human/computer interface (HCI);
- power wheelchair control;
- test course performance with mobile devices;
- medical assessment on physical and cognitive conditions.

All these fields relate at some point to wheelchair navigation. For example, machine teleoperation is mostly concerned with robot remote control in unfriendly environments, but metrics used to check the cognitive effort of the teleoperator provide a good idea on the interface adequacy and mental strain of the controller that are applicable to wheelchair control. HCI studies also provide a good insight on user effort to control the machine. Power wheelchair control metrics are useful to measure punctual performance of the person or also global one in an analytical way (time, η, curvature ...). Furthermore, if a test course is settled, we can measure maneuverability, local navigation hazards and specific difficulties in common environments in a controlled way. Finally, medical assessment is of key importance to evaluate how persons, potentially with cognitive and/or physical disabilities and, possibly, not technology proficient deal with a mobility aid. Also, tests used to evaluate the functional disability of the person are useful to understand the reasons behind a given value of the other indexes.

Obviously, it is not possible to use all metrics in table 4.1 at the same time. For starts, it would take too much time and effort, and some of them are redundant. Furthermore, some are in direct contradiction with each other and can not be calculated at the same time, like *time to stop* and *time to collision*. Others are not valid in some experiments, like calculating *time to collision* in a wheelchair incorporating a safeguard mechanism. Also, human factors are important: doctors would probably not be willing to use all disability scales nor people will volunteer to fill all questionnaires if we take into account that it takes more than 20 minutes to complete each one. In brief, it is important to choose a representative set of metrics for the proposed experiments, to cover all fields but also to avoid redundancy. Through our tests, we concluded that:

- Regarding user's health, following medical advice, MMSE and Barthel together seem to be the easiest way to get a general idea on the person's physical and cognitive skills. IADL is a nice addition if possible for generalization and apraxia needs to be evaluated separately.
- Questionnaires have to be carefully chosen, as it usually takes too long for volunteers to fill them. PIADS seems to be the preferred tool to measure usability in assistive devices.
- Test courses provide a good baseline, but not so much information on everyday situations. In fact, they are rather used to test new wheelchair models, even though some researchers use them to measure the impact of specific disabilities. Furthermore, test courses require space and specific installations except in the most general cases: door crossing and corridor following.

- Task metrics are mostly related to physical skills, whereas psych metrics mostly relate to mental workload. In assisted control, task and psych metrics tend to be coupled and both need to be evaluated.
- Our evaluation methods must be non invasive to be acceptable for medium term use in our tests.
- Highly specific tasks like line tracking are not advisable if both physical and cognitive skills want to be measured in everyday situations, because usability is compromised by the extra attention required to achieve them.
- In wheelchair navigation, a high collaborative profile is better for rehabilitation or to reduce loss of skills.

In the end, we decided to use the following metrics:

1. MMSE, Barthel and apraxia as medical scales
2. PIADS for usability
3. *Door crossing* and *corridor following* as the only activity from test courses.
4. Directness, smoothness and safety as local task metrics. Curvature, *trajectory length* and *time to completion* as global metrics.
5. Disagreement, Inconsistency and Joystick Variation as non invasive psych metrics.

Although this selection was a preliminary approach, it covered all fields and did not require special structures to be build in our test scenarios, nor devices to be attached to volunteers. Most data could be extracted from vehicle operation in a transparent way from the user's point of view and the rest could be supplied by the medical staff. We expected further experiments to show if other scales were necessary.

4.2 Where the Wild Things Are

With a whole new set of things to measure, the aprovement by FSL Ethical Committe and our brand new wheelchair CARMEN, we were now ready to proceed to experiments with volunteers in the hospital. Our target community consisted of persons with minor to mild physical disabilities and, in some cases, also cognitive ones. Most volunteers were not familiar with power wheelchairs, as evidenced in their PIADS questionaries, but most had experience with conventional ones. Medical staff provided the MMSE, GDS, apraxia and Barthel scales for every volunteer. Results are briefed in table 4.2. It can be observed that, cognitively, persons were only slightly under the threshold of dementia (**26**), but the large MMSE deviation shows that some persons presented severe cognitive disabilities, whereas others presented none. All volunteers scored low in GDS and apraxia, i.e. with some exceptions, the commands they provided corresponded basically to what they wanted to do. Their Barthel index was, in average, equal to **64.2**, corresponding to mild dependency. Its variation, however, was almost **30**, meaning that some volunteers presented severe physical disabilities. In any case, it is important to note that the skills of each person depend largely on his specific diagnosis. Some persons may be very capable of performing some complex actions, yet fail to achieve an easier

Table 4.1 Metrics employed in Assistive Wheelchairs

Metric	Type	Relates to
MMSE	User health	Cognitive impairment
IADL	User health	Degree of autonomy
GDS	User health	Depression/well being
Barthel	User health	Daily functioning
CIRS	User health	Comorbid diseases
Digit Cancellation	User health	Sustained Attention
TLX	Usability	Workload
PIADS	Usability	Impact of technology
MPT	Usability	Technology adeptance
FEW	Usability	Hardware ergonomy
QUEST	Usability	User satisfaction
Smoothness	Task	Sharp direction changes
Safety	Task	Closeness to obstacles
Directness	Task	Keeping the goal ahead
Curvature	Task	Global trajectory smoothness
Task Success	Task	Successful task completion
Time to destination	Task	Total time to complete the path
Time/distance to stop	Task	Reflexes
Time/distance to collision	Task	Reflexes
Clearance time	Task	Reflexes
Heart rate, Breathing, Sweat	Psych	Stress
Facial gestures	Psych	Stress
Intervention Level	Psych	Collaboration with machine
Disagreement	Psych	Effort and frustration
Inconsistency	Psych	Indirect measure of cognitive capabilities
Joystick Variation	Psych	Workload
VFM	Test course	Rehabilitation
TAMP	Test course	Motor performance
WST	Test course	Wheelchair skills

Table 4.2 Disability scales for test population

Index	Average	Deviation
MMSE	23.47	8.57
GDS	5.02	3.70
Apraxia	8.94	2.47
Barthel	64.20	29.66

one if, for example, they can not use the left part of their body. This suited well our purpose: to provide assistance on a need basis.

There were three requirements established by FSL Ethical Committee. First, an emergency stop big, red button -tapping directly into the wheelchair motors- needed to be in a visible, easy to reach position. Second, at least one caregiver and one engineer should be within arm distance of the wheelchair during the whole experiment.

Finally, persons were informed that the wheelchair prevented collisions. However, we were not allowed to explain the specific nature of collaborative control, so that they could check if volunteers felt in control through the experiment. All tests were performed in a wing of Hospedale Santa Lucia, in Rome.

4.2.1 A Day in the Life

We performed two types of experiments corresponding to the easiest test course installations: the first one, a corridor path, and the second, a more complex, door crossing path [178]. Doctors reported that these trajectories are the most typical ones in a hospital environment (Fig. 4.1). The target of the first test was to let people get used to the wheelchair. Also, in this scenario, we were allowed to run tests without assistance (standalone mode) to establish a benchmark. In the second case, standalone operation was not allowed, because many people could not cross doors without help. This test was meant to check if persons could achieve in collaborative mode a task they found challenging. We did not paint anything on the floor, nor gave verbal instructions during operation. People were simply asked either to follow a corridor or to do that and then cross a door. Doors in the hospital are 90 cms wide, i.e. wider than in common houses. Experiment supervisors were allowed to move freely in the test environment, but the place was closed to other patients, visitors or staff for safety.

The primary goal of these experiments was to check if we could adapt assistance to the user's needs. If this were the case, the performance of different patients should be similar despite their different condition and skills. Also, we wanted people to participate as much as possible to avoid loss of residual abilities, so our second goal was to check if they were not too aware of received assistance. In fact, we wanted the system to behave exactly like a conventional power wheelchair from the user's point of view, so that it required no extra effort to be controlled. As a final goal, we wanted to check if collaborative control improved learning. To do this, we measured the amount of assistance provided to the user in each trajectory, η_H in standalone mode and time required to finish the trajectory. Users were asked afterwards to fill a PIADS questionnaire.

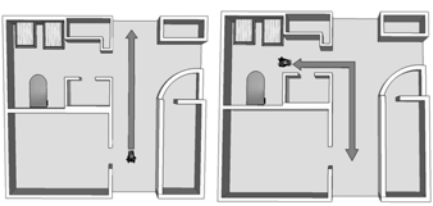

Fig. 4.1 Corridor and door crossing

The presented experiments have been designed taking into account all conclusions provided by Yanco et al in Human/robot interface (HRI) evaluations [193], i.e. the major shortcomings in this kind of experiments are that: i) system designers are often enlisted as test users; ii) HRI evaluations are commonly informal and rarely provide controlled, objective assessment; iii) there is a very limited number of users. It can be noted that in our previous tests we

just flunked all three, but we had learnt the lesson. It was July, 2007 and we felt fairly confident that we had taken everything into account. Once more, we were wrong. Still, these experiments turned out to be clearly more enlightening than the ones with students and the robot, specially as we were fortunate enough to count on the doctors at FSL and a significant group of volunteers presenting different degrees of disability to help us check how reality differs from laboratory tests. Next subsections describe these new experiments and what we learnt from them.

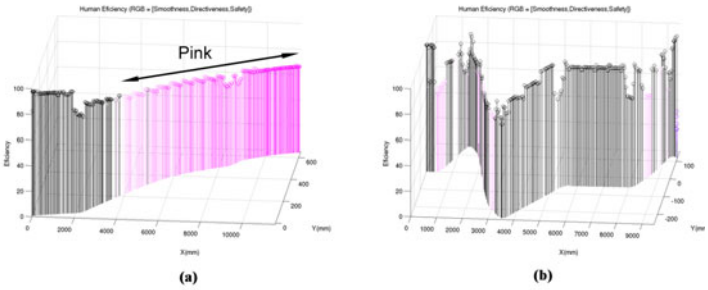

Fig. 4.2 Standalone efficiencies following a straight line for humans: a) usual performance; b) erratic case

4.2.2 Together Alone

First, we present results obtained by users and robot in standalone mode for benchmarking. As commented, doctors forbade to let inpatients cross the door without help so we can only show corridor experiments here.

Table 4.3 briefs the robot performance in both corridor and door situations. It can be observed that the robot was very efficient in corridor tests, but that doors were hard for a purely reactive PFA, as expected. In all standalone runs, the robot performed almost equally. Hence, there was not much deviation in performance, especially in corridor tests. Residual deviation can be attributed to small shiftings in the departing position, people moving around and minor hardware errors. It can indeed be observed that the sum of the path curvature tended to 0 in straight runs and to 90° at door crossings. Oscillations at the door were not reflected in the curvature sum because negative peaks compensated positive ones.

Regarding user's performance, the most significant result in these experiments was that persons tended to drift towards the walls quite soon. Hence, their efficiency in terms of directness was not too good. Fig. 4.2.a shows a typical performance for a random user. It can be observed that η_H was quite high at the beginning, because the experiment was not too complex and mostly consisted of direction keeping. However, efficiency started to decrease very soon and η_H turned pink, i.e. *direcness* (green) was lower than safety and smoothness. Furthermore, it can be noted that η_H deviation was quite larger than in the robot case. Fig. 4.2.b shows a volunteer's particularly bad run, in this case her second try. We can observe that part of the plot

Table 4.3 Statistical results of standalone performances for robot and human.

Test	Corridor	Door
Average η_R *(%)*	91.90	58.84
Variance η_R *(%)*	2.79	9.01
$\sum \rho_R$	1.68	92.64
Variance $\sum \rho_R$	0.56	7.02
Average η_H *(%)*	73.63	N/A
Variance η_H *(%)*	27.52	N/A
$\sum \rho_H$	0.86	N/A
Variance $\sum \rho_H$	19.04	N/A

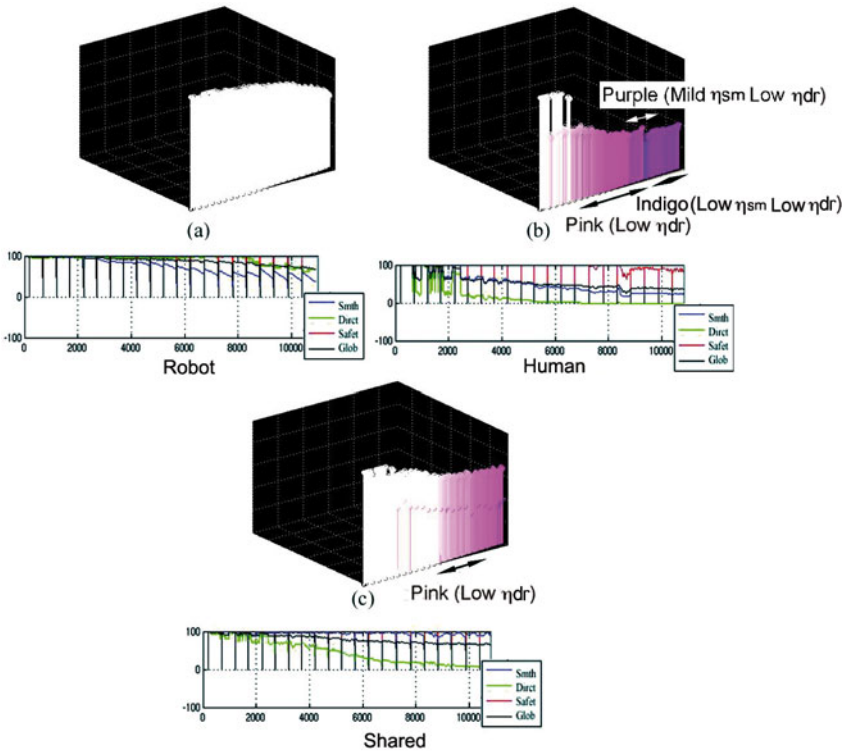

Fig. 4.3 Corridor performance: a) η_R (autonomous); b) η_H (standalone); and c) η_C (collaborative)

is close to black, meaning that local efficiencies were balanced. However, η_H was lower than in the previous case, i.e. not only this person was not better in terms of directness, but her safety and smoothness were also worse.

In average, η_H in corridor tests was equal to 73.63% with an average curvature of 0.86 degrees, due to positive and negative peak cancellation. If we work with the

sum of the absolute value of curvature instead, its average raises to 267.45, with values as high as 353.65 degrees. It is interesting to note that low average curvature values combined with high absolute curvature ones usually meant that inpatients were not able to follow a straight line correctly, but were capable of correcting their trajectories. Indeed, curvature function deviation is up to 19.04. In brief, performance depended largely on users' condition and even changed from one test to the next for the same person. We also appreciated that, in general, young people tended to perform better in average, probably because they were more familiar with technology. Best performance, though, was associated in these experiments to very large times to destination, meaning that people made a considerable effort to achieve the task.

After these tests, we wanted to check if collaborative control could: i) improve directness; ii) reduce variation; iii) enhance efficiency; iv) allow door crossing; and v) reduce mental workload. At the same time, it was important to: i) keep a high Intervention Level to avoid loss of residual capacities; and ii) to keep differences of opinion between the person and the system to a minimum.

4.2.3 An Army of Two

In collaborative control mode, inpatients were asked to perform both the corridor and the door crossing experiments after caregivers had extensively tested the wheelchair themselves.

It must be noted that emergent trajectories could not be directly compared to robot or user's trajectories in standalone mode because their commands are combined at all times and, hence, it is not possible to know what each agent would have done without the other's contribution. Nevertheless, η_C was compared to η_R and η_H in collaborative mode at each time instant to at least know who was contributing more to the emergent trajectory.

4.2.3.1 Corridor Experiments

Fig. 4.3 a-c shows η_H, η_R and η_C at each point of the corridor in a run of an average user. It can be observed that the robot performed quite well all the time, even though global efficiency decreased a bit along the way when it moved ahead. This happened because the corridor wall on the right disappeared at the end of the path into a T opening. The color of η_C is white because all local efficiencies were balanced in this particular run (Fig. 4.3 a). The user, however, made a good start, but, as reported, soon lost directness and started to oscillate to relocate herself in parallel to the walls. This provoked a significant reduction in η_H, that became pink (Fig. 4.3 b). Eventually, direction changes became so sharp that smoothness was not preserved either and η_H went violet. If we check η_C (Fig. 4.3 c), it can be observed that it was clearly better than η_H, even though the trajectory retained the specifics of the driver, as proven by the pink area of the plot at the end of the trajectory.

In brief, it can be concluded from our corridor experiments that volunteers were less efficient than PFA and also than collaborative control mostly in terms of

directness, possibly because no visible marks were painted on the floor. Nevertheless, they performed well in terms of safety and adequately -with variations depending on their condition- regarding smoothness. No inpatient had trouble finishing the task on his/her own within a margin of proximity to the goal of less than $1m^2$, but all of them performed better when collaborative control was enabled. This effect was particularly noticeable at the beginning of the experiment, when they had to start moving the wheelchair, due to inertia and wrong initial commands. Errors at this point seemed to unnerve them and some commands included heavy oscillations, that were filtered out by collaborative control. This control scheme also seemed to follow human guidelines at all times but preserved directness better.

4.2.3.2 The Door-Crossing Experiments

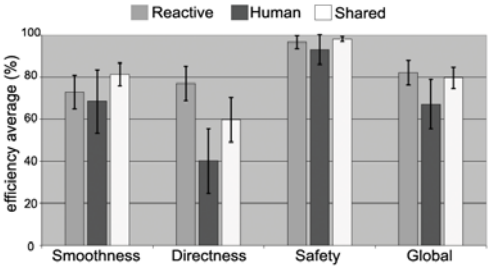

Fig. 4.4 Average efficiency and deviations for all users in the tests.

Door crossing tests were more complex than corridor tests, but also provided more information. Fig. 4.4 shows average η_H, η_R and η_C and their deviation for all users in collaborative mode regarding smoothness, directness, safety. It can be noted that robot's averages were higher than human's in every case. However, collaborative control was better in average than the robot alone in terms of smoothness and safety, meaning that users contributed positively to emergent behavior. Of course, η_R could be improved by using a better version of the PFA, but this was not the scope of this work, as commented earlier. Clearly, the worst human feature was, once more, directness. This was to be expected because machines are more precise than humans. It is also interesting to note is that deviation for users, especially in our target group, was significantly larger than for robots and, also than for collaborative control, proving that collaborative control tends to equalize user performance and assistance is provided on a need basis. Finally, it is necessary to point out that users' best feature is safety, not only because it is their main concern, but also because a safeguard layer was active all the time.

Fig. 4.5 presents η_H, η_R and η_C in these tests for a representative user. The robot usually scored white (all local efficiencies present equally high values), except at door crossing, where pure PFA are not adequate (Fig. 4.5 a). Oscillations at the door frame turned η_R pink (loss of directness). Our user did not perform so well, especially when she needed to correct her heading for corridor navigation. Until the end of the trajectory, her directness was quite low and most her plot is pink. However, she was better than the robot at door crossing: she simply headed in the correct direction and moved ahead (see short white area in Fig. 4.5 b). The full

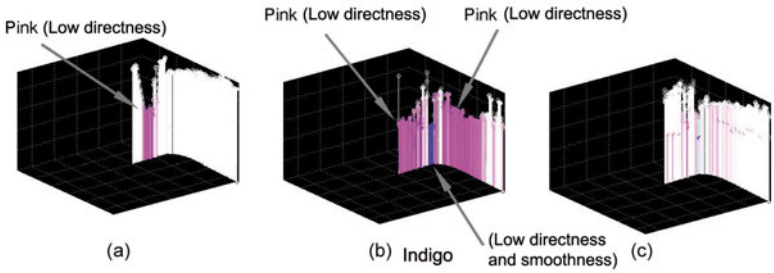

Fig. 4.5 Local efficiencies for door crossing for: a) robot; b) human; and b) collaborative control.

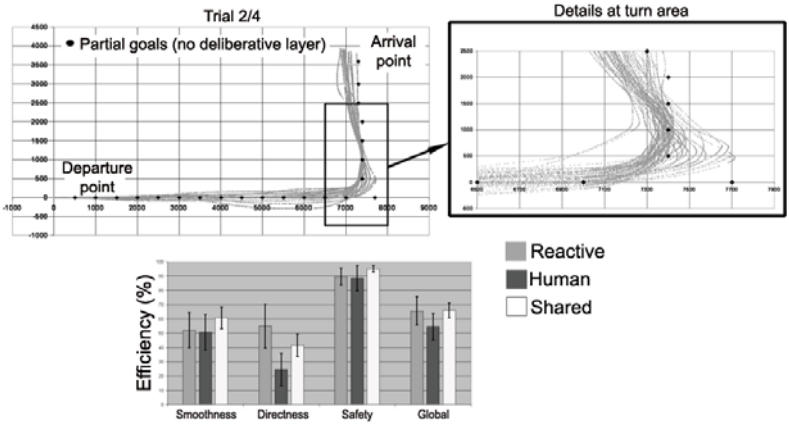

Fig. 4.6 Tracks to move from corridor to room.

potential of collaborative control can be appreciated in Fig. 4.5 c, as η_C was clearly better not only than η_H but also than η_R, benefitting from their combined strengths.

It is necessary to note that moving in or out of our door was not a symmetric task. It was actually harder to come from the corridor, turn and cross the door than to come from the room to the corridor and then, turn. In the first case, the turning point was a key decision to successfully cross the door, whereas in the second one, it was just a matter of facing the corridor closer to the wall or to the center. Even though not all volunteers presented heavy asymmetries, this fact can be clearly appreciated in inpatient 28 performance (tables 4.4 and 4.5). This inpatient had significant cognitive and physical disabilities (MMSE=20,apraxia=10, Barthel=41) and it can be observed that the in-room trajectory was harder for him, as expected. This is clearly reflected in his average times for both trajectories: 49,74 and 62.87s, respectively. Furthermore, in the room to corridor experiment, he reduced his time significantly from one run to the next, whereas in the corridor to room test, he even increased it. Efficiency reduction was mostly related to a lower smoothness, as he changed directions sharply for a while until he finally faced the door and went into the room.

It is interesting to note, though, that collaborative control kept average efficiency similar in both cases, even though his psych metrics were significantly different. He presented a high Intervention Level in both types of tests, even though not as high as most inpatients. The first significant difference appeared in Disagreement, which almost duplicated its value in the second case and presented a much larger variance. It could be argued that collaborative control should match better the user's will in this second case, but if we observe Inconsistency, it can be noted that he was not that sure about his decisions either, as he changed his mind more often than in the previous case. Nevertheless, Joystick Variation was not that large, meaning that Disagreement the inpatient did not seem to be too stressed.

Table 4.4 Metrics for inpatient 28 (room to corridor)

Metric	Type	Average (%)	Deviation
Smoothness	Task	80.35	22.64
Safety	Task	95.44	17.75
Directness	Task	62.76	25.59
Curvature	Task	0.11	0.34
Time to destination	Task	49,74	10.06
Intervention Level	Psych	80,87	
Disagreement	Psych	19.46	13.26
Inconsistency	Psych	8.71	8.20
Joystick Variation	Psych	2.39	6.77

Table 4.5 Metrics for inpatient 28 (corridor to room)

Metric	Type	Average (%)	Deviation
Smoothness	Task	75.32	26.81
Safety	Task	95.28	15.80
Directness	Task	60.88	28.78
Curvature	Task	-0.65	8.43
Time to destination	Task	62.87	8.77
Intervention Level	Psych	80.26	
Disagreement	Psych	36.36	34.23
Inconsistency	Psych	13.06	13.40
Joystick Variation	Psych	2.14	7.29

Fig. 4.6 shows the paths followed by the different users in the first experiment (move from corridor to a room). It can be observed that paths were initially very similar, but they changed significantly when turning to cross the door, as showed in detail on the right of the figure. This happened because no turning point was specified: the users were only instructed to turn left and cross the door. According to their opinion, this was the hardest experiment for most users and, in fact, many of them stopped the wheelchair at the turning point and spent some time there trying to find a way in. Nevertheless, all of them finally managed to move inside. The statistics

in the figure correspond only to this experiment and several conclusions can be extracted. First, collaborative control seems to perform better than reactive and human control in terms of smoothness. Furthermore, its deviation from the mean is lower. In terms of directness, reactive control is still the best choice. Yet, collaborative control efficiency deviation was clearly the lowest, meaning that emerging trajectories were more homogeneous in terms of directness. Regarding safety, both η_R and η_C in average were better than η_H. Indeed, collaborative efficiency was slightly better than reactive, due to the well known drawbacks of pure PFA. Also, efficiency deviation in collaborative mode was lower than the other two. Globally, η_C and η_R were practically the same but, again, deviation was lower in collaborative mode. In brief,collaborative control in these experiments reduced oscillations at the door frame and made performance more homogeneous in terms of efficiency, despite the different users' condition.

Fig. 4.7 shows room-to-corridor results. In this case, users found the trajectory easier and most variations happened when they turned right to follow the corridor (see detail in the figure). Basically, the turning point in this case was not so critical, because the conflict area (doorframe) was already behind. It can be observed that mean η_C was significantly larger than in the previous scenario. Regarding smoothness, collaborative control behaved better than PFA and human control, mostly because oscillations at the door were partially filtered by the user's contribution to control. Deviation was also smaller in collaborative mode. Once again, human's directness was not good, especially because they could decide when to turn at wish. Nevertheless, as usual, collaborative control improved emergent directness. Regarding safety, all human, robot and collaborative control scored quite high and both robot and collaborative control presented a low deviation.

The out-of-the room trajectory also had the associated problem of gaining a straight heading, parallel to the walls, after turning to follow the corridor. Fig. 4.8

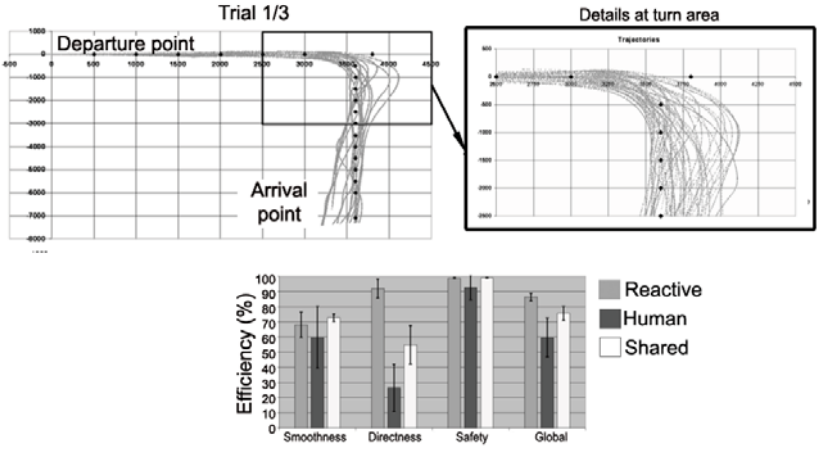

Fig. 4.7 Tracks to move from room to corridor.

shows a representative example of this problem. Fig. 4.8.a presents a conventional plot of η for PFA, human control and collaborative control, including the three local efficiency factors in every plot. The resulting emergent trajectory is presented in Fig. 4.8.b. It can be observed that there is a local minimum η_R, both for directness and smoothness at door crossing, even though this inpatient had not much trouble doing so. As a result, their combined output was worse than human's alone but better than PFA on their own. However, as soon as the inpatient was out of the room and needed to turn, PFA outperformed him. Initially, there are local minima both in η_H and η_R in terms of smoothness, because they needed to steer to head the corridor. However, after this PFA performed basically well -despite minor oscillations due to wall proximity-, whereas the user had trouble heading in the correct direction (parallel to the wall). It can be observed that η_H decreased drastically for a while and became very noisy. This is obvious as well in the resulting trajectory (Fig. 4.8.b), that reflects the user's correction, yet softened by the robot's contribution. It is interesting to note, though, that η_C (Fig.4.8.a) were considerably higher than the η_H, even though the wheelchair still obeyed his commands.

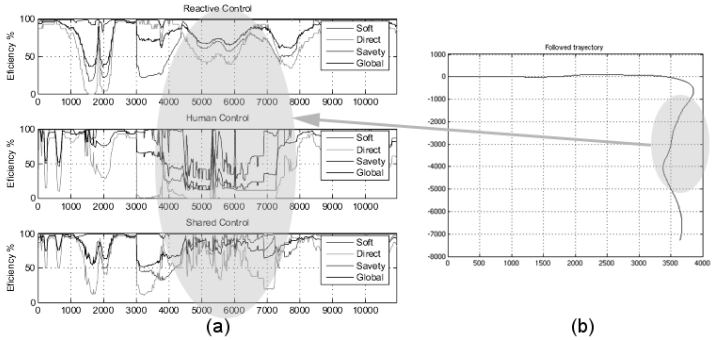

Fig. 4.8 Efficiencies for door crossing for: a) human control; and b) collaborative control

To wrap up, we can observe in detail a random path from a random person. Fig.4.9.a shows a corridor-to-room test. Some partial targets -coming from a deliberative layer- in the area of interest have been marked from 13 to 16 for reference. Fig.4.9.b shows η_{sm} for human, collaborative control and robot at each point of the trajectory. It can be observed at target 13 that the user started to turn and, hence, her smoothness decreased. At targets 14 to 16, the robot was also trying to turn and, consequently, collaborative η_{sm} decreased as well. From target 18 on, this user had less control, but started to compensate the robot's oscillations. It can be observed that robot η_{sm} became quite low around the doorframe (targets 13 and on). Regarding directness (Fig.4.9.c), the user performed quite well until turning (target 13). Obviously, the robot always aimed for the closer partial goal and, hence, its η_{dr} was usually quite good. It can be observed that collaborative control compensated the user's lack of directness and reached its lowest point at door crossing, because the other factors prevailed over directness (targets 16 and on). Finally, in terms of

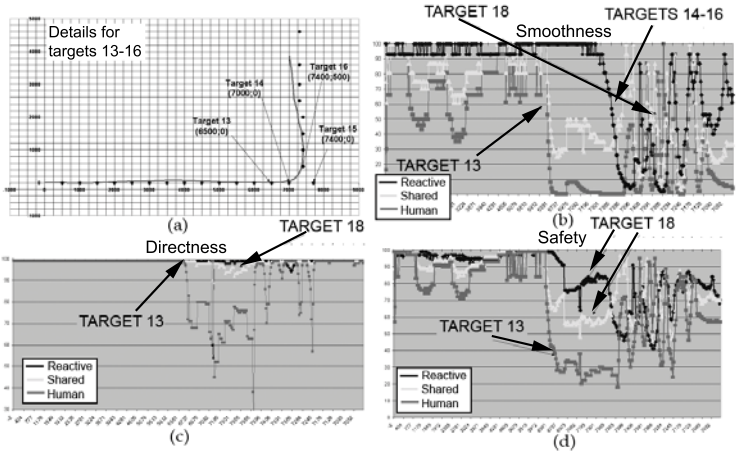

Fig. 4.9 a) Track for inpatient 3 to move from corridor to room; b) smoothness efficiency; c) directness efficiency; d) safety efficiency.

safety (Fig 4.9 d), the user reached a relevant minimum at target 13 while trying to reach a comfortable position to cross the door. However, as soon as the wheelchair approached the doorframe, PFA provoked oscillations that decreased the robot η_{sf}, whereas collaborative control compensated both their weaknesses. Fig 4.9 a shows the emergent trajectory, where it can be appreciated that results were quite good except in terms of directness, as most targets inside the room were not aligned with the heading direction. All through this example, it can be appreciated that local efficiencies are quite correlated in collaborative mode because the emergent behavior is influenced by user and robot and affects both all the time via feedback.

4.2.4 Co-dependence Day

In order to brief the most relevant conclusions from our hospital experiments, table 4.6 shows task and psych metrics for every trajectory in the tests.

4.2.4.1 Safety, Smoothness and Directness

The proposed system has been designed keeping safety in mind above all. As the robot control algorithm is based on a PFA and sharp direction changes and heading Inconsistency are punished in the emergent behavior, the resulting system tends to be very safe. Average efficiency in all our tests was larger than 80% and, in most cases, over 95%, despite the global performance of the user. The worst performance was associated in all cases to poor directness, that, in some cases, was extremely low . Nevertheless, all inpatients eventually reached their targets in collaborative mode. Smoothness was acceptable, as evidenced also by an average curvature equal

Table 4.6 Metrics for all experiments

Metric	Type	Average	Deviation
Smoothness	Task	78.72	25.50 1
Safety	Task	95.48	16.13
Directness	Task	57.15	27.13
Curvature	Task	-0.11	3.78
Intervention Level	Psych	84.07	
Disagreement	Psych	25.13	19.94
Inconsistency	Psych	13.37	13.94
Joystick Variation	Psych	2.19	7.31

to -0.11, meaning that they managed to compensate their derivations to right and left using collaborative control.

4.2.4.2 Collaboration

The proposed collaborative control scheme has proven to require a high degree of collaboration from the user, as evidenced by an Intervention Level higher than 70 % in all cases. Fortunately, this intensive collaboration does not seem to imply a too high workload on users, though, according to Joystick Variation as suggested in [22] [76]. Doctors stated that this is a positive feature of the system, as users will not lose residual capabilities due to an excess of assistance. Regarding the rest of the metrics, Intervention Level does not seem to be correlated with efficiency, but with Disagreement. Usually, a high Intervention Level implies a high Disagreement (15-20) as well, meaning that inpatients tend to intervene more when the wheelchair is not doing what they want, as was expected. Nevertheless, it must be observed that Disagreement is never over 25, as the emergent behavior always takes into account the user's will.

4.2.4.3 Disagreement

High Disagreement and low Inconsistency together are indicators of poor performance. This basically means that the inpatient is prone to random motion that does not match the robot's opinion. Since the robot performs basically well, this provokes a reduction in emergent efficiencies. We have checked, though, that a very large Disagreement may be related to a very good Inconsistency in extreme cases, for example inpatient 4 and 5 (48.55/4.1 and 54.93/4.15, respectively). In these cases, efficiency is typically low as well, with emerging directness around a 45%. These cases are related to persistent driving errors, usually related to high functional disabilities. This means that the person usually makes the same decisions, but that these decisions are systematically bad and, consequently, opposed to the robot. Naturally, this provokes high Disagreement and low η at the same time. Specifically, these inpatients had MMSE close to 28.

Also, a high Inconsistency is not necessarily related to high Disagreement. For example, inpatient 3 in the door experiments has a Disagreement equal to 17.3 in average along with an average Inconsistency equal to 16.4. This basically means that users that do not provide the same commands in similar situations through their performance do not necessarily disagree with collaborative control either.

Finally, it is interesting to note that even in standalone mode there is always a residual Disagreement. It is possibly due to the different expectations users have about the wheelchair response when they provide a command (i.e. mechanical and interface issues). It typically sets down around a 7-8%.

4.2.4.4 Learning

In general, we appreciated that inpatients learnt quickly how to control the wheelchair through practice, even for harder paths. This effect was far more evident in persons who found it hard to control the wheelchair due to lack of experience or minor functional disability. For example, inpatient 5 (MMSE=28, GDS=8, Apraxia=10, Barthel=69) went down from 110.56 s to exit the door the first time (10.8 meters) to 56.01 (10.60 meters). Door entering was, as commented, a little harder. In this case, the inpatient reduced the initial time of 195.90 s. (24.66 meters) to 53.81s (11.01 meters). The travelled distance reduction also indicates that this final run was far more efficient that the initial one. This was also evidenced by a lower Disagreement and Joystick Variation in the final runs of the experiment for the same user. If we evaluate time evolution for all users in every test, it takes them 6.9s less in average, with a variation of 21.1s, to reach their target. This average is not too meaningful, as time required for different trajectories is different as well, but it reflects that experience makes users take less time to complete their tasks even from a rough point of view.

4.2.4.5 Workload

If workload is measured in terms of Joystick Variation, it can be concluded that the users' workload was not too high, as these variations were always lower than 3% in average. However, in a system like the proposed one, where the emergent behavior is quite influenced by the driver and sharp variations are punished, this was to be expected except in case of tremors or any punctual error, which are implicitly filtered out of the system due to its spurious nature. We believe that, in this case, we need another parameter to measure workload. Probably, Disagreement is the closest metric we have to this purpose, but, yet, it does not reflect the reality of inpatients with high functional disabilities.

4.3 Is You Is or Is You Ain't

After all these experiments, involving 30 inpatients, were fully evaluated, several interesting preliminary conclusions could be extracted and used to improve the

proposed collaborative control system. Most of them were derived from human-system interaction and could not be predicted *a priori*. Others were derived from the nature of our reactive bottom-up approach. In some cases, results were totally unexpected, specially those related to Disagreement. These conclusions have been divided into areas.

Regarding control algorithms, we checked that [178]:

- Emerging behaviors are consistent with bottom-up reactive control as expected. Resulting trajectories are smooth, safe and less shaky than human control.
- Collaborative control improves human control in general and, in occasions, even robot control alone in places where PFA is reported to fail. PFA should be replaced with a more appropriate reactive algorithm to avoid oscillations, most likely a VFH, according to studied research. However, this option will not be critical in the approach to be implemented, as commented below.
- The nature of the algorithm is *too* reactive at this point and might not be suitable for persons with severe cognitive or physical disabilities, so some portion of deliberative control needs to be added to avoid this problem. It will require some degree of prediction about the local and global environment and, hence, some environment model.

Regarding HCI, we noted the following. All observations must be taken into account carefully, as the size of the experiment was only of a few dozens of individuals, still we had a detailed medical and cognitive profile for each one. Further data would be required to make a clear and sound statement.

- There is always a Disagreement 10% or higher in all of our tests, even when persons where driving without assistance. This basically means that the outcome of their actions is not what they expected from the wheelchair. This is typical when people are not used to a given device or interface and should be reduced with practice. Still, it is necessary to accept this value as baseline because most volunteers have never used a power wheelchair prior to these tests.
- MMSE is inversely proportional to Disagreement, meaning that persons with less cognitive capacities agree more with the chair. Obviously, Disagreement is also linked to the time to finish the trajectory: an user with a higher Disagreement takes longer to reach a goal.
- *Intervention level* depends on Barthel: persons with better physical capabilities tend to be more cooperative and also present a better smoothness, even though the proposed control scheme tends to equalize performances at these levels (smoothness, directness and safety)
- If MMSE and Barthel are very low **or** very high at the same time, efficiencies are worse than in other cases. This is particularly interesting because it basically means that users with good capacities tend to fight the chair when they realize they are not completely under control.

What surprised us the most was that people with the best scores in disability indexes, that should have profited the most from this approach, actually achieved poorer performances. In all these cases, they usually presented a very high average

Disagreement. At this point, it was only logical to think that maybe if the machine took more into account how the person drives, they would get along better. Thus, we decided to develop a new learning based algorithm for better human/robot adaptation. This system, presented in the next chapter, is the basis of our final approach to collaborative control.

Chapter 5
If I Only Had a Brain

Woolly thinking. Which is like Fuzzy Logic, only less so
- T. Pratchett, Soul Music

Reducing Disagreement by trying to make the machine drive like a person does is, in the best of cases, far from easy. For a start, each person drives differently, even if they have the same goals and/or guidelines. Second, anyone's way of driving is likely going to depend on experience, condition and state, as well as on the vehicle. Finally, most people can not explain to satisfaction the whys of their reactive decisions so that all specifics can be fitted by a function. Traditionally, data blocks that can not be explained by mathematical expressions can be approximated *a posteriori* by statistical tools, like splines. Indeed, it is possible to capture a mild amount of data from a path, processing it with the correct methodology and come up with a set of equations that can do the trick, as proven in the field of field of Inverse Kinematics. These equations would be different each time a new device is employed and they require some analysis and practice to be fixed. Besides, this approach does not leave much space to adaptation and requires calibration of the system for each specific user and, in some cases, whenever the person changes his/her way of driving permanently (rehabilitation or degenerative process). Alternatively, the robot could try to observe how the person acts and mimic his/her way of doing things. Indeed, kids learn to talk before ever reading any grammar book and they probably do not solve any equation to start walking. If we could just ask the wheelchair to learn from its driver, the engineer's life would become far easier. This approach is known as learning by imitation.

5.1 Oobee Doo, I Wanna Be Like You

Learning, at this point, may look like the philosopher's stone, but, still, there is work to do: knowledge needs some parametrization. This is not as hard as it might seem, because parameterizing a process does not necessarily mean understanding how it works [12][14][157][158]. The idea here is basically that one can act in an intelligent way without actually explaining how it is done. For example, let's think

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 93–115.
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of a person serving in a tennis game. This action occurs in a matter of seconds and depends on many factors, both external -like if there is a strong wind in the court- and internal -like if our elbow is hurting at the moment. It is also necessary to take into account the relative position of the ball and ourselves, the racket we are using, the location of our rival at the other side of the net ... and yet, every tennis player can serve after some training. In fact, most likely, not even the best players deliberatively analyze each serve situation to come up with the most efficient course of action, but yet everyone has a tailored service which, better or worse, fits their way of doing things. Indeed, humans do learn different behaviors by social observation of nearby people at early ages [109][161]. If a machine could copy this way of doing things, it could mimic driving behaviors, even if they can not be explained by human nor equations [164].

5.1.1 Learning by Imitation

Learning by imitation has been widely applied to biomimetic navigation in robotics, specially for humanoids, multilegged agents, fish and flying robots and snakes [97][95][115][17]. It is important to observe that true imitation is different from mimicry: it does not only provide the ability to reproduce others' actions, but also to replicate and, through this, learn new skills [7]. Nowadays, it is accepted that only apes and humans are capable of true imitation, whereas mimicry has been observed in many other animals [109][66]. We could accept true imitation as the ability to make ours behaviors observed in others. In a robot, this is a must, because its flexibility and skills will hardly match those of a humans, so behaviors must be adapted in order to be adopted.

Roughly, most approaches to learning by imitation rely on capturing how a person or animal moves via video or wearable sensors and, then, adapting captured movements from the animal body structure to match the robot's. Then, a chain of commands can be obtained to reproduce these movements [36][86][145] (Fig. 5.1a). It can be dully noted that, after all, we did not get rid of equations. The main difference with non-learning approaches is that, rather than trying to manufacture a motion behavior from scratch, we copy it from someone who has already mastered it through practice. Still, maths are required to actually understand how movements can be reproduced by a body different from the one who is actually moving[1].

5.1.2 Teaching by Imitation

Alternatively, it seems more appealing to actually take advantage of the amazing ability of humans to adapt and let others do the hard work for us. For example, anyone who usually drives a car will most likely have no trouble dealing with a rental one, even if the model is pretty different from his/hers. However, if we change

[1] 3D movie characters like Lord of the Rings Gollum or King Kong, both modelled after actor Andy Selkirk, via motion capture techniques are a good example of this adaptation scheme.

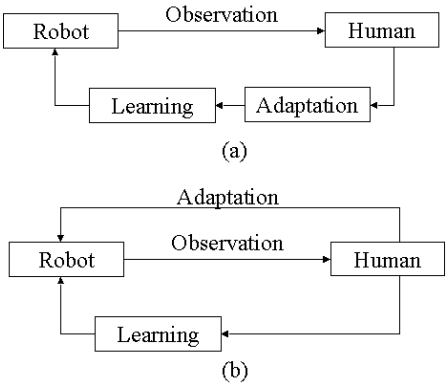

Fig. 5.1 Approaches to learning: a) by imitation; b) by teaching.

a robot's wheels and let it try to do that on its own, we better have a good insurance. The idea here is to move from traditional learning by imitation to novel teaching by imitation: anyone can easily show a robot how to do a thing, like a puppeteer. For a person, given a proper interface, it is a matter of time to actually master the actions of something he/she has never control before. If a robot actually imitates how this person moves its body instead of the person's own motion, these tricky kinematics equations can be removed from our system, as they are implicitly provided by the human (Fig. 5.1b). This might seem impossible at first: how can we actually teach a salamander robot to climb a wall if we are not able to do it ourselves? The key idea here resides in the *proper interface* concept. Let's think of a videogame like Tomb Raider. Anyone can probably do a double back flip with the main character after dabbling a bit with the joystick, even if they do not recognize us in the gym anymore. If we wanted this main character to learn some new movements, it would be simpler -and probably less painful- to just practice with the joystick until we get on screen what we aim to do, rather than trying it ourselves in front of the camera and hope for the software to duplicate it for Croft's body and, again, for our insurance to have a good coverage. In brief, if we get a controller we can handle and somehow map different motion commands into it properly, humans should have no trouble in elaborating creative combinations from the basics, because their brain would translate things for them.

In order to teach a robot by imitation, we first need to determine which factors are relevant to perform a given action and which are not, so we can fix a convenient mapping for our controller. For example, in navigation it is not important if a close obstacle is red or white while we are moving, but rather where it is, so it can be avoided. Specifically, in purely reactive navigation, only moving towards the goal in a safe way is important, so only two factors seems relevant: i) where the goal is with respect to the robot; and ii) where obstacles are with respect to the robot. While the goal is externally provided to the robot, the position of the obstacles is detected in real time by means of on-board range sensors. In fact, it is not so important if

a given obstacle is within a 20 or a 22 cm range, as humans deal with distances in a less precise, more qualitative way. Hence, sensor readings are discretized into only a few distance intervals *[Critical, Near, Medium, Far, No Influence]* to reduce the number of different situations to learn and to avoid learning very similar cases twice. As commented in previous chapters, if a robot is non-holonomic, it is also necessary to take into account its current heading direction, as it can not change *too* abruptly unless we are in a Bond movie [42]. What the robot learns from the human is, obviously, a new heading direction, that only depends on the goal and obstacles position, as desired, but that does not respond to any specific analytical expression and implicitly takes into account the robot kinematics, because the driver has indeed done so. Think, for example, of how we intuitively compensate a deflated wheel by steering a bit when we want to move straightly.

A second concern, as aforementioned, is the human/robot interface. In complex robots like humanoids, hexapods, etc., this might be a problem, even though action videogames prove that, given proper practise, a human can control very complex motion behaviors. In platforms, however, the problem is rather easy to solve, as they are driven in a simple, car-like way. Specifically, for our experiments, we have used a conventional joystick, so that the robot can move in any direction and speed up or down at will. It is interesting to note that, during this process, not only the kinematics of the vehicle are implicitly learn, but also the floor condition, plus vehicle punctual details like different wheel waste, *etc*, as the driver will naturally perceive and compensate all these factors after a while.

Finally, it is necessary to establish how information is learnt, stored and processed. Neural Networks are a natural option, but in this work we use CBR instead, mostly because in CBR systems it is possible to know at any time exactly what the system has learnt and why it is choosing one option or other, as explained in section 5.2.

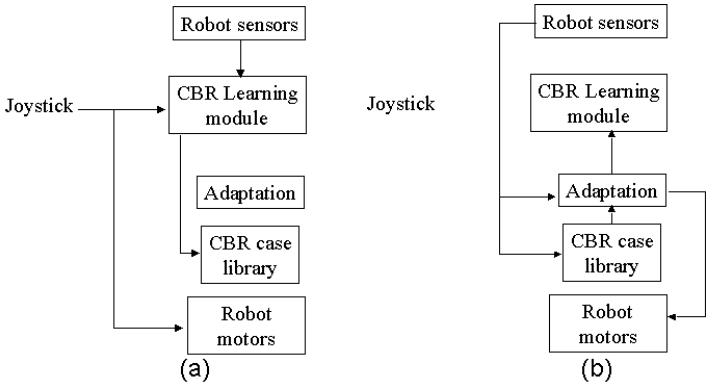

Fig. 5.2 Learning: a) supervisedly; b) by own experience.

5.1.3 Teaching through Collaboration

In wheelchair driving, teaching through imitation is quite easy: user's commands sent to the motors can be captured along with the input situation (Fig. 5.2a). Initially, a person might be not very good at driving, but practice makes perfection, at least within the boundaries of the user's skills. At that point, user's commands will fit whatever he/she feels comfortable with, and this is basically what the system will learn to do. Then, in autonomous mode (Fig. 5.2b), the robot can replicate the user's way of driving on its own. From that point on, the user should most likely not be able to distinguish between the robot's commands and his/her own unless he/she produces anomalous commands or his/her skills decrease or increase.

Obviously, though, it is of no use to have a system that does exactly what the user does, because it would provide no support at all. However, if this learning approach is combined with the proposed collaborative control approach, advantages are more obvious. Initially, each time the wheelchair faces a situation, the system tries to recall a solution to a similar situation. If there is none, the wheelchair operates as described in previous chapters: human and PFA commands are weighted by their efficiencies and combined into an emergent output (see section 3.1) and this solution is stored for future use. If there is one, the system combines this learnt solution with the user's command to produce the emergent one and, then, it will store the new solution for future use. In both cases, a learnt navigation behavior is clearly closer to the person's way of driving than PFA would be. In brief, the system drives like the person would do if they are performing adequately and a modified, improved version of his/her behavior otherwise (Fig. 5.3). Thus, if the system keeps learning, a person improving his/her skills would eventually notice no difference between his/her commands and what the machine does as long as they are not very inefficient or clearly dangerous. Alternatively, if we disable learning after an initial stage, a person losing skills would perceive that the machine drives like he/she did originally, and not notice so many differences. For example, someone who likes to drive very close to walls or to curve sharply would have a machine that does exactly that rather than a conventional *good* driving as long as it is not dangerous to do so.

5.2 Total Recall

CBR is a reasoning, learning and adaptation technique to solve problems by retrieving and adapting past experiences [147] [2]. Its main premise is that remembering, understanding, experiencing and learning cannot be separated from each other: human memory is dynamic and, hence, memory changes as a result of its experiences. Thus, CBR systems rely on remembering old solutions given to similar problems to the one at hand and adapting their solutions for a better fit, instead of solving them from scratch via an analytical expression, functional model or any other traditional meaning.

It might be tempting to think about CBR and Artificial Neural Networks (ANN) on the same lines. There are significant functional differences, though. In its

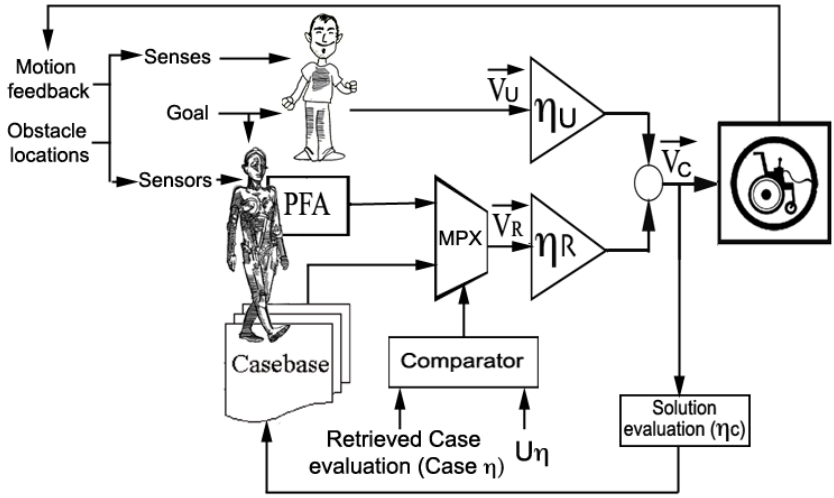

Fig. 5.3 Proposed collaborative control scheme.

simplest form, ANN basically consist of three rows of simple processing units. In order to make them learn, a pattern is presented to the input row, which is connected to a hidden row and then to the output one. Information is, in fact, stored in the connections between neurons, meaning that the activity of one may increase or decrease the activity of another depending on their connection strength. Rather than fixing connections by hand, ANN use feedback (*e.g.* backpropagation) to broadcast the difference between the output pattern and the expected one to the other layers. This error is minimized by changing connection strengths via training with a number of input/output patterns. CBR is mostly derived from the *Theory of Dynamic Memory* [146], that introduces indexing as the key to use experience in understanding. Basically, these experiences are stored in a casebase in the form of cases.

A case consists of a description of a problem, the solution to that problem and some evaluation of the solution. A casebase is very like a database, only it *always* returns a case to any query: the closest one it has in terms of input instance even if it is not an exact match. Given any input situation, CBR cycle consists of four steps (4R schema):

- *retrieve* the most similar *case* to the current one;
- *adapt* the solution in the retrieved case to the new situation;
- *evaluate* the results of the proposed solution in this case;
- *learn* from the new experience by storing it as a new one if necessary.

Qualitatively, the most significant difference between ANN and CBR schemes for non-experts is that cases in CBR are explicitly stored and, hence, a casebase can be intuitively analysed to understand why a given solution is chosen and manually modified if desired. Besides, the casebase can be seeded with *a priori* knowledge to control and enhance the learning process if necessary. This occurs because

casebases store memory rather than abstract knowledge. From a practical point of view, CBR can be steadily handled as a tool by non-experts, stored knowledge is easier to understand, learning can be manually controlled up to a point and it requires far less samples to converge to a suitable problem model.

While handling CBR may be fairly easy, modelling what it stores is not that simple. First, the input problem is characterized via a set of significant parameters, which, along with the problem solution, conform a case. This is probably the most critical part of design, as it is necessary to use *enough* parameters to grant that the solution can be derived from them, but not so many as to blur a case meaning. Selection of a correct instance avoids redundancy and, hence, computational requirements. The second challenge in a CBR system is to find a suitable adaptation function when the retrieved case is not similar enough to the current situation. At worst, random mutation could be applied to get new solutions that could fit or not the input problem, but this is not a very efficient choice. Finally, the adapted case is evaluated and stored for future use.

We can use a CBR reactive layer to teach the robot how to operate in different situations instead of providing an all-mighty analytical function valid for every problem. Besides, the robot may keep learning on its own during operation to adapt to the user's evolution or to hardware and/or environment changes. Furthermore, since cases are explicitly stored, we can get an idea of what the robot has learnt and why it comes to one or another decision. This knowledge, in our case, might even be valuable to doctors to gain some insight on the navigation skills of persons affected by different disabilities or to observe their progress via analysis of cases captured at different times.

CBR has been used in robot navigation before, but typically for high level planning [11][53] rather than to accomplish reactive behaviors. These systems absorb the structure of the environment and are adapted to a specific one. There are also approaches for global planning in dynamic environments based on a topological map of an a-priori known environment [62]. However, in [62] new opportunities can not be discovered when the environment changes unless the topological map is reorganized regularly. Kruusmaa [82] proposed a grid based CBR global path planning method to overcome the aforementioned problem. However, she concludes that CBR-based global navigation is beneficial only when obstacles are large and dense and only few solutions exist. Otherwise, the solution space may become too large.

At reactive level, CBR has been mostly used for behavior selection and transition and selection of behavioral parameters [92] [142]. However, in these approaches behaviors were not themselves developed via CBR. We proposed a purely reactive CBR based navigation approach to avoid kinematic studies when we changed robot platforms in our hybrid architecture [167]. It is the base of the new CBR based collaborative approach. Next subsections cover the basis aspects of our CBR system.

Figure 5.3 presents the proposed collaborative control scheme after CBR learning is included in the architecture. It can be observed that the emerging motor commands are still the linear combination of human and wheelchair commands, which are directly coupled with the sensory input (either human or mechanical) in a purely reactive way. These commands are weighted by their average efficiencies,

so that low human efficiencies imply higher help from the machine. The main difference when we include CBR learning is that cases related to specific situations are stored in terms of what an specific person would do given that situation. Reflexes are implicit in people, so the casebase basically stores how the person drives the wheelchair. Through use, the casebase outputs grow more and more similar to the person's commands. However, if a person drives the wheelchair badly, those cases would also be learnt by the chair. In order to avoid this, we learn cases after they are modulated by either the PFA algorithm or an efficient human command, coming from the PFA block or an already existing case, respectively. Whenever an input situation is detected, the system asks the CBR for the closest case available. If there is none, we use a mix of PFA and human commands as output and learn the corresponding case. If there is any, we use a combination of human and CBR commands as output and, if necessary, learn this combination as well, so that control tends to be progressively more tuned with the person's guidance.

5.2.0.1 Casebase Organization, Domain Description and Case Structure

Trying to recall what a CBR system has learnt is strongly dependent on the case library organization. Main memory organizations are either flat or hierarchical. Flat memories always retrieve the set of cases that match best the input case. Moreover, adding new cases to memory is cheap. However, they have a major drawback: retrieval time grows fast because every case in the memory is matched against the current case, commonly using a Nearest-Neighbor (NN) algorithm [184]. There are also hierarchical memories, such as shared feature networks, prioritized discrimination networks/trees or redundant discrimination networks/trees. In such memories, the matching and retrieval processes are more efficient and faster because only few cases are considered for similarity assessment purposes after a prior discriminating search in the hierarchical structure. They also have some disadvantages: keeping the hierarchical structure in optimal conditions requires an overhead on the case library organization and the retrieval process could miss some optimal cases by searching a wrong area of the memory. This second problem becomes specially hard in prioritized discrimination networks/trees. A purely reactive process should be modeled by a reduced number of cases, so a flat memory can be used to avoid losing cases in the retrieval process.

In flat memory casebases, the most commonly used representation is a plain feature-value vector, where a case can be regarded as a vector in an N-dimensional space. Domain specifics are represented by means of a descriptive model. Relevant features are captured from the domain either by expert selection or by some automatic feature selection or feature weighting algorithms. We already know what we want, what we have and what is important for a purely navigation system, namely to reach the goal, laser readings and encoders and to preserve local efficiency. What it does with this information is what the robot is expected to learn from its driver. In brief, a case for the proposed system would include (Fig. 5.4)

- *the goal direction* with respect to the mobile heading
- the instant readings of *all on-board sonar sensors*.

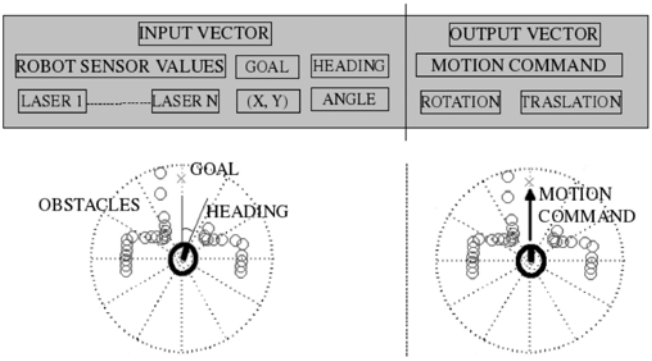

Fig. 5.4 *Case* definition.

- *the current direction of the mobile*, specially if it is non-holomic.
- The *direction chosen by the driver*, which corresponds to the solution of the problem at hand.

Case efficiency is represented by the usual three factors: safety, smoothness and directness.

5.2.0.2 Retrieval Process, Case Similarity Assessment and Case Evaluation

In flat memories of CBR systems, the retrieval task consists of a one-step sequential process, where all cases from the casebase are matched against the new current case. As we mentioned before, the best similar case or cases are usually selected by means of some evaluation heuristic functions or distances, possibly domain dependent, typically known as nearest-neighbour (NN or k-NN) algorithms [184]. The evaluation function usually combines all partial matchings through a dimension or case attribute into a full dimensional partial-matching between cases. Commonly, each attribute has a determined weight.

In this particular application, all laser readings are related. Thus, rather than evaluating the distance between the set of vectors in terms of differences between isolated components, it is better to evaluate the similarity between the global shape of the vectors they conform. This basically means that a situation where we are in the center of a small square room with an open door in front of us would look more similar to the system to the same in a slightly larger room than to the original room one with the door closed, even though in this second case only a minor part of the wall has changed. In brief, similar sensor readings are related to situations where obstacles are slightly further or closer to the mobile, but things are basically in the same relative positions. We consequently work with the *Tanimoto* distance [34], which proved useful in previous works on this subject [167].

It is important to note that minor differences between sensors readings usually correspond to slight robot shiftings rather than to different situations. These differences should not consequently involve creation of new cases. Since it has been

proven [140] that it is better to combine discrete and continuous attributes in CBR systems to fully exploit the domain knowledge, the problem instance can be improved by discretizing the sensor readings. There are many discretization techniques [40], but all of them roughly belong either to automatic partitioning of parameter domain or predefined partitions. In the first case, methods rely either on equal width interval binning or using clustering methods to group partitions relative to the case frequency. In the second case, an expert can define reasonable partitions. Since the robot and the sonar behaviour is known, we have predefined a partition. For our purely reactive layer, far obstacles are not important, but the closer an obstacle is, the more dangerous the situation is. Thus, we discretize laser readings into 5 non equal intervals that have proven to be valid for a typical indoor environment: i) critical (0-20 cm); ii) near (20-50 cm); iii) medium (50-100 cm); iv) far (100-150 cm); and v) no influence (more than 150 cm). These intervals have proven adequate for indoor environments [167].

To define the CBR system, it is also necessary to determine how good a solution is. As commented, in a purely reactive layer, only factors at hand at a given time instant can be evaluated to estimate the efficiency of a case. Thus, we can not rely on global factors like, for instance, the distance required to reach a given goal. Instead, we use directness, safety and smoothness as usual.

5.2.0.3 Training, Learning and Adaptation

Learning is a key cognitive task of CBR systems. There are two major learning approaches in CBR: *learning by observation* and *learning by own experience*. Learning by observation [91] happens when the case library is seeded with a set of initial cases, either by an expert or by direct observation of real data. Learning by own experience [146] is done after each cycle of the reasoner: if the proposed solution has been a succesful one, it can be stored and used for future reference; however, if it has been a failure, the system must prevent itself from making the same mistake in a future.

Learning from success usually consists of inserting new experiences in the appropriate place in the case library. This process basically involves updating the memory indexing structure and organization. *Learning from failure* occurs either when there are no similar cases to the input one in the library or when an existing similar case has not been succesfully retrieved. In the first case, new relevant experiences need to be included in the data base, while in the second one the case library structure needs to be reorganised [180]. Also, some systems maintain a separate case library of failed cases [63] to avoid repeating previous errors.

In our system, learning can be done both by observation and by own experience. Initially, the system may learn either from the driver alone or from collaborative control, if necessary, to navigate like him/her. During operation, the wheelchair keeps learning to converge to smooth reactive navigation and also to look progressively more and more similar to the user. If the system is learning from collaborative control, it will acquire from the automatic navigation algorithm any action that the user can not do. Motion may be shaky at first, but eventually the robot achieves suitable

results after a short training. Naturally, if a person is improving, the wheelchair will navigate progressively more similar to his/her. Yet, learning may be disabled at some point if desired. so if someone is losing capabilities, we can freeze the machine to drive as he/she did while at their best.

In order to learn by observation, a user simply guides the wheelchair from one point to another. In absence of obstacles, the trajectory is as close to a straight line as possible. However, during training one or more obstacles are purposefully positioned between the departure and arrival points, so that the driver can teach the robot how to avoid them.

Learning by own experience is achieved as follows. Given a situation, the CBR module starts to work and returns the most appropriate stored case available. in order to avoid unnecessary case switching, CBR is only triggered when the difference between the current situation and the most recently processed one is larger than a threshold U_{cs}. In order to learn by experience, the distance between the current case and the retrieved one evaluated. If it is is larger than threshold U_{cs}. If the distance is lower, the solution in the retrieved case is adopted. Otherwise, it is decided that the robot is in a new situation which needs to be solved and stored.

In order to solve a new situation, a simplified version of the PFA is used: the goal acts as an attractor and obstacles act as repulsors, so that the combination of all involved vectors provides the resulting trajectory. However, in order to take into account previous experiences, the resulting direction of the retrieved case in also included in the vector combination. This case adaptation process can consequently be considered as a modulation by repulsion fields of the response of cases to be adapted. Obviously, an adapted case might not be suitable either. This is typically related to the wheelchair getting too close to obstacles or too far from the goal. Naturally, in these cases the input instance changes fast. Thus, the CBR module is immediately retriggered and more cases are created, where each new case is progressively more affected by obstacle repulsion and goal attraction, until a safe course to the goal is reached. New cases extracted by own experience are evaluated and stored in the library for future use.

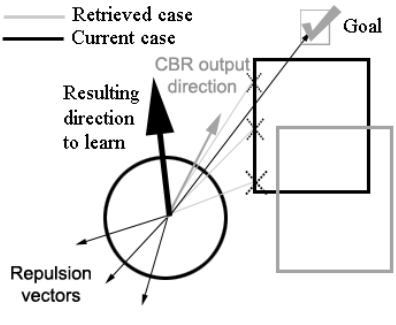

Fig. 5.5 Learning by experience

Fig. 5.5 shows an example of learning by own experience. When the robot is moving towards the goal, a nearby obstacle on the right, printed in black, is detected. The most similar case stored in the database corresponds to a situation where an obstacle was also on the right, but in a different position. The location of the obstacle in the retrieved case is printed in gray in the figure and it can be observed that the solution of the case, also printed in gray, is not valid for this new situation because the robot would collide with the obstacle. Naturally, this is detected

because the sensor readings are quite different in the current case and the retrieved one. Thus, a new case is created by handling the obstacle as a repulsor and the goal as an attractor, as represented by the thin black arrows in the figures. After adding these vectors to the solution of the retrieved case, a new heading solution is obtained. It can be checked that this solution does not involve a sharp curvature change, makes the robot move towards the goal and also avoids the obstacle in the way. If further correction is needed, more cases are generated.

When the casebase is not being used, all stored cases are clustered into classes according to their similarity. The prototypes of the classes are equal to the average of all cases within the class weighted by their respective efficiencies. These prototypes become the stored cases after the library is rearranged. However, learnt cases are preserved for future library rearranging. This clustering process had several goals. First, it avoids too large casebases, as similar cases are averaged into a prototype. Second, cases associated to similar sensor readings but different joystick outputs tend to provoke oscillations. These cases,too, are averaged into the same prototype. Finally, the clustering process filters punctual cases due to errors and remove them from the casebase.

It is important to note that, since during the learning stage the robot stores the best options to solve a given situation for its sensor configuration in the work environment, no considerations about its hardware structure, kinematics, sensor errors or environmental factors need to be explicitly taken into account. Thus, if any of these factors change, the system simply adapts through navigation to the new configuration. *This is an interesting feature because it makes the system valid for different robotic platforms without any reprogramming and also spares evaluation of kinematics during the design stage*.

5.3 A Game of Memory

In order to test the presented theory, we decided to settle with data we already had before moving back to the hospital. Indeed, we had records of every experiment at FSL during summer 2007, performed by volunteering inpatients presenting different degrees of disabilities, either physical, cognitive or both (section 4.2). Using data from any of those inpatients, we could teach the robot to drive like him/her.

Specifically, experiments followed the layout in Fig. 5.6. In one case (Fig. 5.6.a) the inpatient has to move out of the room, turn right and then follow the corridor for 8 m. The second (Fig. 5.6.b) is the reverse path, so the inpatient has to follow the corridor and then turn left to come into the room. It is necessary to recall that trajectories are not symmetrical: it is easier to move out of the room, while facing the door, and turn right whenever the user decides to, than to choose exactly when to turn left to face the door and cross it.

Since each inpatient did several trajectories, the best way to check emulation results was to create the casebase from a single random trajectory and then compare emulated paths with other real trajectories by the same inpatient [124]: if paths and efficiencies were similar for the same person, it would mean that CBR emulation worked fine. However, it is also necessary to observe that different inpatients

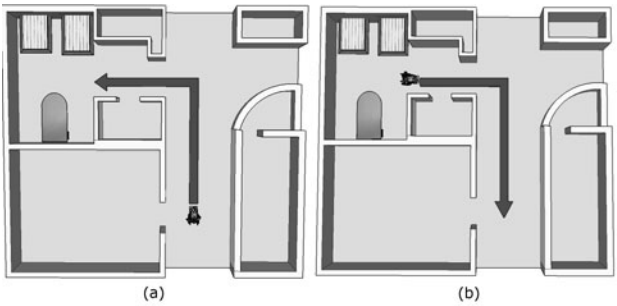

Fig. 5.6 Paths of the experiments: a) From corridor to room; b) From room to corridor.

behave differently. At this point, we did not try to relate disabilities with driving tendencies, and probably never will, as that would be a complex medical goal. We simply wanted to check if a robot could imitate how a given person drives. Figs. 4.6 and 4.7 show how most inpatients diverged at the turning point to either face the door or enter the corridor. There were differences also in straight trajectories, but the most visible ones occur at the door.

During these experiments no mutation nor adaptation of the CBR cases was allowed in order to maintain the integrity of data from the experiments. Hence, resulting trajectories were not necessarily efficient: they depended on the efficiency of the emulated inpatient. However, they should not be too bad, either, because data was captured from experiments where collaborative control was enabled, so when people was performing too bad, the system compensated for them.

5.3.1 Robots Do It Better

First, we calculated how a PFA based wheelchair would do the routes in Fig. 5.6 without human intervention so that:

- differences with human drivers can be appreciated;
- pure PFA problems at door crossing can be observed; and
- we can compare emulated inpatient behavior with an analytical one to prove that human specifics are captured in the casebases.

Fig. 5.7 shows the PFA based robot path, as well as its efficiency at every point of the trajectory. It can be observed that the emerging trajectory is smooth and fairly straight, and efficiency is about 95% average with a minimum of about 80% when crossing the door. This was to be expected due to oscillations provoked by pure PFA when crossing narrow spaces.

It is interesting to note that, given a departure and arrival location, if sensor errors are dismissed, the resulting analytical trajectory given by PFA must be the same, no matter how many times we repeat the test. Obviously, in real environments this is not always the case, as errors do exist. However, using a laser range sensor and in

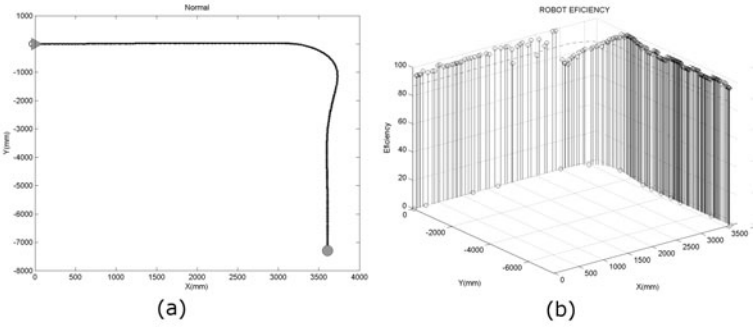

Fig. 5.7 Path (a) and efficiency (b) of an autonomous robot based in PFA in the experiment environment.

trajectories as short as the ones in our experiments, these errors were not so significant. Thus, we assume that PFA return the canonical purely reactive trajectory for an initial/departure point pair in our experiments.

5.3.2 Room to Corridor Tests

At this point, we were ready to work with our CBR system. For a first set of tests, we used data from the first type of trajectories to simulate the behavior of an inpatient moving out of a room. These experiments consisted of choosing a random trajectory of a given inpatient to fill a casebase. Then, we emulated a trajectory departing from a slightly different location and compared this emulated trajectory with a real one **not used** to fill the casebase that departed from the same point. If both trajectories are similar enough, this means that the inpatient relevant driving features were correctly gathered by the system.

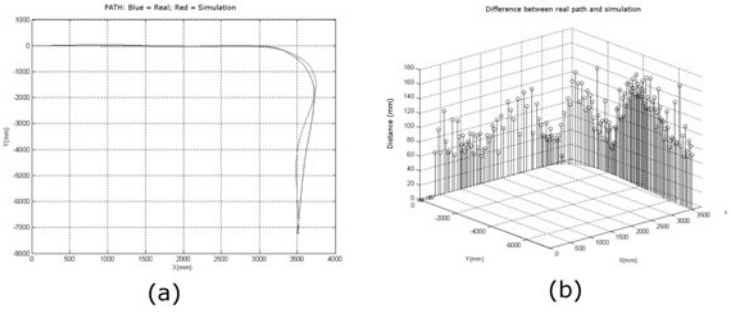

Fig. 5.8 a) Path of the simulation and the real experiment; b) differences between real experiment and simulation in millimeters.

Fig. 5.8 a shows simultaneously a real path (blue) used to capture a inpatient case base and the emulated path (red) that would result, given the same departure and arrival points, for the same inpatient. This may seem like a loss of time: we are using a person's trajectory to get exactly the same trajectory. However, it needs to be noted that CBR does not capture all gathered data, but just the features described in section 5.2. This is meant to be a checking step to see if we can reconstruct the original trajectory of a given person using a limited set of memories. It would be like checking is someone can recall a film with some precision given limited information like the main cast, soundtrack and some key scenes in the movie, only we tried to choose data specifically to do so. If we can achieve this reconstruction, we know that the system *is* driving like the user, at least in the current situation.

It can be observed that both paths are really similar, although there are obviously some minor differences. The figure scale is in millimeters, so the maximum deviation between the original path and the simulated one is 16.5 cm, and average deviation is 7.02 cm. In a 11 m long route, this deviation is negligible. Differences are due to non systemic driving behaviors, corresponding either to input instance discretization or to non repetitive action/reaction pairs that do not appear so often in a trajectory and, hence, are not captured by the CBR. In some cases, if the casebase is trained with a large enough number of trajectories, these errors might be reduced, but, still, we expect that there will always be some differences due to the unpredictable nature of human beings.

The same test was made with other two trajectories performed by the same inpatient. Now, those trajectories were not used to create the casebase. This should not be a problem because, for us, all trajectories are decomposed into a limited set of punctual decisions that, all together, return a whole, like musical notes in a song [2]. As long as our decisions are consistent, i.e.t given the same situation our output is always the same, results should be similar in both cases. Indeed, similar deviations were obtained in these tests (see Table 5.1).

Table 5.1 Differences between Simulated and real paths in the first experiment.

Simulation vs. real traces	Mean Deviation (cm.)	Max Deviation (cm.)
Experiment 1	16.5	7.02
Experiment 2	16.3	7.04
Experiment 3	15.8	7.14

Furthermore, local efficiencies of simulated subject trajectories and real ones follow each other fairly precisely, meaning that they operate on the same principles

[2] Naturally, if we just answer to a note with another, prespecified learnt one, we will get a single song. However, as a driver is exposed to the extern world, the situations he/she faces tend to dynamically change, so even though the number of elements used is the same, the emergent trajectories might be different. Also, the system keeps learning new cases, which would be like incorporating new notes to the scale and fitting them in our song, so it adapts all the time.

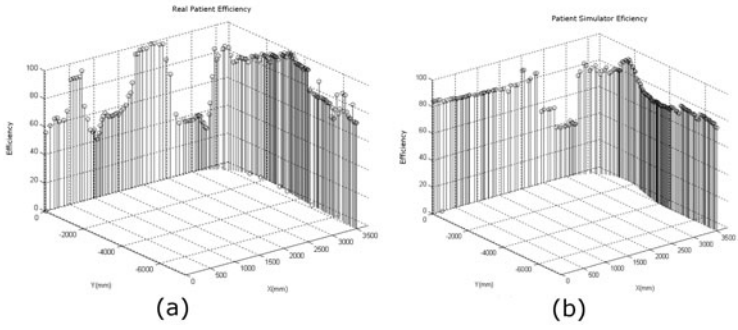

Fig. 5.9 Efficiency for a) real inpatient; b) simulated inpatient.

all the time (Fig. 5.9). Naturally, this was to be expected, as efficiency factors were precisely what we learnt in our casebase.

After observing Fig. 5.9, we can extract the following conclusions:

- Both efficiencies are similar in general through all the trajectory. There are bigger differences at the beginning (inside the room) and at the end of the path (in the corridor). Despite this, both graphs are very similar, meaning that the simulated inpatient and the real one move similarly. The mentioned differences could be attributed to some initial errors in control, filtered out of the casebase as soon as the user is in better control of the chair, and to some indecision about where to end it, as the destination point was not marked on the floor, but simply indicated to the user.
- Efficiencies in real inpatients are more random than in simulated ones. This happens because:
  - CBR quantifies training inputs depending on ranges, in order to keep a bounded casebase and to grant faster access to the cases, as commented. This means that minor differences in the input vector are filtered out of the casebase. Thus CBR returns the same output vectors to very similar input vectors. Since the environment in our test is not too complex and has no moving obstacles, our inputs are not that different. Hence, efficiency in simulated inpatients is more homogeneous in corridor and room section than the real inpatients one.
  - The robot simulator (not the subject simulator) is not completely realistic, as it does not cover sensor errors. Real sensors are not perfect, so in real experiments wrong measures, noise, *etc* do appear depending on the environment conditions. Our robot simulator uses ideal sensor models and this makes inputs from simulated sensors more repetitive than real ones.
- In general, the average efficiency is similar in the simulated and in the real subject: 76.03% versus 74.39% respectively in the experiment in Fig. 5.8. However, the standard deviation for the real subject doubles the simulated one: 11.25% versus 22.35%, respectively. This happens for the aforementioned reasons, mainly

that people are tipically unpredictable. Our CBR system could be tuned to be more sensitive to differences in the input, but this could make the platform unstable and the response of CBR system slower.

5.3.3 Corridor to Room Tests

At this point, we moved to the second, more complex test: following corridor and, at some point, deciding when to turn to enter a room and move inside. The procedure is the same than in the previous subsection.

Fig. 5.10 a shows simultaneously the path of the subject simulator (red) and the real subject (blue). It can be observed that both paths are, once more, similar, although, again, there are some differences. In this case, the maximum deviation between the real path and the simulation one is 16.5 cm., and average deviation is 7.02 cm. As in subsection 5.3.2, this deviation is considered negligible for an 11 m. long trajectory.

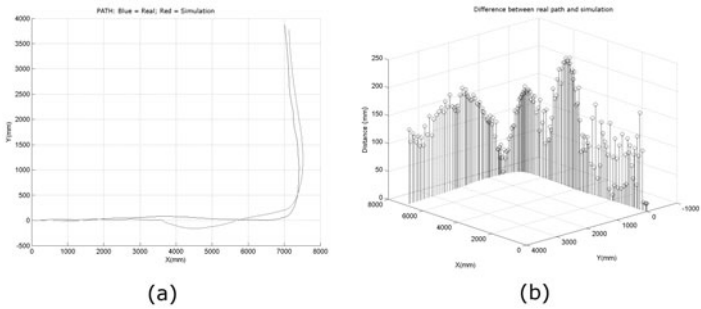

Fig. 5.10 a) Path of the simulation and the real experiment; b) Differences between real experiment and simulation in millimeters.

Again, we used the casebase to compare emulations with other two real trajectories of this type performed by the same subject. Similar deviations were obtained (see Table 5.2):

Table 5.2 Differences between Simulated and real paths in the second experiment.

Simulation vs. ...	Mean Deviation (cm.)	Max Deviation (cm.)
Experiment 1	23	10.23
Experiment 2	19.5	10
Experiment 3	20	8.99

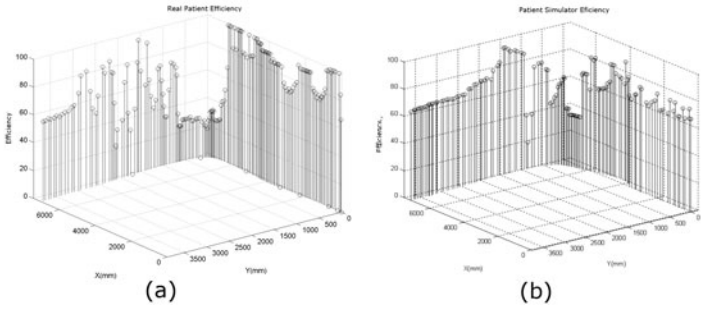

Fig. 5.11 Real subject (a) and simulated subject (b) efficiency.

Fig. 5.11 shows efficiency for an emulated and real path. It leads to the same conclusions than in section 5.3.2. CBR emulations present less random behaviors than real subjects. However, general behaviors are similar enough for performance evaluation.

5.3.3.1 Corridor to Room with Room to Corridor Data Tests

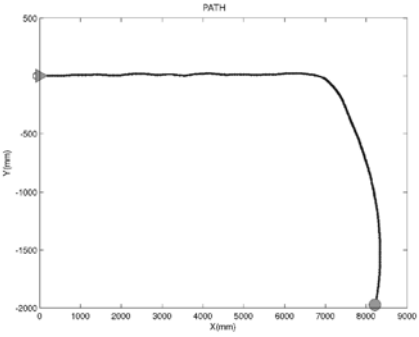

Fig. 5.12 Path of the simulated subject when a trajectory type 2 is trained with type 1 data.

Since things seemed to be going well, we decided to go for a harder test: we would repeat the last experiments with the second type of trajectories, but using learnt data from the first type. As adaptation was explicitly disabled in these experiments, the wheelchair would not learn new tricks, meaning that, since in all traces significant turns were made to the left, it would never turn right on its own. However, critical factors in trajectories type 2, like when to turn depending on the relative position of wheelchair and door, where not present in trajectories type 1, so results might be interesting. In this case, if situations were not really symmetric at all, we expected the simulated subject to move correctly through the corridor but probably not to come into the room and, indeed, this was the case (Fig. 5.12). This is not really a drawback, as whenever either adaptation, collaboration or both are enabled, either the person or the PFA would eventually decide to turn and, after a while, CBR would learn to do so also, but it proves that the system operates on memory, as expected.

5.3.4 Room-Corridor-Room Tests

After stating here and there that complex trajectories can be decomposed into simpler situations and, hence, limited learning is enough to navigate fairly well, we decided that we could partially prove this by emulating a more complex trajectory using available data. Again, we needed to keep in mind that the system would not be able to invent situations it could not remember, as stated in subsection 5.3.3.1, so we went for the basics. In the data we had, persons went either in **or** out of a room, always turning left when necessary, so we prepared and scenario where an emulated person should go in **and** out of two adjacent rooms in the same trajectory, turning left when necessary. The casebase was created from two trajectories type 1 and 2, respectively. In these cases, door crossing should not be a problem, as it is a task performed in both directions. If complex trajectories can really be generated from a limited set of cases, this should work just fine. This would be particularly useful for designers and caregivers to get some idea a priori about how a person presenting a given profile -as extracted from previous trajectories- would behave in a complex or somewhat hazardous situation or in a given specific environment.

The new trajectory to check in presented in Fig. 5.13.a and we used the FSL hospital layout rather than inventing a new one. The path consists of leaving a room, turning, heading for the corridor in a straight way for about 8 m. and then entering into another different room. The entire trajectory is about 14 m. long: 4 to navigate in/out of each room and 8 in the corridor.

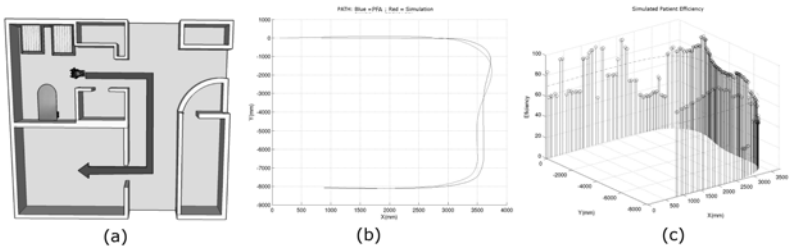

Fig. 5.13 Real subject (a) and simulated subject (b) efficiency.

In this case there was no real trajectory to compare results with, so we repeated the experiment using PFA and compared the simulated subject with results obtained with the PFA just to check that they were different, meaning that our path was influenced by the person's behavior. Fig. 5.13.b shows simultaneously the path of the subject simulator (red) and the PFA trajectory (blue). It can be observed that PFA trajectory is smoother than the simulated subject, as usual. The maximum deviation between the two paths is 21.0 cm, and average deviation is 10.07 cm. Fig. 5.13.c shows the emulated user's efficiency. It is similar to the real subject's efficiency in real experiments: Average efficiency is 70.42% and typical deviation 17.60%. As in previous sections, deviation is lower than in real subjects, as expected.

5.3.5 *Subject with Specific Disability Tests*

Thus far, we had checked -at least to a point given available data- that:

- CBR can imitate how a person drives;
- CBR driving is solely based on memory;
- adaptation is necessary; and
- complex trajectories can be derived from limited learning.

However, we still wanted to check how precisely the specifics of a given person could be captured in a casebase even if his/her behavior was very different from an analytical one. This would not only be interesting for better adaptation to the driver. In a best scenario, it also could mean that a doctor could check how someone drives and possibly learn about his/her condition and/or evolution. Thus, we decided to go for the room to corridor experiment with a particular subject. In our experiments, most of the subjects did a trajectory close to the expected one in this particular experiment, as paths were fairly simple and decisions about when to turn where not as personal as in trajectories type 2. However, some subjects with higher disabilities were not able to operate the wheelchair correctly, despite assistance provided by collaborative control, so they followed trajectories remarkably different to the average one (Fig.5.14).

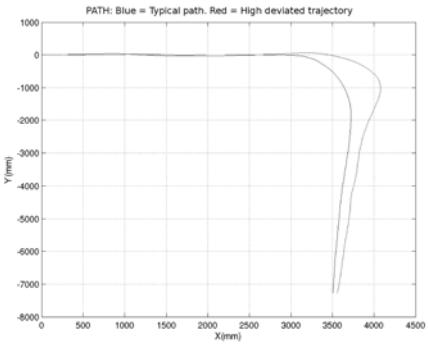

Fig. 5.14 Path deviation with respect to the typical trajectory in a specific subject with high apraxia.

Our chosen person suffered from high apraxia. Apraxia is a neurological disorder characterized by loss of the ability to execute or carry out learned purposeful movements, despite having the desire to and the physical ability to perform the movements. Specifically, this subject has an apraxia index equal to 3 (being 0 the worst index and 10 the best one). This figure shows how the subject drifted away from the expected path, specially when he had to turn after moving out from the room. Numerically, the maximum deviation in his trajectory was 0.5 meter with respect to the PFA one, even though collaborative control tends to homogenize performances. If CBR really imitates how a person drives, the emulated path should be similar to this subject and not to the usual one, even if this trajectory was not efficient: the proposed system at this point is not expected to judge when to imitate humans or not, just to do so.

Fig. 5.15.a shows simultaneously the path of the real subject (blue) and the path of the simulator (red). Indeed, the emulated trajectory is very similar to the real one. The maximum difference between both is 17.5 cm. (Fig. 5.15.b) and the average deviation is 8.3 cm.

Fig. 5.16 a-b shows the efficiency of real and emulated subject respectively. Both efficiencies are very similar, although, as in prior experiments, the real subject has more variations than the simulated one. Specifically the average efficiencies are similar in the simulated and in the real subject: 61.11% versus 62.00%. However, the standard deviation, as in previous experiments, is a bit different: 21.57% for the real subject and 12.99% for the simulated one.

The key idea extracted from this last test is that a casebase acquired from a person with a significant disability yields information about his/her condition that can be evaluated off-line by authorized staff to evaluate him/her. Given a large enough amount of data, it might be possible also to check if persons afflicted by similar disabilities tend to present similarities in their casebases as well, as this would turn those casebases into diagnosis tools. However, at this point we had not enough subjects affected by the same problems, as the sample space had been chosen to be varied so we could not conclude anything to this respect yet.

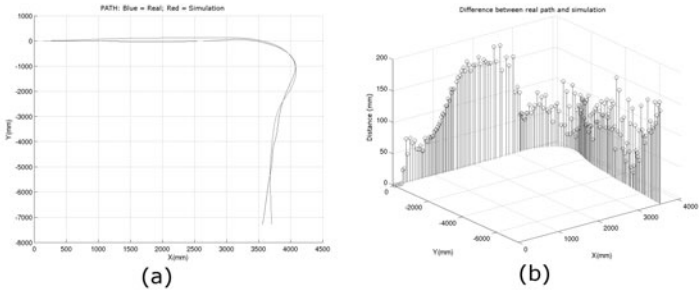

Fig. 5.15 a) Emulated and real subject paths; b) differences between the real experiment and the emulation in millimeters.

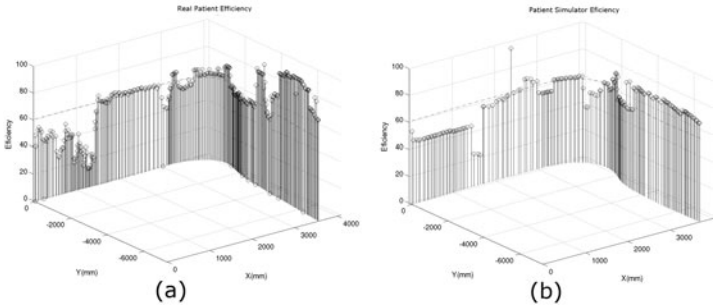

Fig. 5.16 Real subject and emulated subject (a) paths; (b) efficiency.

5.4 To Learn or Not to Learn

After concluding this first batch of experiments with learning, we extracted some interesting conclusions:

- A CBR emulated subject and the real one during the experiments provided very similar paths. Specifically, their trajectories and global efficiencies were very similar, meaning that CBR can successfully learn from imitation and adapt to the user.
- However, global efficiency is less random in emulated subjects than in real ones in all cases. Usually, the standard deviation of the efficiency in real subjects doubled the corresponding simulated one. This means that there will always be spurious, unexpected actions that the CBR system will not be able to capture.
- A limited set of cases is enough to generate trajectories, even some that where not present in the training set as long as we do not expect new behaviors to be generated from scratch. If adaptation is enabled, though, new behaviors can be generated on-line, even though they might not fit the user's way of driving at least at the beginning. On-line learning also allows capture of these new behaviors as long as the user is able to perform them. Collaborative control would ensure that the wheelchair can do some tasks for the system to learn even when the user can not.
- CBR can capture the specifics of a given subject, even if they are not common or his/her behavior is to be expected. This might mean that casebases could be used to assist diagnosis, but this remains to be proven.

Experiments also highlighted some lacks in our scenarios. First, we found out something we should have known from the beginning: *if we do not run tests in standalone mode, we do not have any real idea about how a person would behave without assistance*. Checking what the person does and what the system does in collaborative mode separately is no use. Indeed, one never knows how persons would react in hazardous situations because collaborative control never really allows people to get into them by correcting them harder when needed. Running tests with real subjects without any robot assistance would require more people to be around at all times and, still, the safeguarded more to stop the chair in case of imminent collision was a hard constraint, but in the next experiments it would be a must.

Regarding the sample space, we checked that persons with low disability indexes tended to perform very similarly in such simple scenarios. In order to really check the extent of the system, we needed either a more complex scenario, persons with higher disabilities or both. In any case, this would mostly depend on FSL and involved medical staff, so we made the request and, fortunately, got lucky. Also, as good as it may seem to have persons with conditions as varied as possible for experiments so that it can be checked that collaborative control homogenizes everyone's performance, from the point of view of extracting conclusions from the amount of assistance received by a given group, it might be of interest to have groups of control. However, medical goals are far from our area of expertise, so we could only suggest this possibility to specialized staff.

Finally, even though we had managed to prove that driving can be adapted to the user, we still needed to run the system on-line to check if having the robot drive like the user would provide a better outcome. Naturally, we could run experiments on collaborative control using CBR and available real data, but it would be a closed system: persons would not produce anything new because everything was already pre-captured. As long as we did not know what someone would do if the wheelchair basically wanted something he/she had previously done in a difficult situation, we could not be sure if the new system was a good idea. If persons changed their mind a lot at such situations, the system would never converge. If people detected minor differences in such situations, it would also not be of use. Real tests would be our next target.

During this new experiment design,though, it was critical to decide where to learn from. Should we learn from standalone human data? In such a case, if a person is unable to do something, the CBR system will not be able to help either. We could also learn from collaborative control data but, as proven, such data is equalized, meaning that it does not retain that much the specifics of the driver unless they are very remarkable. As both choices had drawbacks, we went for a compromise. We would learn from standalone data, but collaborative control would be modified. PFA, CBR and human control would be running at all times. At each point, the efficiency of CBR and human would be evaluated. If both of them were under a given threshold, the emergent command would be the combination of PFA and human commands instead of CBR and human ones and, also, CBR would learn the emerging case. This basically means that if someone is not able to perform a particular action, the system would help and learn until they can. This action would be less similar to the person's way of driving than the rest but, without a reference, we could not do better. At some point, it might be interesting to check for similar casebases among available ones to see if the wheelchair can actually copy a missing action from someone who drives like us, so that the outcome is more familiar to our perception, but it would be necessary first to establish a measure of similarity between casebases as a whole.

Chapter 6
Once More, with Feeling

No, No, Yes, No, I tired that, yes both ways, no I don't know,
no again, are there any more questions? Good.
- Xena, the Warrior Princess

At this point, we knew the protocols by heart, so we followed every step once more, only this time it was decided to work in a house-like environment [173][177]. This would provide a more realistic place to run our tests and, also, we could work with persons with higher disability indexes and not interfere with hospital activity. FSL kindly provided access to Casa Agevole (Fig. 6.1), a 60 m^2 house built within the hospital complex in Rome (http://www.progettarepertutti.org). Casa Agevole has the *minimum* requirements to be standard-compliant, specifically meaning, in our case, that doors width and room sizes are very reduced, yet appropriate for wheelchair navigation and should fit our needs. Or, in other words, if our wheelchair can not navigate within this house, it could be of no use to operate in a common one.

6.1 A New Beginning

Our new experiment setup consisted of entering the house via its main door (150 cm wide), moving on to the main room and then turning right to enter a second room. This second room was split in two by a cupboard, that the person would face immediately after turning right. Then, he/she had to move between the wall and the cupboard, separated approximately 90 cm, and again to the right, to reach a table in that area. The only guideline provided to the person, after a short tour of the house, was to reach that table. Since we also wanted to check the impact of cognitive disability in direction keeping, it was not allowed to provide further instructions while driving, but, as in previous experiments, there was always someone walking behind the wheelchair to stop it in case of emergency. A tentative trajectory is printed in Fig. 6.1, along with some views in key points of the path, but it must be noted that each person would most likely follow a different path depending on how soon or fast they turn, how close they get to obstacles, etc.

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 117–144.
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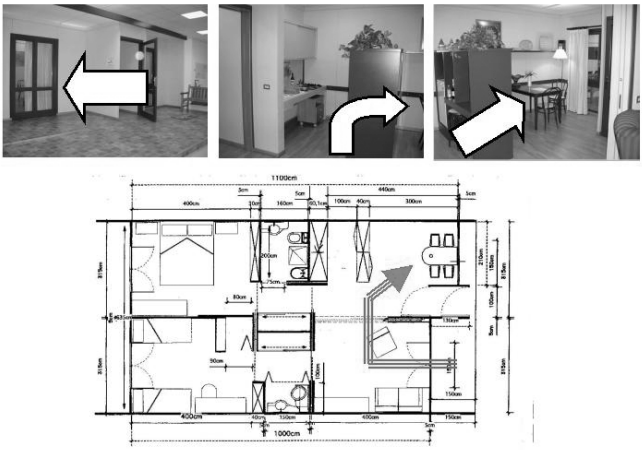

Fig. 6.1 A diagram of Casa Agevole and a proposed path

The population involved in these experiment is briefed in table 6.1. In this case, some persons presented severe disabilities so severe that some of them required mechanical help to be transferred to the wheelchair. Others had a very low MMSE, and in some cases it was even hard for them to remember what they had to do during the tests. In fact, they had been specifically chosen by the medical staff to test collaborative control to the limit with a population structured to cover all disability profiles we could think of.

Fig. 6.2 Interpretation of a video sequence augmented information

In this case, they trusted us enough to let us capture benchmark trajectories for every volunteer in standalone mode, as long as the safeguard layer was always active[1]. Then, we repeated the test with collaborative control. From this second trajectory, we captured traces to let the system learn how the person drove and made a third go with the proposed CBR based technique. It is important to note that our CBR actually learns from collaborative data for two reasons: i) some persons were not even able to cross the doorway on their own; and ii) if a person was not capable of a certain action, the system would neither be if it just copied the person's actions. If we

[1] The wheelchair stopped if obstacles were closer than 30cm.

learn from collaborative control, the system drives like the user whenever it is possible and like the user assisted by the machine in the rest of the cases, which is, in any case, closer to the person than PFA.

The first goal of these experiments was to check the effect of PFA based collaborative control on persons with i) minor cognitive and physical disabilities; ii) mild physical and minor cognitive disabilities; and iii) mild cognitive and physical disabilities [177]. Then, we could check if CBR based collaborative control improved performance in any of these scenarios [124]. Results are briefed in table-format for a representative member of each group and then presented as follows:

- First, we provide results in standalone mode, in terms of trajectory, efficiencies along the path, Intervention Level and Joystick Variation. This is meant to evaluate *how* persons perform on their own, in terms of efficiency, effort and workload.
- In collaborative control η_H, η_R and η_C are compared along the trajectory.
- Disagreement is analyzed at each point of the path. Since it is suspected to be related to situations where machine intervention is acknowledged by users, Disagreement is also correlated with η_R to check if it is larger when robots clearly outperform human drivers.
- To check if users are coherent when they disagree with the machine or they simply try to struggle for control, Inconsistency is evaluated and we check the appropriateness of decisions in clusters with large variation.

In order to illustrate better the results of the experiments, this time we asked either the volunteers and their caregivers if we could record the tests in video. Naturally, only part of them agreed, but it was enough to gain a better understanding of what happens and when. At each point of the trajectory, we overimposed to the video frame information about the local and global efficiencies at that point both for the person (strong colored bars) and collaborative control (darker ones inmediately below). We used red for smoothness, green for directness and blue for safety, and combined them all into an RGB bar for global efficiency (Fig. 6.2). We also included in the bottom right corner of the frame the joystick shadow, in red, what the robot intends to do, in green, and what collaborative control actually does, in purple. Text data is provided at the bottom of the frame to check for numerical values, if necessary.

6.2 The B Team

In this case, we ran tests with new volunteers, that we will call subjects 1-18 from this point on. Medical staff in FSL provided their disability profile (see chapter 4). All significant data concerning these persons is briefed in table 6.1.

6.2.1 Good Physical and Cognitive Skills

Our first group of volunteers mostly managed to finish the trajectory on their own, except for a few ones who had problems controlling the wheelchair, like subject 15.

Table 6.1 Volunteers in the October 2008 experiments.

Inpatient	Pathology	CIRS	MMSE	GDS	Barthel	IADL
1 (F/56)	Multiple sclerosis	1.38	26	6	100	8
2 (F/68)	Paralysis from medullary lesion	1.53	27.4	3	49	7
3 (F/69)	Left Hemiplegia (Stroke)	1.92	23	4	68	3
4 (M/36)	Left Hemiplegia (Cerebral Hemorrhage)	1,23	29	5	52	4
5 (F/72)	Left Hemiplegia (Cerebral Hemorrhage)	1,77	NC	NC	8	0
6 (M/61)	Left Hemiplegia (Stroke)	2	21,9	2	41	2
7 (F/76)	Ischemic Stroke	2,1	20,3	0	29	1
8 (F/75)	Ischemic Stroke (Left Hemisphere)	2	22,7	12	68	2
9 (M/45)	Right Hemiplegia, Aphasia	1,38	19	7	75	0
10(M/84)	Bedridden syndrom	2	19,4	4	44	1
11(M/67)	Ischemic Stroke, Left Hemiplegia (Stroke)	1,53	17,2	2	36	1
12(M/64)	Left Hemiplegia (Stroke)	1,8	23,2	1	39	1
13(F/62)	Guillain-Barre	1,38	23	0	28	1
14 (F/50)	Right Hemiplegia and Epilepsy	1,9	20	0	96	8
15 (F/66)	Right Hemiplegia, mixed Aphasia	1,8	23,2	12	62	2
16 (M/76)	Mixed aphasia	–	–	–	–	– / –
17 (F/82)	Hemiplegia (right) - mixed aphasia	2	3,1	3	47	1
18 (F/70)	Brain hemorrhage	–	–	–	–	–

It needs to be noted that most volunteers in these tests were below the dementia threshold, so we choose people with the highest MMSE for this group. In general, these volunteers did not increase much their global efficiency in collaborative mode Subject 15, for example, moved from 57.93% to 64.63%, but her directness decreased a 3% in exchange for a 6% increase in smoothness. However, it assisted those who could not finish the trajectory on their own. These people mostly had just punctual problems, but sometimes, delayed decisions brought them to complicated spots where it was too difficult to maneouvre any further. Subject 15 (Fig. 6.3) did not have major problems with Disagreement. In fact, it remained approximately the same (18%) in standalone and collaborative mode. However, her Inconsistency was larger than usual and collaborative control reduced it to a half (4.38%). She also benefited significantly in terms of Intervention Level, which decreased from 98.3% to 75.26%, not because subject 15 stopped operating the joystick, but because she agreed mostly with the wheelchair outcome in collaborative mode and, hence, benefited from mechanical inertia.

The most representative subject in this group is volunteer 1, a 56 years old female affected by multiple sclerosis. It can be observed in table 6.1 that she is autonomous: this person could walk with the help of a walker, but had no previous experience with power wheelchairs. This can easily be observed in the high Disagreement that she presents in her first try, even though she is in standalone mode (25.18%). Table 6.2 briefs her performance in her five tries: standalone, PFA and CBR shared control. It can be observed that this person repeated the PFA shared control test three times and, indeed, the third time was the worst of all. She is the person who made us realize that people with this profile may have trouble accepting assistance. In fact, she failed

Fig. 6.3 Inpatient 15 video footage (Good cognitive and physical skills)

to finish her last two PFA based paths and reported that "the wheelchair was not working" while trying to move it into a wall. Hence, she is very representative for this group.

6.2.1.1 Standalone Mode

In standalone mode, the only robot intervention allowed was safeguard triggering. This explains the minor differences between human and collaborative performance in the first column in table 6.2. η_H is equal to 67.56%, mostly derived from a very safe driving. Directness is not that good: local targets are not printed on the floor, so many users, like subject 1, try to turn too late from the system's point of view.

Fig. 6.4 shows the complete standalone path, η_H represented in the proposed RGB coding and her Joystick Variation. Intervention Level is always very high because, despite the control mode, the wheelchair can not move unless there is some human input. Thus, we simply represent points where the subject stops with red dots over the Joystick Variation plot. These points are mostly related to locations where the person stopped to decide what to do next. It can be observed that subject

Table 6.2 Subject 1 Test Data

Control type		Autonomous	Shared PFA	Shared PFA	Shared PFA	Shared CBR
Global efficiency (%)	Robot	—	63.12	65.73	58.97	68.61(69.23)
	Human	67.51	65.17	60.7	57.05	70.6
	Both	67.56	68.4	67.88	64.0	74.5
Smoothness (%)	Robot	—	56.45	57.37	36.81	52.2(78.73)
	Human	66.4	65.91	56.4	61.26	66.62
	Both	66.33	65.1	63.17	61.96	74.6
Directness (%)	Robot	—	43.85	51.6	48.75	61.98(34.13)
	Human	44.28	37.46	38.42	22.0	48.61
	Both	44.39	45.75	44.85	37.0	52.73
Safety (%)	Robot	—	88.9	88.24	91.39	91.81(94.92)
	Human	91.95	92.34	87.41	87.94	96.55
	Both	92.03	94.45	95.59	92.96	96.22
Intervention Level	%	99.73	70.73	77.85	97.95	82.83(82.56)
Disagreement	%	25.18	21.37	29.87	47.31	20.89(25.11)
	dev	25.18	14.96	18.02	27.7	18.72(26.63)
Joystick Variation	%	0.09	0.2	0.07	0.06	2.38
	dev	1.12	2.37	1.08	0.99	3.65
Inconsistency	%	6.73	7.7	8.58	4.91	6.69
	dev	6.73	7.7	8.58	4.91	6.69
Total Length	m	6.7	6.68	4.98	4.8	6.4
Completion time	sec	30.67	38.2	31.61	32.22	30.63

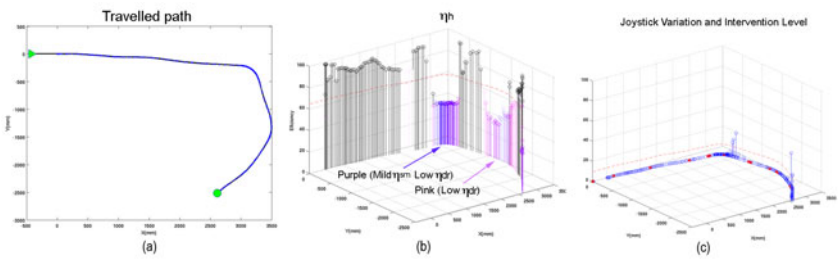

Fig. 6.4 Inpatient 1 standalone mode: a) path; b) η_h; c) Joystick Variation and Intervention Level.

1 standalone trajectory was quite smooth and efficient, even at door crossing. The worst performance appeared at the second turn, where she got too close to obstacles comfortably to turn right. In turn areas, η_H was either pink -loss of directness- or purple -loss of directness and smoothness-, meaning that she had to perform mildly sharp direction changes to correct her path. Subject 1 operated the joystick most of the time (99.73%), as expected. Also, her Joystick Variation was quite low (0.09%) and mostly related to purple areas. In brief, her way of driving was quite coherent, only the right turn took too much time. She reached her goal -the dining room table- in just 30.67s after travelling 6.7m.

It is interesting to observe what the user did and what she did not. If we cluster her decisions according to the relative positions of wheelchair, goal and obstacles, we can observe that subject 1 had trouble fine-tuning turns, i.e. she either turned too much or not enough. This basically explains why her trajectory got her so close to a wall. Fig. 6.5 shows some clusters to illustrate this assessment. In all cluster figures, the wheelchair is heading in the 0 degrees direction and the goal is marked with a cross, whereas obstacles detected by the laser are marked with circles. The user's chosen direction is marked with a dark blue joystick shadow, and the system outcome is marked in pink. In standalone mode, though, the system only has influence in two things: i) speed limit; and ii) emergency stop (safeguard navigation). Hence, in this mode system and user directions do match. We can observe that in the first case, at an early stage of the path, subject 1 tried to correct her trajectory slightly towards the right, but overdid her turn. In the second cluster, we observe the contrary: she should had turned slightly to the right, but she kept moving ahead. This kept happening in her trajectory, mostly at points with low Intervention Level. The effect is that she typically turned late and could not steer with precision. This fact seemed to be coherent with her diagnosis from our medical staff point of view.

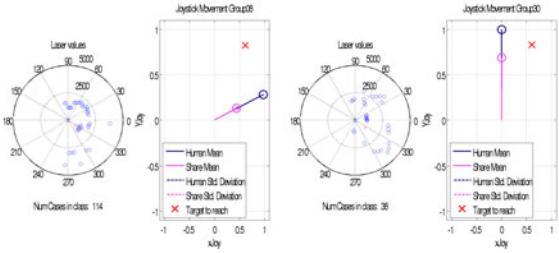

Fig. 6.5 Turn difficulties for subject 1 (standalone)

6.2.1.2 PFA Based Collaboration

Next 3 tries were performed with PFA based collaborative control and, in fact, not only did global efficiency not increase significantly but even decreased in the last try. As reported, this is typical in persons with negligible cognitive and physical disabilities presenting high Disagreement, when they realize the system is helping them, whether they like it or not. In her last PFA based run, when subject 1 was close to the table, she had apparently realized that she was not completely controlling the wheelchair and apparently wanted to check her theory: she turned right, towards a wall instead of left, towards the table, even though she was completely aware of her goal. Obviously, the wheelchair tried to correct her and they struggled for a couple of seconds. Her directness dropped down to 22% and η_S decreased drastically. In this particular run, Disagreement became as high as 47.31%, meaning that half the time human and collaborative commands were in conflict. Also, her Intervention Level, which was lower in collaborative mode than in standalone mode while she had not acknowledged assistance, grew to 97.95%. Subject 1 reported that the wheelchair "was not working" when it did not allow her collide into the wall.

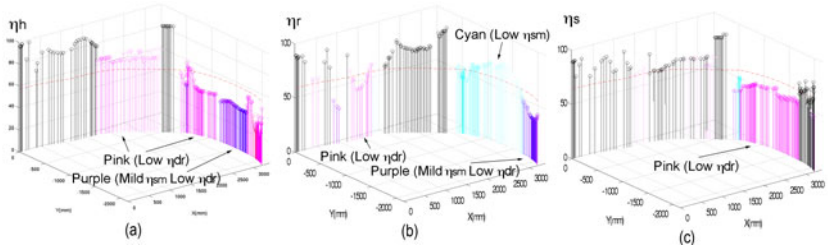

Fig. 6.6 Subject 1 PFA based collaborative mode: a) human efficiency; b) robot efficiency; c) collaborative efficiency.

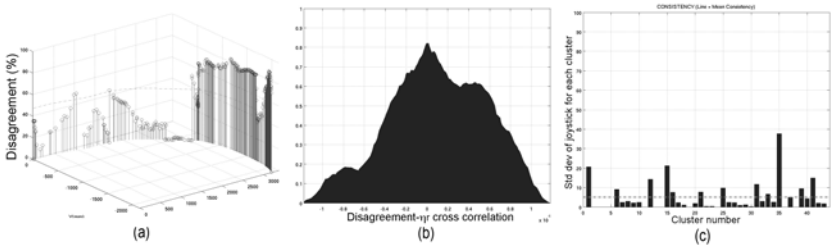

Fig. 6.7 Subject 1 Disagreement for PFA based shared control: a) cross correlation Disagreement/η_R; c) Inconsistency;

All figures from now on refer to this last PFA based test, after the inpatient had already guessed the nature of the system. Fig. 6.6 shows η_H, η_R and η_C, respectively. Initially, things went smooth, because a PFA based robot is affected by oscillations at door crossing and this person had no trouble at all moving forwards. Hence, in this case the wheelchair mostly obeyed her. However, as soon as the robot started to outperform the user and, hence, had a noticeable effect on the trajectory, she started to lose efficiency, trying to avoid the robot pushing her in a given (correct) direction. After that, the rest of the trajectory is an struggle for domination that the robot could not compensate despite its efforts to compensate direction changes (cyan η_R area) and, even though collaborative control combined commands as expected and equalized performance for a while, η_C became clearly pink, and subject 1 failed to finish the trajectory.

To support further our explanation to efficiency loss, Fig. 6.7 shows how Disagreement was distributed through the path. It is obvious that the subject did not finish the trajectory, both in the path length (4.8 m with respect to her average 6.7 m) and in Fig. 6.7, where she finished at (3.2,-2.2) instead of at the table position: (2.5, -2.5), approximately. It can be observed that Disagreement was higher at the last part of the trajectory, as we guessed from casual observation. Indeed, Disagreement was very correlated with η_R, meaning that it grew with the robot's impact on emerging commands. Furthermore, if we check the inpatient's Inconsistency in the test, we can observe that, in fact, she was driving far from her average: from the 43

different commands clusters that she typically used to solve the proposed trajectory in standalone mode, 25 -corresponding mostly to turn decisions- had a large standard deviation. This basically means that her decisions were statistically erratic, as proven by her larger Joystick Variation when she faced similar situations.

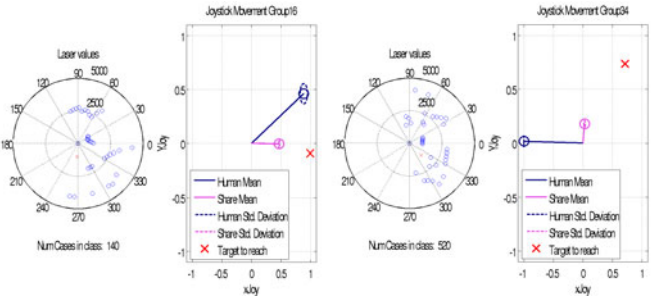

Fig. 6.8 Subject 1 sample clusters for PFA based collaborative control

This can be appreciated in detail in Fig. 6.8, where two clusters, corresponding to turn correction and strong Disagreement are presented. Since these clusters correspond to collaborative control, user and emerging commands are not the same anymore. Cluster 6 is generated at the beginning of the trajectory, when the first turn decision needs to be taken. As usual, subject 1 delayed her turn, but this time the robot contributed to motion, so, to avoid getting as close to the front wall as in standalone mode, it forced a sharper right turn. The emerging command, no longer equal to the user's, was practically a 90^0 right turn, only much slower than the user's command (shorter vector). At this point, the user was already fully aware of collaborative control and had started to fight it, but, eventually, the struggle became so intense that clusters like the second one were generated, with a goal on the right side of the wheelchair, obstacles on the left and yet, the user pushing the joystick hard into that direction. Since η_H was very low at the point, the robot won and the emerging command was slow forward motion. This eventually got the wheelchair so close to obstacles that further, safe maneouvre was not possible and subject 1 failed to finish the trajectory.

6.2.1.3 CBR Based Collaboration

Fig. 6.9 a shows the path in CBR based collaborative control. It can be observed that it is smoother and safer than the standalone path. As commented, the casebase was filled with data coming from the previous runs in PFA based collaborative control, specifically run 0, which was the person's best run so far. We could have added the other runs, but η_H had been so low that practically no case would have been added to the casebase. Unfortunately, data from a single path was not enough to correctly represent all possible situations in this experiment, because cases may be quite different depending on wheelchair maneuvers even for similar trajectories. As

commented, if a situation was not available within the casebase (low η_h), we used PFA based collaborative control at that specific location and stored it for future use.

The areas where it happened are very noticeable in Fig. 6.9 c, where Disagreement between the user and the system is presented. We have marked with red dots locations where collaborative control switches from CBR to PFA, but it probably would not have been necessary because Disagreement increased significantly at those areas. Indeed, average Disagreement (slash line) was mostly concentrated in those areas. It was typically low when CBR can be used. In any case, we can observe in Fig. 6.9 d that Disagreement was no longer so correlated with η_R, because CBR can be efficient, but it is usually similar to the person's habits. There is still some correlation, mostly because of PFA based areas. Further learning should reduce this as well. We can observe, also, that even though Inconsistency was similar in average here and in standalone mode (Fig. 6.7), there were less command groups, they were more homogeneous and their deviation was lower.

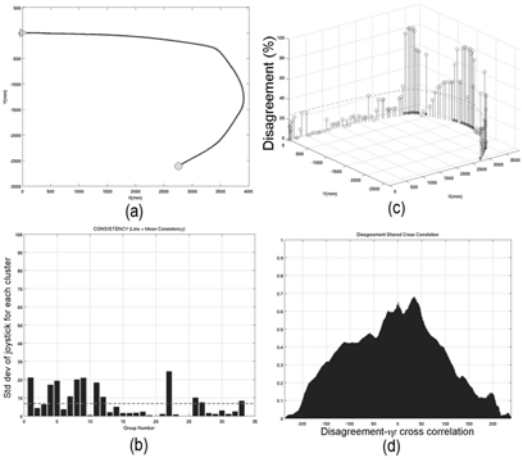

Fig. 6.9 Subject 1 CBR based collaboration: a) path; b) Inconsistency; c) Disagreement with PFA and CBR; d) correlation between Disagreement/η_R.

The results of these tests are briefed in the last column of table 6.2. Due to the nature of the system, we calculate what PFA would do all the time, but PFA commands are not used unless: a) there is no suitable CBR case to solve the situation; or b) η_C for human and CBR goes under a safety threshold. η in this case grew to 74.5%, higher than in any of the previous runs, including standalone mode. This was better than PFA based collaborative mode -in this case, 68.61%-, CBR alone -69.23%- and human control -70.6%-. More specifically, smoothness was boosted to 74.6%, even though CBR was in our case, by definition, worse than PFA - 78.73% to 52.2%-. This happened because: i) the casebase was still not full enough; and ii) PFA are designed to preserve smoothness, whereas CBR may induce mildly sharp direction changes when switching from one discrete case to the next.

The inpatient had practically the same smoothness than in standalone mode, which means that she was not fighting the machine anymore.

Directness, though, was quite low for CBR with respect to PFA, but the subject compensated it and, at locations where η was too low, PFA took control of the situation, so that combined directness raised to 52.73%. Safety, as commented, was preserved by all control combinations in the experiment, but it was a bit higher in this final mode. We have experimentally checked that this happens when users are

comfortable with control and drive smoothly, as, in these cases, they tend not to get too close to obstacles.

In order to show that decisions are closer to human wishes in CBR collaborative mode, Fig. 6.10 presents two clusters corresponding to approximately the same location (see the relative position of obstacles in overimposed plots) of the environment. The one in faded colours corresponds to PFA based collaborative control, whereas the other was obtained from CBR based collaboration. PFA based collaborative mode corrected directness and reduced variability, but CBR based collaboration reduced Disagreement as well, because the user was not fighting the wheelchair.

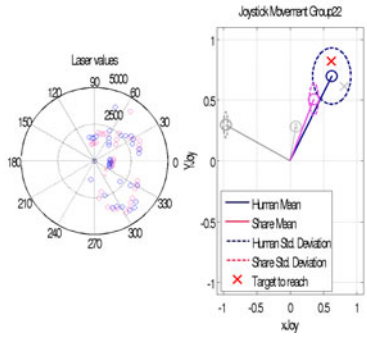

Fig. 6.10 Inpatient 1 cluster comparative for the same location for PFA and CBR based collaboration

6.2.2 Good Cognitive Skills, Low Physical Ones

The most relevant feature of persons in this group is that they typically had problems controlling the wheelchair. Fig. 6.11, for example, shows how subject 12 failed to finish the path on his own. This was very evident when we checked Disagreement. For subject 12 it was equal to 78.38% in standalone mode. This Disagreement is not due to struggle with the wheelchair, but to lack of required skills to drive it. In fact, these users seemed to accept assistance quite well in general. Subject 12 reduced his Disagreement to 24.97% in collaborative mode. All in all, assistance was focused on specific problems in this group. In general, their global efficiency grew in collaborative mode, but not enormously. However, there was a major increase in directness, e.g. 36.7% to 49.93% in subject 12, that modulated their commands enough to avoid difficult situations. They all finished the path in collaborative mode. Fig. 6.11 shows how subject 12 got too close to a cupboard in standalone mode to further maneuver into the living room. It can be observed that PFA tried frantically to correct the user's commands at that stage, but they are not considered in standalone mode. It can be also observed that his main problem was turning right, which is exactly what collaborative control did for him in the last stage of the trajectory. It can be observed how the green bar (the second one) in the figure is much larger in frames 8-10 for collaborative commands than for human's. Furthermore, the rest of the time, i.e. where subject 12 had no problems, collaborative commands basically follow human's ones.

A good representative of this group is subject 2, a 68 years old woman affected by spinal cord injury. Her MMSE was equal to 27,4., well over the dementia threshold However, even though she was almost autonomous (IADL=7), her Barthel index

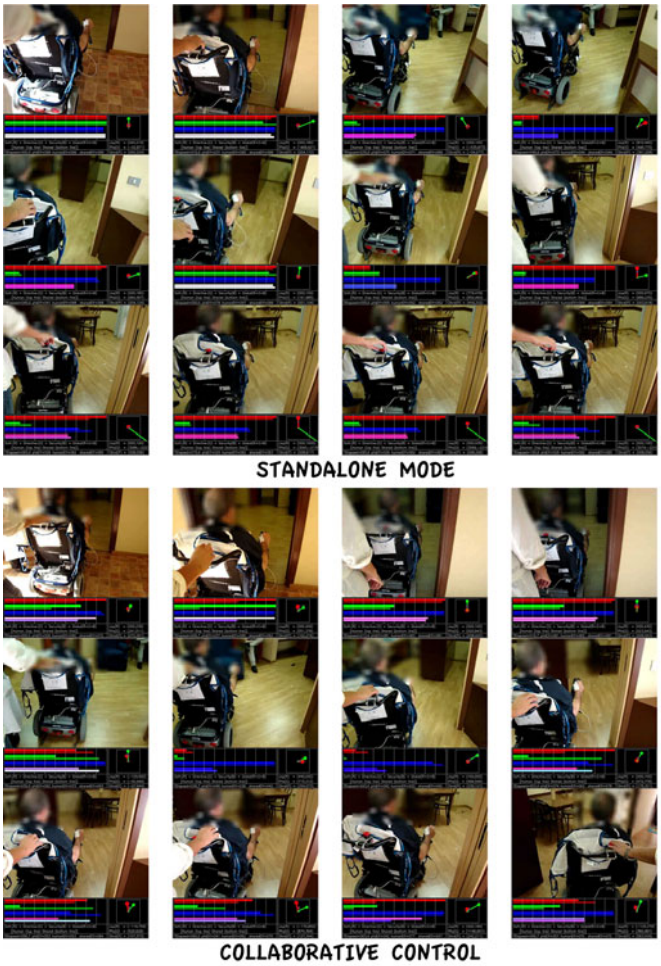

Fig. 6.11 Inpatient 12 video footage (Good cognitive and low physical skills)

was just 49. Indeed, she could not walk, but had no previous experience with power wheelchairs. All her statistics are presented in table 6.3.

6.2.2.1 Standalone Mode

In standalone mode (Fig. 6.12), subject 2 reported that she found it hard to finish the path. η_H was, in fact, not that high: around 60% in all cases except one. In her first run, it was equal to 63.95%, because her smoothness and directness were pretty low: 55.09 and 42.65%, respectively. Her Intervention Level was very high, meaning that she was trying hard to finish the path. Also, her Disagreement was equal to 28.15%, even though the robot commands had no effect in standalone mode. This meant

that, indeed, she was having trouble controlling the wheelchair. Unfortunately, and despite her efforts, she did not manage to finish the path on her own, as can be observed in Fig. 6.12. She just managed to move 4.33 m, as she had serious trouble with right turns and got stuck in a position where it was impossible for her to do anything. In that location, she was facing a cupboard at safeguard distance and had to turn right in a narrow area. Difficulties at turns are clearly appreciated in η_H, which turned pink and cyan (loss of directness and also loss of smoothness, respectively). Joystick Variation raised to 40% in the area, as subject 2 frantically tried to get out of there. We can note that areas where Joystick Variation was very high also corresponded to locations where Intervention Level dropped to 0, meaning that the user stopped moving the joystick after trying something drastic. We concluded from observation that, for some reason, this person had serious trouble with right turns.

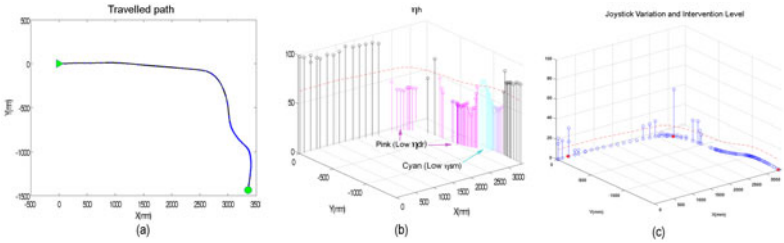

Fig. 6.12 Inpatient 2 standalone mode: a) path; b) human efficiency; c) Intervention Level and Joystick Variation.

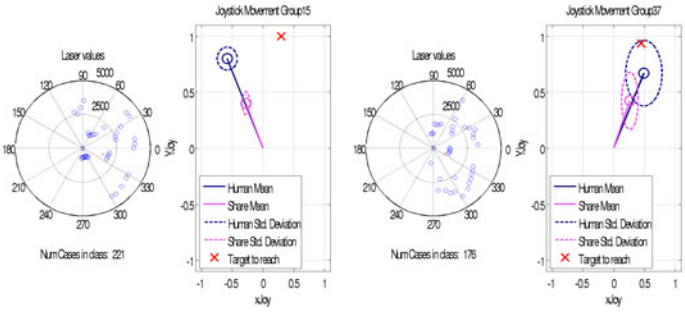

Fig. 6.13 Inpatient 2 sample clusters in standalone mode

Clusters in this particular experiments turned out to be quite revealing. For some reason, as commented, this subject tended to avoid right turns. Clusters in standalone mode supported what we suspected: this person favored left turns all the time. From the 39 clusters defined in this experiment, 17 corresponded to left turns -in a test where left turns should be minimal and only used to correct trajectories slightly and, at the end, to reach the table-, and there are only 14 clusters for right turns, none too efficient. One could suppose that left turn clusters only corresponded to

Table 6.3 Subject 2 Test Data

Control type		Autonomous	Shared PFA	Shared PFA	Shared CBR	Shared CBR
Global efficiency (%)	Robot	—	58.77	69.61	37.72(44.44)	72.23(70.92)
	Human	63.78	62.49	67.3	38.11	67.73
	Both	63.95	68.07	73.36	44.01	76.29
smoothness (%)	Robot	—	42.31	59.17	31.32(46.14)	54.69(76.48)
	Human	54.88	73.57	63.31	36.14	61.45
	Both	55.09	66.2	68.19	41.89	70.54
directness (%)	Robot	—	48.51	60.81	29.62(31.34)	67.86(43.72)
	Human	42.66	21.48	41.59	22.5	43.66
	Both	42.65	41.96	54.76	34.19	60.73
safety (%)	Robot	—	85.69	88.86	52.17(55.93)	94.12(92.78)
	Human	94.07	92.66	97.16	55.78	98.16
	Both	94.2	95.99	97.13	56.01	97.62
Intervention Level	%	99.56	90.94	81.31	45.61(95.75)	83.85(80.95)
Disagreement	%	28.15	39.08	24.59	16.23(10.24)	21.74(21.12)
	dev	21.69	22.27	16.96	21.38(14.5)	15.51(18.09)
Joystick Variation	%	0.08	0.07	0.06	2.1	1.73
	dev	1.29	1.18	1.02	7.33	3.09
Inconsistency	%	4.19	7.11	5.5	5.99	3.52
	dev	4.19	7.11	5.5	5.99	3.52
Total Length	m	4.33	5.43	4.12	4.26	6.25
Completion time	sec	22.11	31.25	21.28	35.32	28.34

punctual path corrections, but some included as much as 221 cases, like cluster 15, and were in average much more coherent than turn right clusters, like 10 or 37 (Fig. 6.13). In fact, in all clusters from 10 to 29 subject 2 should be turning right and she was consistently trying to go left, while right turns from 30 to 39 basically moved the wheelchair towards the obstacles ahead.

6.2.2.2 PFA Based Collaboration

In PFA based collaborative mode, η_s raises up to a 68.07%. directness does not improve that much, but smoothness increases to 66.02%. In any case, the most remarkable issue is that the subject manages to finish the trajectory this time. In fact, we do not aim in general at improving largely the efficiency of a given user, but rather to enable him/her to achieve maneouvres that, otherwise, would limit his/her ADL.

Hence, assistance in general might not improve much η from a statistical point of view, but could be of key importance to solve a given situation. Fig. 6.14 shows the η_H, η_R and η_C in the new path. It can be observed that η_H was pink (low directness) almost all the time after door crossing.

This could have provoked a new *stuck-up* situation, if subject 2 had faced a position where she could not manoeuvre anymore. However, the robot contribution compensated this problem and raised η_C so that it did not happen this time. In the

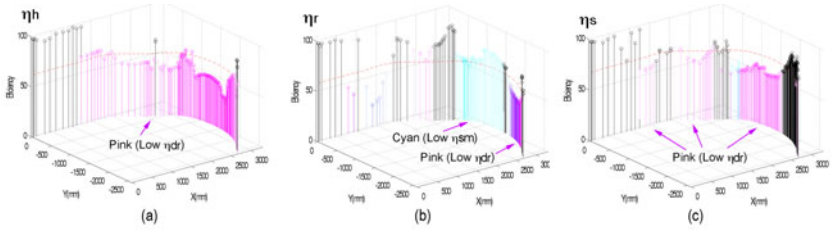

Fig. 6.14 Inpatient 2 collaborative mode based on PFA: a) human efficiency; b) robot efficiency; c) collaborative efficiency.

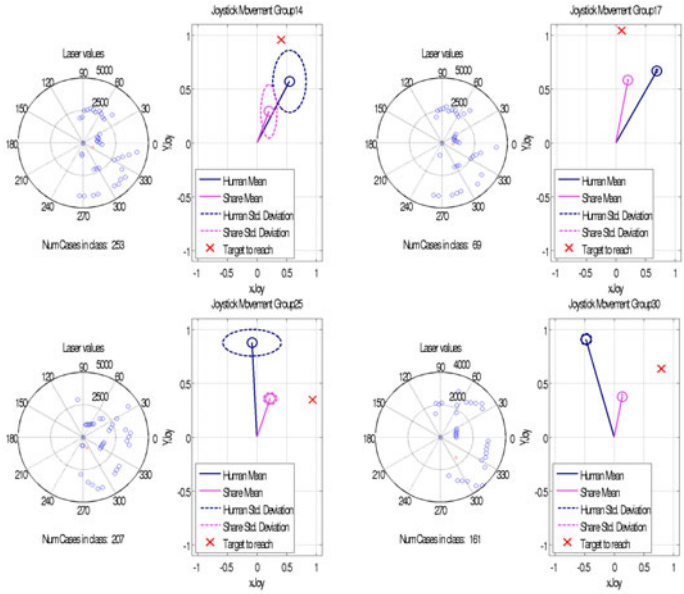

Fig. 6.15 Inpatient 2 clusters details for collaborative control based on PFA

turn area, though, PFA could not preserve smoothness and compensate at the same time, so η_C became cyan for a while.

It is interesting to note that Disagreement raised to 39.08%, meaning that subject 2 did not agree with 4 of each 10 emerging actions. We could just assume that what she did and what she wanted to do was not actually the same in this case, due to her low Barthel index, but it is necessary to note as well that her Inconsistency increased to 7.11%. This could have happened because she counteracted the machine by doing something she would usually not do. If we observe Fig.6.16, it is obvious that Disagreement was larger in the turn area, where the robot was not smooth to compensate for the subject's lack of directness. In fact, Disagreement was not too correlated with η_R this time, meaning that subject 2 was trying to fix what she

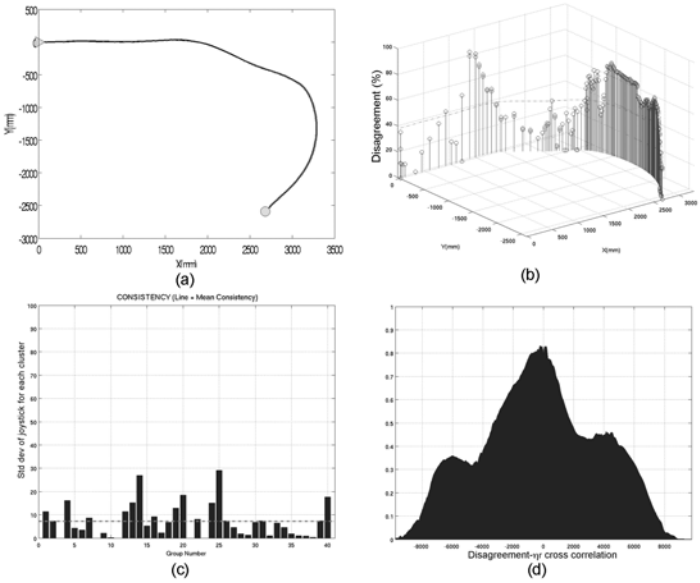

Fig. 6.16 Inpatient 2 PFA based collaboration: a) path; b) Disagreement; c) Inconsistency; d) Correlation between Disagreement/η_R.

felt as uncomfortable, rather than trying to gain more control in an area where she acknowledged that she could not drive well.

If we check clusters in this case, we can notice again a lack of right turns. In fact, when subject 2 managed to turn right, she underactuated, meaning that if a 90° right turn had been necessary, she would have probably gone for a 45° one or might even have tried to go left in some cases (clusters 25 and 30 in Fig. 6.15).

Specifically, clusters with large variations were all related to lack of decision in right turns (clusters 14 and 25 in Fig. 6.15). At some point, subject 2 reached an area where turns were required or, else, she would get stuck again. This time the system compensated correctly, but Disagreement became very high, in this case because the user could not provide the required command. This explains perfectly why the subject got stuck in the standalone try, as the experiment basically consisted of right turns and doing otherwise would get the wheelchair into an obstacle-cluttered area, where it is difficult to manoeuvre. This was a bit worrying, as it meant that if the robot would, for example, preserve smoothness to avoid Disagreement -just by

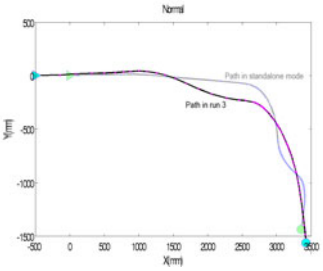

Fig. 6.17 Paths for subject 2 collaborative mode based on PFA with Smoothness preservation and standalone mode

increasing smoothness weight in η calculation- subject 2 probably could not guide the wheelchair well enough to reach the goal in a path based mainly on right turns as this one. This problem is illustrated in another PFA based try, in the third column in table 6.3. η_C was higher than before: 73.36% and the robot smoothness was also better. Disagreement decreased to 24.59% and Inconsistency to 5.5%. Unfortunately, the lady got stuck in approximately the same location than in standalone mode (Fig. 6.17). Ideally, it would be perfect if the system could go in charge only at right turns and leave everything else to the user, but we would set for the user not forcing a left turn when a right one is required.

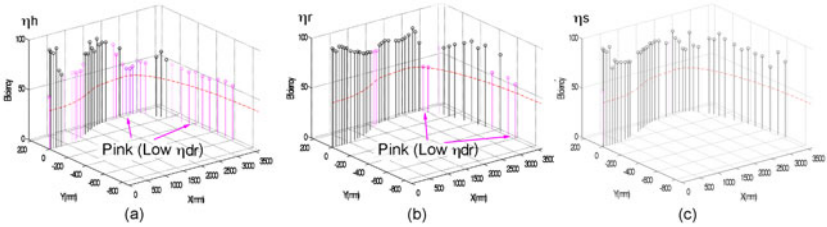

Fig. 6.18 Subject 2 CBR based collaborative run 0: a) η_H; b) η_R; c) η_S

6.2.2.3 CBR Based Collaboration

It stands to reason that CBR based collaborative control would not help much this particular person: if the system copies her commands and her right turns were not good, CBR should not be able to do so either.

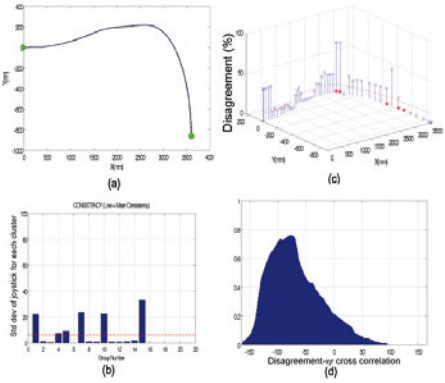

Fig. 6.19 Inpatient 2 CBR based collaboration run 0: a) Path; b) Inconsistency; c) Disagreement; d) correlation between Disagreement/η_R

In fact, if we check results for her first test with CBR (table 6.3), we can observe that: i) rather than growing, efficiency dropped to 44.01%; ii) smoothness was worse than ever: 31.32%; iii) directness was not good either and even safety dropped below the usual levels; iv) Disagreement was very low and *consistency* was good, as usual with CBR based collaboration; v) unfortunately, the subject did not finish the trajectory in this case, either. All this was to be expected: we had already commented that in casebases with a low number of cases, switching from one to another may provoke sharp direction changes and, hence, a decrease in smoothness. Usually, the advantages of CBR based collaboration overcome this problem, but not in this case, as the

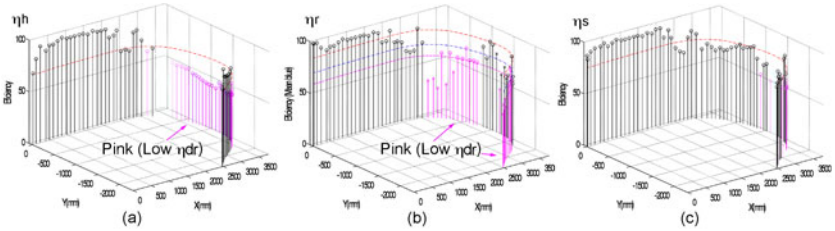

Fig. 6.20 Inpatient 2 CBR based shared control run 1 efficiency: a) human, b) robot; c) shared

system was cloning the problems of the subject with right turns and, consequently, directness was affected. Joystick Variation was clearly larger in this case, because the subject realized that her performance was not very good and tried to compensate.

Fig. 6.18 shows η_H, η_R and η_C in the first CBR run. It can be observed that η_R was quite similar to η_H, even though it was higher and less pink. In fact, η_C is balanced, but, as commented, the person got stuck in the usual spot. The path was in this case pretty biased towards the left, because robot and human agreed on that very specific behaviour, yet right turns were more natural. Unfortunately, the arrived late (Fig.6.19). Disagreement with CBR was low: now both the robot and the subject agreed on not turning right at key points. On the bright side, the CBR based collaborative system is behaving much better at door crossing than in PFA based collaboration, as expected, because subject 2 was consistently good at it. Correlation between Disagreement and performance seemed displaced, as if corrections were applied in response to perceivable robot actions that were, most likely, due to sharp case switching.

Still, CBR has a very interesting feature: it keeps learning. After adding new data acquired during the first CBR trial, a second CBR run returned much better results (Fig. 6.20). For a start, subject 2 managed to finish the trajectory. Efficiency was, once more, up to a 76.29% and smoothness increased up to 54.69%. There were only 8 extra classes with respect to the original training, but they worked as transition between previous ones and, hence, improved class switching. Directness grew up to 67.86%, well above the 43.72% that

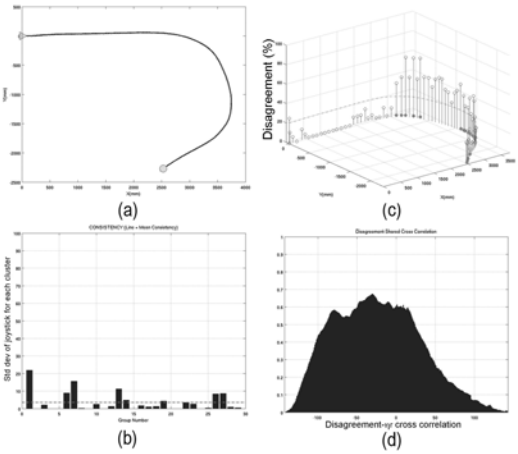

Fig. 6.21 Inpatient 2 CBR based collaboration run 1: a) Path; b) consistency; c) Disagreement ; d) correlation between Disagreement/η_R

PFA would have provided, had it been triggered due to lack of CBR proper output. Safety was also higher than ever, 94.12%, because subject 2 did not get stuck in any spot where the safeguard layer would be continuously triggered. Disagreement is higher than before because the output is a bit less similar to the user's commands, but closer than in PFA based collaborative control. *Inconsistency* was also better than in any other try: just 3.52%. This run even took a bit less time than her only previous successful try.

Fig. 6.21 shows the almost perfect path that subject 2 achieved this time. Disagreement was quite good this time until we started switching to PFA collaborative control for lack of CBR cases, marked with red dots as usual. Disagreement was mostly related to turn areas. Yet, we have to recall that this subject had trouble turning right, so it was only natural that she could not provide a command similar to the wheelchair if it was doing so. This basically explains not only the larger Disagreement, but also why she managed to finish the path this time, as CBR filled for her.

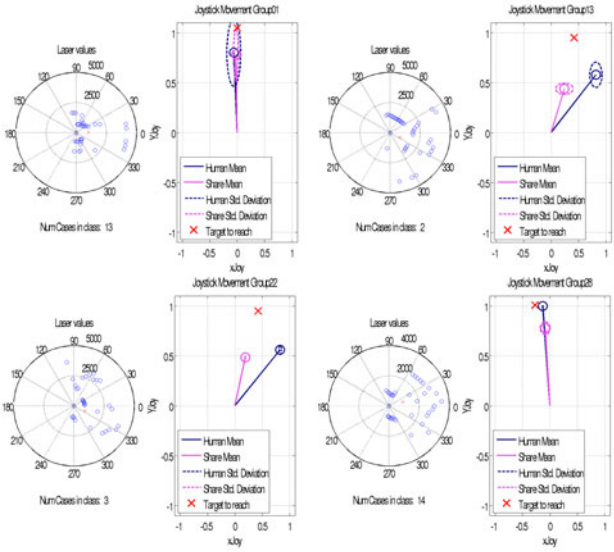

Fig. 6.22 Inpatient 2 cluster details for collaborative control based on CBR run 1

Still, she did not seem to be very affected by this larger Disagreement, which was not correlated to robot performance, as expected, and, in fact, her consistency was very good, meaning that she made the same decisions under similar circumstances. In other words, inpatient 2 acknowledged that the wheelchair was assisting her when needed and did not fight this assistance; she simply could not produce the required commands at conflict points.

Clusters in this particular run show that machine and person got along better. Disagreement was lower than in previous runs and Inconsistency decreased. Indeed, there was only one cluster with a large deviation (cluster 1) corresponding to the

initial stage of door crossing. Fig. 6.22 shows some of the clusters in this run. It can be observed that larger deviation is in most cases related to pushing the joystick stronger or softer. There were, as commented, some new clusters with just a few mutated cases. They were important because they provided the required support to turn right at the necessary places. Final clusters correspond to table approaching, which was not represented in unfinished runs.

In brief, CBR based collaboration seems to help persons with mild physical disabilities, but needs some training (in this case, just two runs were enough; in other cases, further learning might be necessary). The most obvious effect, along with achieving things that the user can not do alone, is a reduction of uncertainty in actions, lower Inconsistency and lower Disagreement. Subject 2 reported at the end of these tests that she was very happy with the wheelchair and even asked if she could rent one.

6.2.3 Low Cognitive and Low Physical Skills

Our last group is probably the most favored by collaborative control. Persons with low cognitive and physical skills are the ones demanding more assistance from the system and, hence, improving more in terms of efficiency. For example, Fig.6.23 shows the standalone and collaborative run of subject 10. His efficiency raised from 48.38% to 81.59%. This increase mostly obeyed to a 38% improvement in terms of directness. His Disagreement, originally equal to 85.23% meaning that he could not control the wheelchair, decreased to 23.31%, within the population average. His Inconsistency decreased from 19.8% to 3.79%, meaning that he actually took better decisions in collaborative mode. All this was to be expected because this particular volunteer did not even manage to cross the doorway in standalone mode. It can be observed in Fig. 6.23 that his commands were quite erratic and the safeguard layer did not let him move closer to the door frame. After 64s, we simply interrupted the test. In collaborative mode, though, the system provided the right amount of directness to help him steer correctly and he just took care of pushing the joystick ahead most of the time. This, however, is an extreme case and many individuals in this group performed better.

The effects of collaborative control on a person with both low physical and cognitive skills can be appreciated in subject 11, a 67 years old male with ischemic stroke (left hemisphere). His MMSE was equal to 17,2 -quite low for someone of his age and education- and his Barthel index was equal to 36. Indeed, he found quite difficult to drive the wheelchair and, in fact, got very distressed the first time he tried to do it in standalone mode, because he steered continuously and got stuck at the door due to the safeguard layer. Furthermore, when he finally entered the house, we checked that he tended to move very, very close to the right walls in the house. Table 6.4 shows the results of his tree runs: standalone, PFA based collaboration and CBR based collaboration.

Fig. 6.23 Inpatient 10 video footage (Low cognitive and physical skills)

6.2.3.1 Standalone Mode

Fig. 6.24 shows the path and global efficiency of subject 11 in standalone mode. He finished the trajectory on his own, but his efficiency was quite low all the time, changing from bluish-purple at the door -i.e. loss of directness and smoothness- to pink the rest of the path, because his directness was very poor. He achieved an average efficiency equal to 55.97% on his own, slightly higher in combination with the safeguard layer. His smoothness was not good, just 59.48%, as expected after visual observation of the test. When he got anxious, while trying to cross the door, he produced

sharp, random joystick movements. This can also be observed in directness, 19.03%, and, specially, in the significantly larger time it took him to finish this first path with respect to the other tries: 64s with respect to approximately 40s.

This extra time was invested in struggling with the wheelchair at the door frame. In absence of the safeguard layer, we agreed with the doctors that he would have collided with the door frame. Not surprisingly, Disagreement was as high as 62.9%, meaning that he had major trouble maneuvering the wheelchair.

Subject 11 Intervention Level was high most of the time. Particularly, his Joystick Variation at the door was very large -in this case his distress was visually obvious- and had some peaks along the trajectory. In terms of Inconsistency and clustering, subject 11 used almost 50 different classes -around 20 more

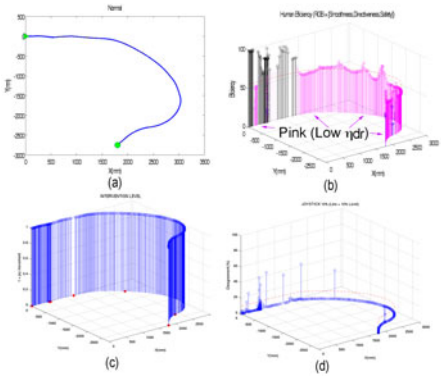

Fig. 6.24 Inpatient 11 standalone mode: a) path; b) human efficiency; b) Intervention Level; c) Joystick Variation.

Table 6.4 Subject 11 Test Data

Control type		Autonomous	Shared PFA	Shared CBR
Global efficiency (%)	Robot	—	62.58	61.47(60.23)
	Human	55.97	57.64	55.63
	Both	56.02	65.98	73.17
Smoothness (%)	Robot	—	51.12	52.02(58.61)
	Human	59.48	54.74	52.14
	Both	59.37	64.67	72.05
Directness (%)	Robot	—	46.12	42.91(28.93)
	Human	19.03	25.63	20.36
	Both	19.31	38.35	50.94
Safety (%)	Robot	—	90.43	89.37(92.93)
	Human	89.65	92.44	94.44
	Both	89.62	94.79	96.65
Intervention Level	%	74.7	86.05	84.99(63.22)
Disagreement	%	62.9	31.86	36.43(40.84)
	dev	30.37	18.16	25.13(24.92)
Joystick Variation	%	2.01	2.75	2.46
	dev	4.85	7.59	7.01
Inconsistency	%	9.0	10.76	9.45
	dev	9.0	10.76	9.45
Total Length	m	5.73	5.69	5.83
Completion time	sec	64.06	40.61	42.49

than the rest of our volunteers- to solve situations in the path. Far worse, clusters 7 to 40 corresponded to very bad decisions in terms of directness and, in many cases, safety. In some cases, his decisions were completely opposite to what the system should do. Fig. 6.25 shows classes presenting the largest *Inconsistency*, at door crossing and at the end of the trajectory, plus two of the classes where user's commands were opposite to the local target.

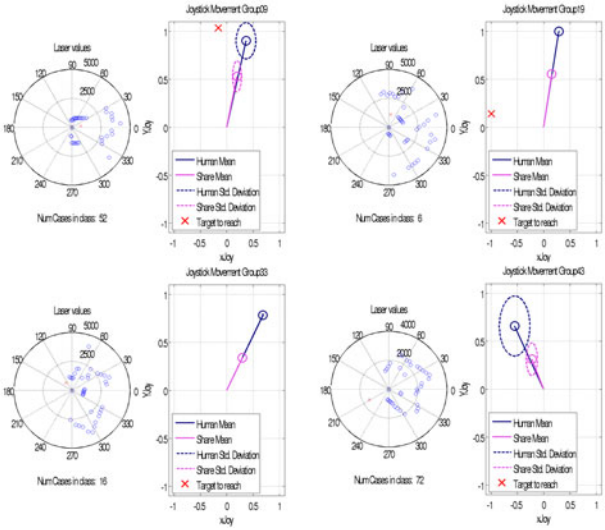

Fig. 6.25 Inpatient 11 clusters details for standalone control

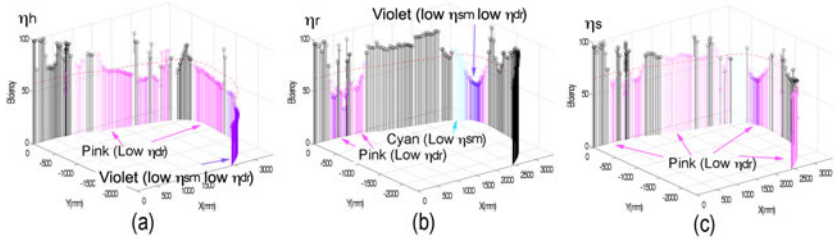

Fig. 6.26 Inpatient 11 collaborative mode based on PFA efficiencies: a) human; b) robot; c) shared.

6.2.3.2 PFA Based Collaboration

A new try with PFA based collaborative control returned better results. Global efficiency grew up to 65.98%, mostly because directness increased from 19.3 to 38.35%. Safety and smoothness also increased approximately a 5%. This time, there was no struggle at the door frame and Disagreement decreased to 31.86%. In fact,

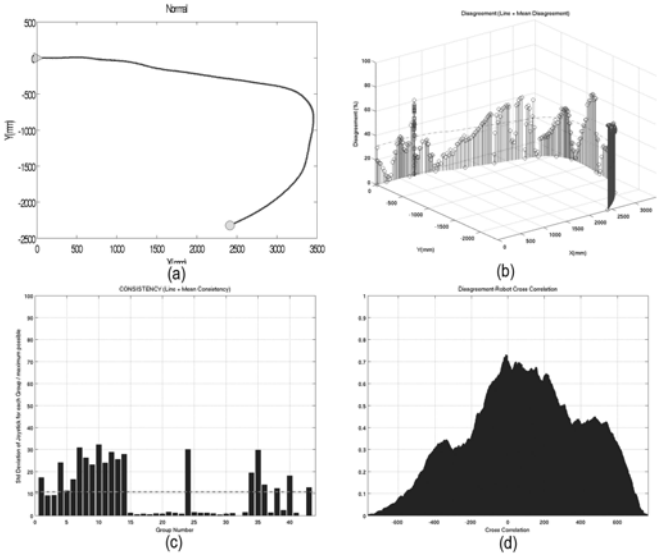

Fig. 6.27 Inpatient 11 PFA based collaborative mode: a) path; b) Inconsistency; c) Disagreement; e) correlation between Disagreement/η_R

his *completion Time* decreased a 33%. Fig. 6.26 shows η_H, η_R and η_C in this path. In this particular case, there was a lucky effect: the subject outperformed the robot at locations where PFA did not behave too well, so collaboration was profitable for everyone. It can also to be noted that a new color appeared in the plot: violet (low smoothness and directness together).

The emerging path in this test (Fig. 6.27) was smoother and more coherent than in standalone mode. Disagreement was distributed along the trajectory with no particular purpose. It grew higher where the robot did perform well, but it also grew at other parts of the path for no particular reason until a change, like a turn, was necessary. Furthermore, it did not seem to be correlated with the robot performance, meaning that it was probably not related to the person rationally realizing that he was receiving help. This seems to be usual in persons with low cognitive skills in our experiments. Also, there were groups of commands that were consistently inconsistent (4 to 15 or 34 to 36), whereas others (15 to 34 except 24) were very homogeneous. It can also be checked that in commands with wide dispersion, subject 11 tended to favour his right side. Clusters with low dispersion were typically related to punctual commands and included very few cases inside. From a global point of view, the number of clusters was just 40, meaning that the user solved the problem with a reduced number of options. Disagreement was not too large except in the last few classes, so subject 11 did not seem to have a strong position against assistance. *Inconsistency*, though, was quite significant both at the beginning and at the end of the trajectory, but clearly reduced by collaborative control with respect to standalone mode.

6.2.3.3 CBR Based Collaboration

Even for this group, results with CBR were better than PFA based collaboration. Global efficiency raised to 73.17%, even though CBR alone did not perform significantly better than PFA in this particular path (61.47% to 60.23%). In fact, smoothness clearly improved in CBR based collaborative mode (72.04%), even though PFA performed better to this respect than CBR (58.61% to 52.02%). This probably happened because CBR and human got along better and, hence, provided a smoother combined trajectory. Directness was also clearly improved, both globally and in terms of CBR with respect to PFA. *safety* was slightly increased. but, again, PFA was a bit better than CBR in this particular factor. Disagreement with CBR, as expected, was lower than with PFA.

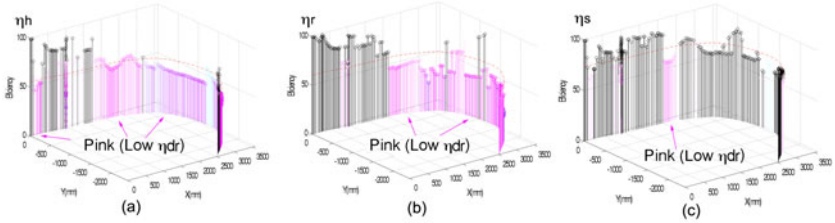

Fig. 6.28 Inpatient 11 efficiency for collaborative mode based on CBR: human, robot and CBR based collaborative mode.

Fig. 6.28 shows the human, robot and shared efficiency along this trajectory for subject 11 in CBR-human based collaboration. It can be observed, for example, that the inpatient outperformed PFA at door crossing and, hence, so did CBR. It needs to be noted, though, that CBR learnt from a PFA-based collaborative run, because the inpatient was not that good at door-crossing alone. Still, the human component in the mix made our learnt behaviour better than PFA alone at the door. Naturally, CBR navigation was similar to human navigation at the second half of the trajectory: efficiency was pink due to lack of directness, even though it is higher than in the previous tests. In any case, collaboration between CBR and human provided better results than any of them alone.

Fig. 6.29 shows the path in this test, plus Disagreement, Inconsistency and correlation between Disagreement and robot efficiency. Disagreement was lower than in previous runs, and more correlated to areas of larger robot control, specially in spots where CBR did not offer a suitable case and we had to switch to PFA based collaborative controll. These areas corresponded, as usual, to turn regions, where the input instance depended largely on when the wheelchair had started to turn. The path became smoother and as short as previously. Inconsistency, however, did not improve clearly, meaning that the user had doubts in basically the same situations than before. This is also coherent with the CBR approach, because the system is not supplying additional knowledge to the system, unless necessary. Since Disagreement was low in general, clusters were reduced to 35 and became quite coherent, despite

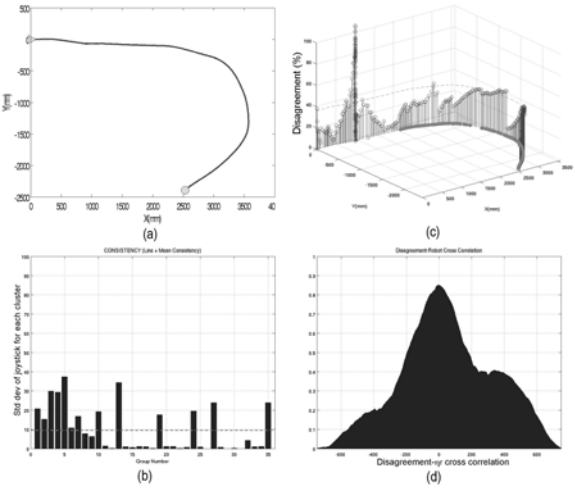

Fig. 6.29 Inpatient 11 CBR based collaborative mode: a) Path; b) Inconsistency; c)Disagreement; d) correlation between Disagreement/η_R

the commented variance in punctual situations, usually related to areas packed with obstacles.

6.3 Closer, But Not Yet!

After testing CBR based collaboration with volunteers with different and, sometimes, very significant disabilities, all in all, results were quite good. As expected, when the robot used CBR, it cloned the user's way of driving. CBR learnt from a previous PFA based collaboration run so that the system could provide what the user could not do.The proposed path in a house environment involved door crossing, tight turns and narrow places. In fact, if the first turn was performed too late, it might be difficult to finish the trajectory because of obstacles in the environment.

In general, most volunteers improved their performance in collaborative mode in terms of efficiency metrics: 6% in average. Table 6.5 presents the difference between collaborative and standalone mode per user in terms of efficiency. Some users benefited remarkably from collaborative control (e.g. volunteers 2, 10, 11, 14 and 17). However, it is remarkable that others performed better in average in standalone mode (e.g. volunteers 4, 7, 9 and 15). We observed that this happened when users had very good cognitive skills and acknowledged very early that the wheelchair was not doing exactly what they were commanding. In these cases, these people actually fought assistance and their efficiency was globally reduced. In general, this effect was local to areas where Disagreement between user and machine was large, i.e. the user was not performing well. CBR helped to reduce this effect significantly. Unfortunately, since the casebase includes a discrete number of cases, case switching provokes some control discontinuity that users find uncomfortable and reduces

Table 6.5 Volunteers' efficiency improvement

	Efficiency Factor			
Volunteer	Global	Smoothness	Directness	Safety
1	0.84	-1.23	1.35	2.41
2	9.41	13.09	12.10	2.92
3	0.60	-8.06	5.75	3.70
4	-2.86	-11.27	1.18	1.27
5	7.64	-7.19	26.24	3.58
6	-1.90	-9.45	2.28	1.04
7	-2.54	-7.14	-0.12	-0.78
8	1.95	3.82	0.29	1.17
9	-5.50	-2.10	-12.38	-2.40
10	20.19	13.43	29.47	17.78
11	9.96	5.30	19.03	5.17
12	0.11	-17.72	13.17	4.89
13	7.23	-0.72	23.30	-1.21
14	10.38	11.78	15.24	4.01
15	-3.02	-5.37	-3.00	-0.80
16	9.91	4.31	24.44	0.65
17	34.68	48.36	42.33	13.07
18	11.12	5.88	14.59	12.58
Mean	6.01	1.98	11.96	3.83
Std. Dev.	9.21	3.81	3.71	2.32

efficiency as well. This can be noted in the larger decrease in smoothness with respect to the other two local factors affecting the commented users. However, we also checked that some of these users were not able to finish the path in standalone mode, i.e. even if their efficiency decreased, at least assistance enabled them to achieve tasks they could not do on their own.

Even though most users benefited from collaborative control, it is necessary to check if the increase of efficiency in our tests was significant or not compared to the standalone test. We used ANOVA to test this hypothesis (H_a) upon global efficiencies in both cases. We obtained a p-value of 0.016, which rejects the independence hypothesis (H_0). This means that differences in efficiencies between standalone mode and collaborative mode are indeed significant. ANOVA data is summarised in table 6.6.

Results can not be generalized in terms of how assistance adapted to each person because, although we did test with 17 inpatients, their conditions were very

Table 6.6 One way-ANOVA statistics

Source	degrees of freedom (df)	Sum of Squares (SS)	Mean Squares (MS)	F test (F)	probability (p)
Groups	1	279.96	279.97	6.29	0.0163
Error	40	1781.6	44.54		
Total	41	2061.56			

different (e.g. some persons could not turn in a given direction, others could not drive straight...). In general, users' performance depended mostly on their physical skills unless their MMSE was very low (lower than 20). Volunteers with good physical and cognitive skills (e.g. volunteer 1 and 3) performed very well in all experiments and did not require much assistance. Hence, we divided the different volunteers in groups, depending on their cognitive and physical disabilities. We concluded the following:

- Persons with good physical and cognitive skills improved performance significantly when the system was based on CBR, because Disagreement decreased as expected. These persons required minor assistance and seemed to prefer not to be helped unless necessary. Still, collaborative control improved their standalone performance.
- Persons with good cognitive skills but low physical ones seem to accept assistance better. Yet, they also improve with CBR based collaboration.
- Persons with low cognitive skills but good physical ones mostly benefit in terms of directness. Disagreement is not so large in these cases, but if it is significant, performance also improves with CBR based collaboration.
- Persons with low physical and cognitive skills may not present enough consistent patterns for CBR to capture. In these cases, PFA based collaboration is enough, as CBR would eventually converge mostly to PFA in the end. In any case, Disagreement is rather erratic for this specific population, so is not useful to reduce it.
- Extreme cases with very low physical and cognitive skills -e.g. subject 17- can definitely not be modelled into CBR because most times there are no valid patterns to capture. In these cases, it may be advisable to modulate the assistance component so that the robot weight is larger. However, it is not easy to decide how much to help and, in our tests, we simply followed guidelines from the doctors.

All in all, CBR had done its work, but we still had two problems to cope with: case switching related discontinuity and extreme cases of disability.

Chapter 7
Yes, We K-an: Modulated Collaborative Control

Yeah well, if she doesn't give us some extra flow from the engine room to offset the burn through, this landing is gonna get pretty interesting.
`Define interesting.`
Oh god oh god we're all gonna die?
- Wash and Mal, Serenity

In previous episodes of our hospital series, we saw how collaborative control equalized the performance of persons with different cognitive and physical disabilities. In almost every case, they were able to finish mildly complex trajectories. However, it was only a matter of time until we found a person with disabilities so severe that assistance provided by our control scheme was not enough for her to finish a trajectory. We also observed that control glitches in complex areas where both robot and human efficiency changed very quickly led to remarkably lower average efficiencies. This was also the case when CBR was used, specially after short trainings where only a reduced number of cases had been learnt and robot control switched a lot from PFA to CBR. Naturally, these problems could be solved, at least partially, if the amount of assistance provided could be stabilized during a certain time period, condition or situation. However, we did not want to lose the reactive nature of our algorithm, that had worked so fine for us thus far. In fact, there is a pretty classic approach to solve this problem in a strictly analytical way: modulation of the control function.

7.1 Surfin' the Wave

This effect of modulation is very easy to observe in Fig.7.1. Let us take, for example, a simple gaussian envelope (Fig.7.1a), and two periodic functions: a fancy one, all full of nifty ripples (Fig.7.1b), and a boring triangular one (Fig.7.1c). If we simply combine them into a third one, we get something in the middle (Fig.7.1d). However, if we previously modulate the sum with our envelope, *voila!*: a modulated control function all ripply where the envelope is high and triangly when it is close to zero (Fig.7.1e).

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 145–180.
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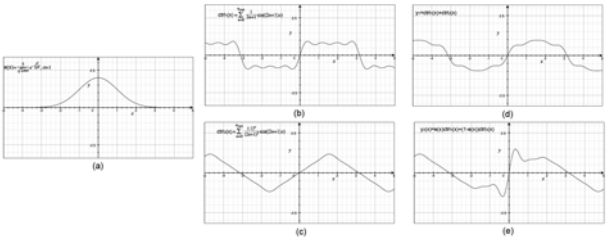


Fig. 7.1 Wave modulation: a) a gaussian envelope; b) control function 1; c) control function 2; d) unmodulated control function 1-2; e) modulated collaborative control function 1-2.

Our collaborative control equation (Eq. 3.5) is very easy to modulate. We only need to multiply human contribution by an amplification factor ($e(x)$) and robot contribution by its complementary (1-$e(x)$) to modulate their combination, as in (Fig.7.1.e). Thus, assistance is still controlled by human efficiency, but emergent commands are more or less affected by punctual efficiency driftings depending on $e(x)$.

A short discussion with the medical staff at FSL seemed to point out that, in fact, it might not be advisable to make $e(x)$ a continuous function. As commented over and over, disability is not easy to define -much less to quantify- and it would make no sense to fine-tune control in terms of something we can not really grasp. Instead, their advise was to use just a discrete function K_H that adopts only a few values, depending on how much assistance the person seems to need:

- In human standalone mode, K_H=1. Yet, it needs to be noted that the safeguard layer is always on in our system, so collisions can not happen.
- K_H=0.75 if the person does not need much assistance. In any case, if the user performs poorly, his/her contribution to control will be low, yet, in general, they will be dominant.
- K_H=0.5 corresponds to non modulated collaborative control, as seen in previous chapters, where human and robot contributions to control are merely a function of their respective efficiency.
- K_H= 0.25 corresponds to robot dominance in control if the person can not or is not performing adequately.
- K_H=0.01 corresponds to robot standalone performance. We never use K_H=0 because the robot is not supposed to move unless the person is operating the joystick. Yet, his/her contribution to control is neglectable in this case.

$$\mathbf{v}_S = (1 - K_H) \cdot \eta_R \cdot \mathbf{v}_R + K_H \cdot \eta_H \cdot \mathbf{v}_H \tag{7.1}$$

where η_R and $\mathbf{v}_R$ are the robot command and its efficiency, η_H and $\mathbf{v}_H$ are the human command and its efficiency and K_H works as our wave envelope.

The problem at this point is, obviously, to decide how and when to change K_H. Mainly, K_H may change depending on the person's condition -as stated by doctors-, state -as determined by biometric sensors, when available-, or the person's general performance -in absence of any other information-. In case of severe disabilities or

neglectable ones, K_H can be fixed a priori. This first solution was somehow improvised to fix a problem in the experiments presented in the previous chapter. Still, a person might need more or less help if stressed. In other cases, also, disabilities affect some actions far more than others. Some persons, for example, might be able to correctly cross a narrow door but lack the skills to turn left in a corner, so assistance could be increased in problematic areas or if he/she has been consistently driving with low efficiency for a while or at a given environment. Next sections correspond to automatic modulation of the collaborative control function according to the commented three methods: fixed K_H[170], biometrics based modulation[176][47][48] and medium term performance evaluation [175], respectively.

7.2 In Docs We Trust

There was one question begging to be answered in the last chapter: is there not a single person who could not finish the proposed trajectory using collaborative control? Unfortunately (for us) he answer was yes. We found a single problematic case in our experiments: inpatient 17. This 82 years old lady was affected by hemiparesis-left mixed aphasia. She had been brought to the hospital after a brain stroke and she had the lowest MMSE we had dealt with: 3.1. Her Barthel index was also low: 47. She needed help for practically everything (IADL equal to 1) and she even had trouble to understand how a power wheelchair operated. Unfortunately, she was not strong enough to operate a conventional one. Each time a run of the experiment was about to start, her doctor patiently explained her how to move the joystick and what she should do to reach the target, but, at some point, she would forget about the trajectory and she would basically move the joystick erratically until we stopped the wheelchair. Table 7.1 shows the results of her standalone mode and PFA based collaborative control. In both cases, subject 17 was unable to finish the trajectory. In standalone mode, she did not even manage to cross the doorframe. In collaborative mode, she got disoriented before turning right into the second room and did not know where to go. Obviously, CBR based collaborative control did no good for this person.

When a person is diagnosed a priori with a severe disability, it is expectable that a larger amount of assistance is going to be needed. Medical indexes like Barthel [98] or the the MMSE scale [33] may provide information about the person physical and cognitive skills, but, still, there is no analytical function that can magically turn them into the perfect value. However, we had something better up our sleeve: we simply changed K_H when doctors told us to do so. In this case, we reduced K_H to 0.25, so that the robot had more control. This third try was successful and results are also briefed in table 7.1.

7.2.1 Standalone Mode

The first run corresponds to standalone mode. In this run, inpatient 17 did not even manage to cross the doorway. Fig. 7.2 shows some frames of this run. It can be

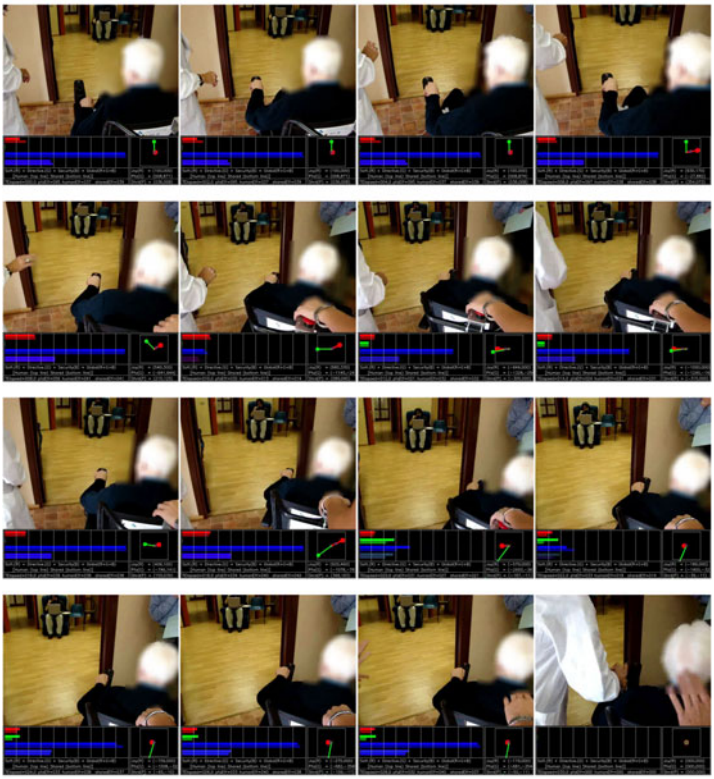


Fig. 7.2 Inpatient 17 standalone mode video footage.

observed that she immediately drove the wheelchair towards the door frame and when the safeguard layer stopped her she just moved the joystick randomly. It can be observed that the robot was frantically trying to move her away from the door, only it could not act in standalone mode and the volunteer got stuck at the door frame.

Fig.7.3 shows the path -which ended in the door frame-, inpatient 17 η_H, her Intervention Level and her Joystick Variation. η_H was never above 40% and decreased when the inpatient tried to cross the door frame. At this spot, there was also a stronger Joystick Variation, which can also be observed in the video, for example in frames 6-7 or 10-11 in Fig. 7.2.

7.2.2 *Original Collaborative Control*

Fig. 7.4 shows the efficiency of inpatient 17's first collaborative control test (K_H=0.5). It can be observed that η_H was quite low all through the trajectory, around 40 % in average. It went from pink (low directness) to blue, as only safety was

Table 7.1 Inpatient 17 Probes Data

Test number		1	3	4
Control type		Autonomous	Collaborative K_H=0.5	Collaborative K_H=0.25
Global efficiency (%)	Robot	—	67.51	70.58
	Human	34.56	37.92	51.38
	Both	33.49	65.62	68.18
Smoothness (%)	Robot	—	59.14	63.38
	Human	16.14	30.01	43.61
	Both	15.67	60.04	64.04
Directness (%)	Robot	—	51.81	57.1
	Human	6.72	8.08	21.57
	Both	4.54	42.21	46.88
Safety (%)	Robot	—	91.59	91.28
	Human	80.67	75.58	88.79
	Both	80.41	94.59	93.49
Intervention Level	%	69.27	85.99	76.48
Disagreement	%	93.66	37.87	33.9
	dev	62.14	19.97	13.37
Joystick Variation	%	1.82	2.91	1.15
	dev	5.03	8.66	3.52
Inconsistency	%	21.46	16.22	4.54
	dev	21.46	16.22	4.54
Total Length	m	0.51	5.91	6.03
Total Curvature	degrees	267.4	142.77	136.9
Curvature	mean	-0.99	-0.35	0.17
	dev	31.02	10.27	0.38
Completion time	sec	33.22	34.67	50.72

preserved. Lowest efficiencies were related to the door area and also to the first turning point. As commented, she did not manage to finish the trajectory, so there was no second turning point. As usual, the robot was basically good everywhere except at door crossing, so collaborative control mostly cloned what the robot did. However, the user's contribution made it impossible to proceed any further and, eventually, inpatient 17 dropped the joystick and the wheelchair stopped.

Fig. 7.5 shows video footage of collaborative control, with a K_H equal to 0.5 as in all previously presented experiments. In this case, inpatient 17 managed to cross the doorway (frames 1 to 10). In fact, she basically did the same than in the previous run: randomly move the joystick from left to right. However, since her efficiency in this case was quite low, PFA managed to compensate these oscillations. The combination of both commands was a forward motion, slower when robot's and person's commands opposed and faster when they agreed. Unfortunately, when she reached the point where she should have turned right to head to the next room, she did not remember what to do and decided to stop. Again, inpatient 17 was not

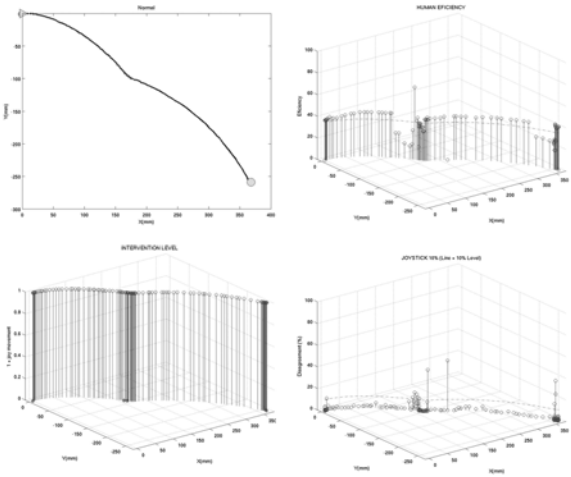


Fig. 7.3 Inpatient 17 standalone mode

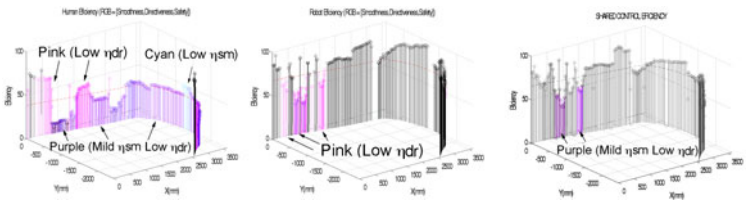


Fig. 7.4 Inpatient 17 collaborative mode based on PFA (K_H=0.5)

able to finish the trajectory, even in collaborative control mode. However, η_C raised to approximately 65%. Directness was now equal to 51.81% and smoothness to 60.04%. Even safety was higher, because the safeguard layer did not need to be triggered so often.

Fig. 7.6 shows the resulting path, Disagreement along the way, Inconsistency and the correlation between Disagreement and η_R. Disagreement was quite homogeneous along the whole trajectory and not too correlated with η_R, meaning that joystick motion was quite erratic and the robot contribution was not perceived by the user.

Fig. 7.7 shows some of the clusters defined in this path. Even though some of them presented a large deviation, like cluster 10, others were coherent and, in some cases, decisions were even correct, like cluster 2, related to moving ahead while crossing an area with obstacles right and left and the goal ahead. However, most of these clusters included only a few cases (16 and 12 in clusters 15 and 31, respectively), i.e. they might be due to sheer luck. In most other cases, though, much assistance was required. For example, the chosen direction in cluster 31 would have led to collision with the right wall.

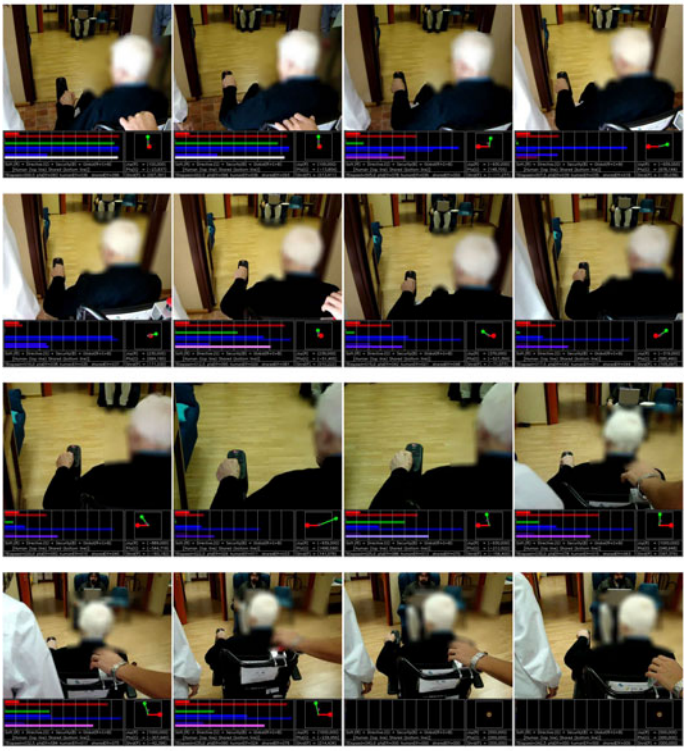


Fig. 7.5 Inpatient 17 collaborative mode K_H=0.50 video footage.

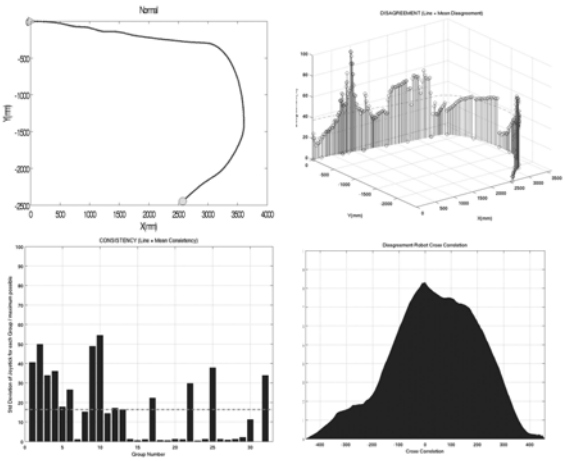


Fig. 7.6 Inpatient 17 collaborative mode $K_H = 0.50$ path and Disagreement.

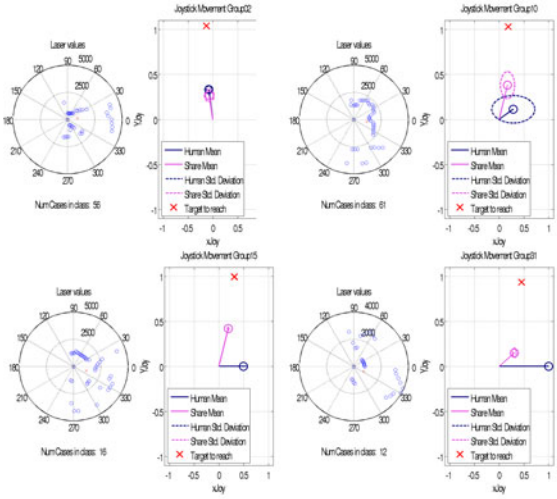


Fig. 7.7 Inpatient 17 collaborative mode K_H=0.50 clusters.

7.2.3 *Collaborative Control, Robot Predominant*

At the end of these tests, doctors asked if the inpatient could receive more help, so we decreased K_H to 0.25. As commented, this change basically modulated the emerging function so that the robot had a larger weight in decisions. As usual, the wheelchair would not move unless the user was operating the joystick. Fig. 7.8 shows η_H, η_R and η_C, respectively. The most interesting feature of this experiment is that subject 17 improved her own performance when assistance was increased, not only collaborative efficiency. We believe that, in this case, the person finished the trajectory, basically because it was easier for her to go with the flow and move in the robot's preferred direction than to move the wheelchair in any other direction. She arrived correctly to the target point following the path of minimum effort for her.

The same results, in detail, are presented in Fig. 7.9, a video capture of this experiment. As in the K_H equal to 0.5 case, inpatient 17 crossed the door with some (much) help from the wheelchair. She actively manipulated the joystick, as proven by an Intervention Level equal to 76.48%, even larger than in standalone mode

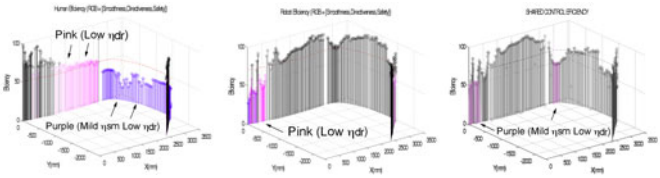


Fig. 7.8 Inpatient 17 collaborative mode based on PFA (K_H=0.25)

(69.27%) where the person stopped frequently, but smaller than in the previous case, because the robot had more influence in the outgoing trajectory. It can be observed that sometimes human commands were remarkably corrected (e.g. seventh frame) whereas in other cases, the person just went along with the system (e.g. frames 11 and 12). The most interesting -and unexpected- part of the experiment came at this point. Even though most of the time subject 17 did not seem to be aware of the trajectory she had to complete and simply operated the wheelchair in an easy-going way, when she saw the table at frame 13, she seemed to recall what she had to do and, in fact, became more active with the joystick and directed the wheelchair in the right direction. After some punctual corrections, she reached the goal and turned to all people in the house, doctors, engineers and caregivers, looking pleased with herself and happily expressed that she had done it. It can be globally observed that the robot mostly corrected directness, but, yet, the inpatient managed to improve her skills to follow directions and put her memory at work.

Fig. 7.10 shows the path, Disagreement, Inconsistency and correlation between Disagreement and η_R, as in the previous experiments. It can be observed that Disagreement was lower than in the $K_H = 0.5$ case along the way, because the user was driving better and, hence, agreed with the robot decisions more often. This is also reflected in a relatively low correlation between Disagreement and η_R, that means that the user got along with the robot even though it had more weight in emerging decisions and, hence, its influence was easier to perceive. Inconsistency was also lower: only clusters 10, 27 and 36 had a mild deviation. Furthermore, this deviation was mostly related to pushing the joystick stronger or softer. Fig. 7.11 shows some examples of clusters distributed along the trajectory from start to end. The effect of collaborative control is clearly appreciated in an increase of directness and a lower Inconsistency.

It is important to note that these results, good as they are, can not be extrapolated as such to other inpatients with similar conditions, as we had no other volunteer in this situation to corroborate them. However, they are coherent with the conclusions extracted from previous experiments, so it is expectable that persons with very severe disabilities could benefit from modulated collaborative control as well.

7.3 Don't Panic!!

In experiments presented so far in FSL [169][173], tests were mostly successful except in case of very severe disabilities, as commented in previous section, or when users got very stressed or nervous during tests, because in these cases their driving became too erratic and assistance could not be well adjusted to operate in a fairly complex environment. After some discussion, it was decided that live biometric monitorization could help, at least partially, by providing extra assistance under stress [176].

There are many biometric sensors in the market, ranging from very invasive, like electromyography, to non invasive ones, like sweat sensors. Some may operate continuously, like EEG, while others are punctually used, like thermometers. In some

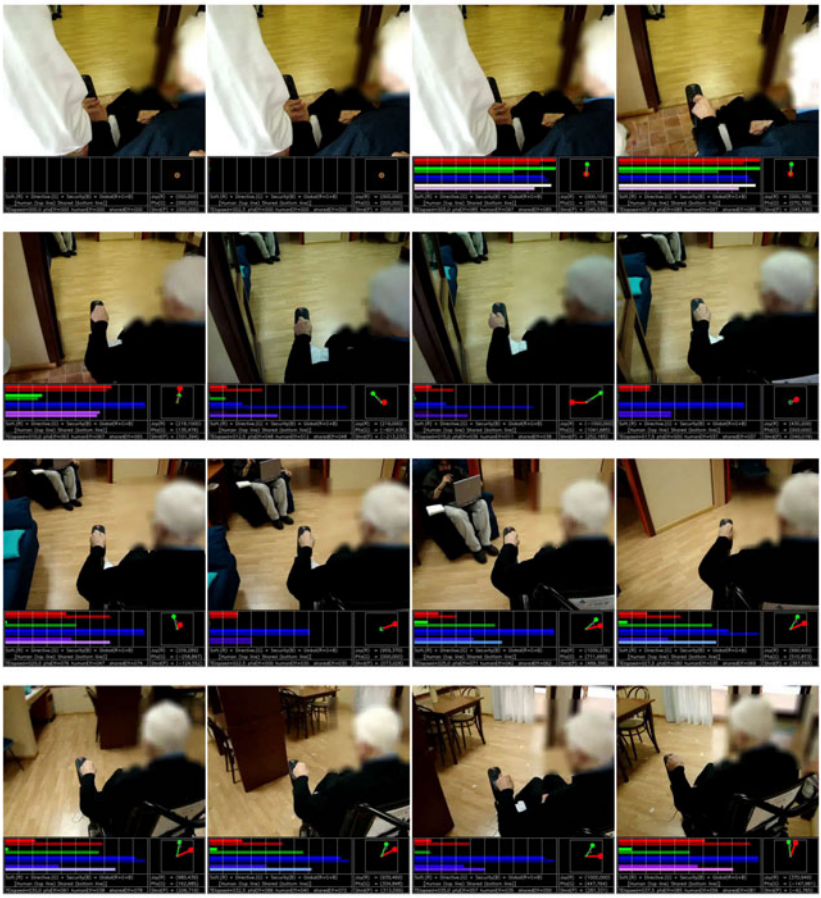


Fig. 7.9 Inpatient 17 collaborative mode K_H=0.25 video footage.

cases, they are easy to attach, like pulse watches, but they may require some expertise to place them correctly, like Electro-Cardiogram (ECG). Physiological Magnitudes to be measured while a person is driving a wheelchair should be calculated externally, without human intervention and in a reasonable period of time. Furthermore, user acceptance is of key importance, especially when talking about a system that is expected to be used 24h a day. Hence, even though in extreme cases invasive devices are acceptable (e.g. electromyography for wheelchair control), in our case only non invasive monitorization will be taken into account to make it comfortable for long term monitoring. Also, mobility in this case is of key importance, so we require low power consumption wireless sensors that can operate for long time periods. This prevents the user from being attached via wires to the wheelchair to ease the user's tolerance to the system. At this point, in current market, the only feasible off-the-shelf technology that matches all these requirements are Bluetooth (BT) wearable devices.

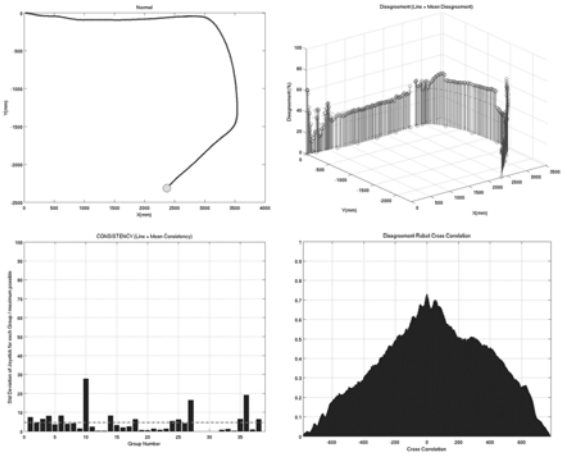


Fig. 7.10 Inpatient 17 collaborative mode K_H=0.25 path and Disagreement.

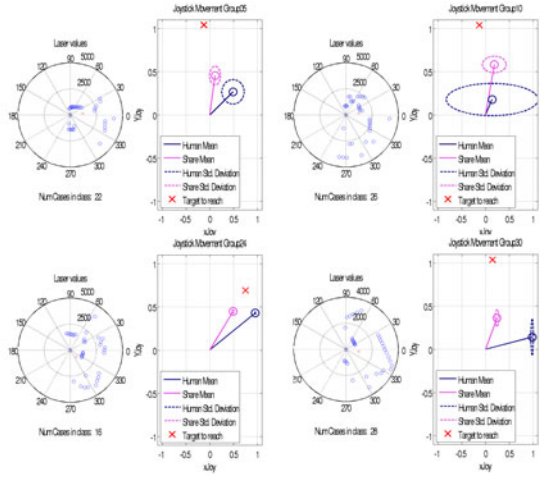


Fig. 7.11 Inpatient 17 collaborative mode K_H=0.25 clusters.

7.3.1 Every Beat of My Heart

The most typical BT commercial sensors for non specific diseases include blood pressure, heart rate, frequency rate, blood oxygen saturation and body temperature. Table 7.2 presents some of the most promising wireless devices in the market, ranging from 2000 to 5000 USD. Obviously, it is technologically possible to develop a new one (e.g. [113]), but it is easier to go for off-the-shelves solutions because: a) devices must be safe, as they must not cause damage (electric shock, interferences

Fig. 7.12 Nonin 4100 Bluetooth Pulse Oximeter

with pacemakers, device warming, etc.) to the user; ii) compatible with the usage of other medical devices (e.g. pacemakers), but also with everyday devices such as mobile telephones and PDAs; iii) devices should be standard-compliant. All these requirements must be met by devices prior to commercialization, so they are taken for granted when using those devices.

Among the aforementioned magnitudes, only heart rate is related to states of stress or anxiousness. ECG could also be useful, but less comfortable. Also, commercial wireless ECGs currently operate with just three derivations and are not so reliable, specially if the user is not keeping still, which will be the case while driving a wheelchair. Galvanic Skin Response (GSR) is also feasible in combination with pulse, but current BT commercial systems are still a bit bulky to carry on for long periods, specially in combination with a pulse oximeter. Some of the devices in table 7.2 tagged as belts include pulse and GSR, but in add-on format, meaning that sensors must be added to the basic belt and carried around as well. Our best choice would have been BT2, but we could not purchase one within the experiments deadline. Hence, we chose a simple pulse oximeter for comfort in our tests.

It is important to note that pulse is not enough to assess stress or nervousness in a person, but it gives some insight on the subject's state and will be used to modulate assistance in this work. After an in-depth study of the biometric sensors market, the chosen device is the 4100 pulse oximeter from Nonin (Fig. 7.12). Such a device fulfills the requirements that have been previously exposed. It provides heart rate and the blood oxygen saturation (SPO2) via a BT serial port profile (SPP) with an acceptable frequency. In the PC we used a Parani SD100 commercial adaptor to capture the BT signal.

Obviously, heart rate is not the same for every person, and it is affected by different factors like age, weight, habits, etc. This basically means that there is no such thing as a standard, so our system works as follows. First, the person wears the device for a while in a relax situation. During this time, his/her heart rate is averaged to establish a baseline for that specific person. Afterwards, when they are operating the wheelchair, their rate is compared to their specific baseline. Major variations with respect to that baseline are accepted as stress situations. Fig. 7.13, for example,

presents the shifting in average of a volunteer during the calibration stage and after a short period of exercise, that raised her pulse in average from 76.9 to 89.24 bpm. Alternatively, pulse rate could have been calculated via a shifting time window, but then slow, yet significant variations in pulse would not be detected.

In fact, heart rate is reliable only up to a point, i.e. subtle or minor variations do not necessary have a meaning. In our case, as commented, doctors advised not to establish too many situations, but rather to split possibilities into a few bins, roughly corresponding to normal, stress and alarm situations. These bins will be used as explained in next subsection.

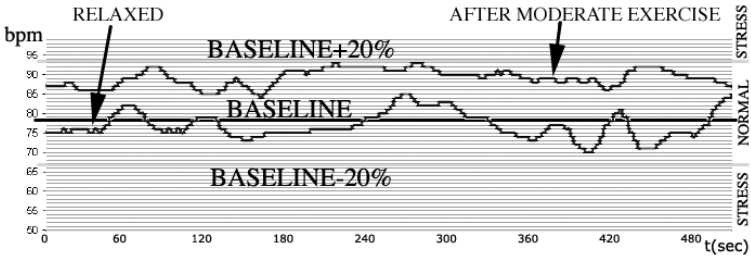


Fig. 7.13 Heart rate provided by Nonin 4100 for a 58 years old female: a) relaxed; b) after moderate exercise.

Table 7.2 Wireless biometric commercial devices

Device	Manufacturer	Measures	Wearable
Bioharness	Zephyr	ECG, temperature, heart rate, breathing, activity, body position	belt plus add-ons and electrodes
BT2	Exmocare	Heart rate, GSR, temperature, activity	wrist sensor
EQ-01	Equivital Systems	ECG, heart rate, breathing, temperature, activity, body position	belt plus add-ons and electrodes
Lifeshirt	Vivometrics	Heart rate, breathing, temperature, activity, body position	belt
Sensewear WMS	Sensewear	Accelerometer, temperature, GSR	armband

7.3.2 Laboratory Tests

In order to check the proposed system, we performed two types of tests: i) in a controlled environment with a well established path; and ii) in Casa Agevole in FSL, with volunteers presenting different degrees of disability. The first kind of experiments are useful to test all possible values of K_H and evaluate its effect. The second ones are more reliable to check how potential users deal with the technology and how their performance is affected.

Our first set of experiments was carried out in our facilities in Malaga, with 15 volunteers presenting no known disabilities. We prepared different situations to check how the mobile would behave in extreme conditions. We present results in a narrow corridor as test environment (Fig. 7.14). The width of this corridor was fixed so that PFA alone failed to move safely within. These experiments cover all possible values of K_H to extensively test the system's response. First, the system was tested in autonomous mode, to set a baseline for results in next steps. Then, K_H was forced to predetermined values: pure collaborative control with K_H=0.5, robot domination (i.e. K_H equals 0.25) and user domination (i.e. K_H equals 0.75). Finally, in the last experiment the biometric sensor was used to change K_H in a dynamic way.

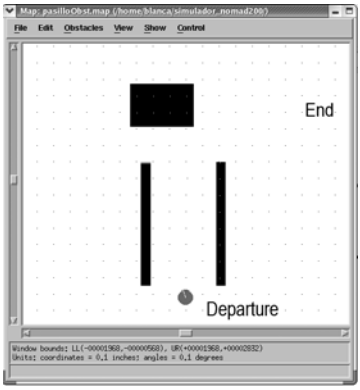


Fig. 7.14 Layout for the experiments.

7.3.2.1 Full Autonomous Control

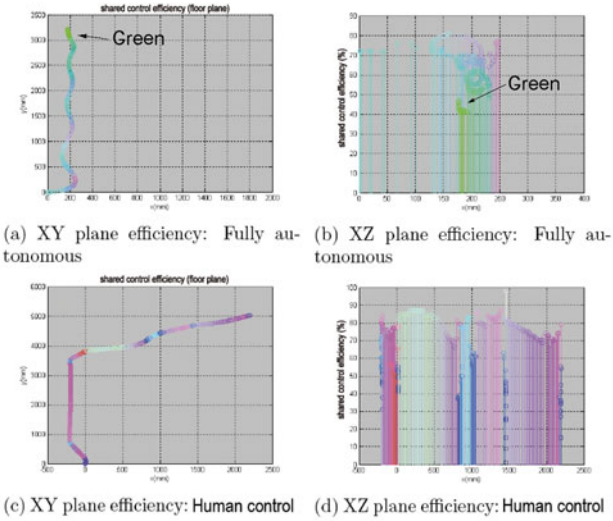
Figs. 7.15a-b show results obtained when control was totally exerted by the robot (K_H= 0). As commented, in this case the wheelchair did not reach the target because the corridor was tailored to be narrow enough that PFA can not deal with it unless humans provide some contribution. Indeed, Fig. 7.15a clearly shows oscillations caused by the PFA in the proximity of obstacles (the side walls of the corridor). At the end of the path, efficiency became a very unusual green, meaning that only directness can be preserved a ft this point. This can be solved by choosing an improved version of conventional PFA for robot navigation, but our collaborative control scheme also avoids these problems.

7.3.2.2 Human Control

Figs. 7.15c-d show results when system was completely controlled by a person. Differences with the previous case (Figs. 7.15a-b) are clear in the corridor area. Oscillations were mostly avoided and the plot color indicates major improvement in smoothness (red), while in autonomous mode the main contribution was directness to goal. As expected from humans, who are not as precise as robots with respect to targets, efficiency was mostly pink, due to lack of directness. At some points, though, it became blue, when only safety was preserved. It can be observed that the user reached the target correctly on her own.

7.3.2.3 Basic Collaborative Control

In this case, modulating factors were forced to 0.5 (basic collaborative control based on efficiencies) (Fig. 7.16).



(a) XY plane efficiency: Fully autonomous (b) XZ plane efficiency: Fully autonomous

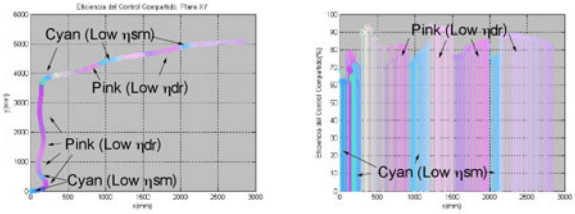
(c) XY plane efficiency: Human control (d) XZ plane efficiency: Human control

Fig. 7.15 Efficiencies without collaborative control

There were still oscillations in this mode, but better efficiencies led to whiter points, where all factors were approximately equal and high. There were some blue areas, specially at turns, which were fairly sharp in this environment, and also pink ones where human contribution made the mobile move with less directness. It can be observed anyway that average global efficiency was higher in this case than in non cooperative ones.

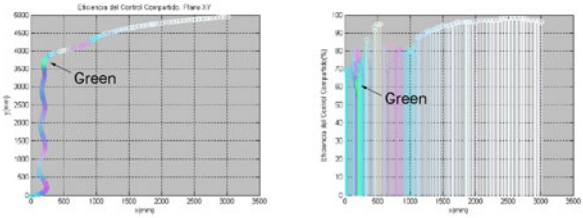
7.3.2.4 Robot Predominant

K_H was now fixed to 0.25, i.e. given the same driving efficiency, the robot would have more control over the system than the user, even though the user always had influence in emerging commands. Figure 7.17 shows that, also in this case, average efficiency was much higher than in situations without collaborative control. The XY plane plot (fig. 7.17) shows that, once the wheelchair had left the corridor, efficiency improved, as areas in white represent high values in all three (R, G and B) efficiency factors. This is due to the absence of obstacles that would cause oscillations when the robot had a dominant role, and also due to the higher directness that robots tend to provide due to their higher precision and PFA specifics. In this case the wheelchair reached the target thanks to the user's contribution, though, as the robot failed to do it on its own and, once more, had difficulties here that are solved by the person, as evidenced by a single, short green efficiency area.



(a) XY plane efficiency: Basic shared control (b) XZ plane efficiency: Basic shared control

Fig. 7.16 Basic collaborative control efficiencies



(a) XY plane efficiency: Robot predominant (b) XZ plane efficiency: Robot predominant

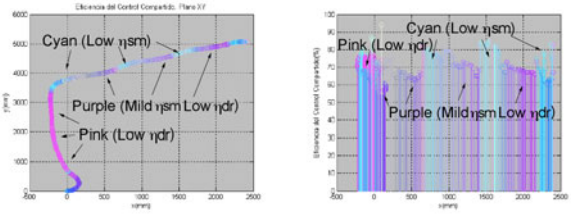
Fig. 7.17 Robot predominant efficiencies

7.3.2.5 User Predominant

In this case, we gave the user more control (K_H=0.75) over the wheelchair. A first thing to note is that oscillations were practically absent from the path, yet directness is not that good. The efficiency color distribution was, in fact, similar to conventional collaborative control (Fig. 7.16), but darker, meaning that efficiencies are lower than in that particular test. It is interesting to note that the path and efficiency distribution was more similar to the K_H=0.5 case than to the K_H=0.25 one, meaning that in this particular environment, the mobile tended to pay more attention to the user's way of driving -as the environment was designed purposefully for PFA not to operate correctly- even for K_H=0.5. Yet, as the robot could help less in this case, efficiency was reduced with respect to that one.

7.3.2.6 Dynamic Variation of K_H

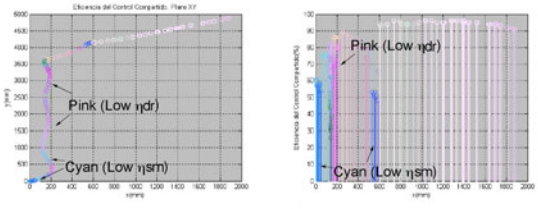
Finally, instead of prefixing the values of modulating factors, K_H was extracted from the readings of the pulse oximeter in real time. That implies that the the amount of control given to the user at every moment was derived not only from his/her efficiency, but also from his/her current state of nervousness as derived from pulse. It needs to be noted again that pulse is not enough to decide whether a person is calmed or not, but the proposed approach is easily extendable to new wearable



(a) XY plane efficiency: User predominant (b) XZ plane efficiency: User predominant

Fig. 7.18 User predominant efficiencies

sensors that meet the criteria in section 7.3. Figures 7.19,a-b show this test provides the highest average efficiency among all situations exposed in the proposed environment. Initially, the person's pulse was a bit high, so the robot had a larger impact on performance, as reflected in the oscillations at the beginning of the path. However, he recovered during corridor crossing. A new pulse raise at the end of the corridor, while steering right, gave more control to the robot, which dominated the rest of the way. All in all, efficiency was mostly white except during corridor crossing, where it was mostly pink, even though there were some blue areas due to oscillations. In this case, we got the highest efficiencies from all presented tests.



(a) XZ plane efficiency: Dynamic variation of k_U (b) XZ plane efficiency: Dynamic variation of k_U

Fig. 7.19 Dynamic variation of K_H efficiencies

7.3.3 Back on Track

After extensive testing in our labs, we performed some tests with 10 new volunteering inpatients in FSL in May 2009 for a K_H variable collaborative control approach after approval by the Ethical Committee and the medical staff [175]. The robot used in our tests was, once again, CARMEN. All volunteers were asked to follow the route in Fig. 7.20, where shots of the departure and arrival points of the path are included. It can be observed that they had to cross a door and turn right to enter the kitchen area in Casa Agevole. The path was very similar to the one in subsections 7.3.2.1 to 7.3.2.6, but obstacles in the way were less homogeneous.

In this case, we present the example of a volunteering inpatient in FSL, a 60 years old male affected by an ictus. Cognitively, he had a minor disability (MMSE

Fig. 7.20 Tentative path in Casa Agevole.

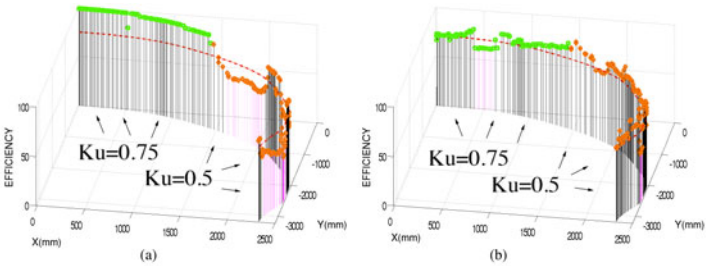


Fig. 7.21 Dynamic variation of K_H efficiencies

equal to 24,2), but he also had a mild physical disability in terms of hemiplegia and apraxia (Barthel equal to 87).

Figs. 7.21.a and b show efficiencies when he drove on his own and in collaborative control mode, respectively. In this second case, local efficiencies have been topped with a green dot when K_H is equal to 0.75 and yellow when it is 0.5. It would have been red for K_H equal to 0.25, but there were no such points. White efficiencies (smoothness= safety= directness=1) have been swapped to black for the sake of visibility in these plots. It can be observed that, although the volunteer finished the trajectory in both cases, in the first one efficiency was clearly lower and presented more pink areas, where directness was not very good. In the second case, efficiency was colorless except at door crossing and, just for a short time, at the end of the trajectory. Even in these areas, average efficiency was clearly higher than when the person drove on his own. It can also be observed that, except at the beginning of the path, when the user was still unfamiliar with the wheelchair, K_H was equal to 0.75 all the time. If we observe the specifics of these tests (table 7.3), we can appreciate

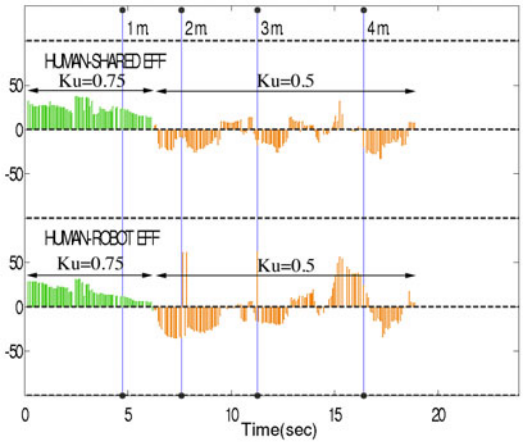


Fig. 7.22 Efficiency substration for K adaptive test.

that, indeed, all local efficiency factors increased when collaborative control was used.

In standalone mode, the robot contribution was calculated, but ignored. The robot only had effect when a safeguard layer -that stopped the robot if obstacles were too close to the wheelchair- was triggered. Thus, combined efficiencies in this mode were practically equal to human's, only slightly lower when the safeguard layer was triggered very often. We can observe that the η_H improved from 65.36% to 71.59%, but directness, the person's worst feature, increased from 40.02% to 53.66%. It could be argued that smoothness only increased from 67.26% to 69.14%, but it is interesting to observe that the person improved from 67.62% to 77.46% thanks to collaborative control. Safety was quite similar because in both cases the safeguard layer avoided getting too close to obstacles, only this time it was less triggered than before. Fig. 7.22 shows the substraction between human and collaborative control and human and robot control in the K_H variable test in Fig. 7.21. Green and yellow lines correspond to K_H equal to 0.75 or 0.5, respectively. It can be observed that at the beginning of the trajectory, where PFA mostly oscillated, the driver performed clearly better than collaborative control or robot in this case, as received assistance was not that good. As commented, this can be solved by using an enhanced PFA version. However, as soon as K_H went green, it can be observed that collaborative control was usually better than human's and it presented less peaks than human and robot difference. This is specially remarkable around the 4m point, where human clearly outperformed the robot, but not collaborative control, which tended to perform like him when he drove well. It is also interesting to note that, despite the increase in efficiency in collaborative control mode, differences are more homogeneous when collaborative control is applied, meaning that the user will be less aware of assistance.

Table 7.3 Inpatient 8 Probes Data

Test number		3	4
Control type		Standalone	Adaptive K_H
Destination		Kitchen	Kitchen
Global efficiency (%)	Robot	—	70.03
	Human	67.81	74.97
	Both	65.36	71.59
Smoothness (%)	Robot	—	53.54
	Human	67.62	77.46
	Both	67.26	69.14
Directness (%)	Robot	—	69.14
	Human	46.97	56.49
	Both	40.02	53.66
Safety (%)	Robot	—	87.26
	Human	89.01	91.59
	Both	88.96	91.84
Intervention Level	%	85.55	87.75
Disagreement	%	14.11	15.14
	dev	11.29	12.06
Joystick Variation	%	2.3	1.92
	dev	6.94	7.17
Total Length	m	4.72	4.73
Completion time	sec	23.35	18.9

Efficiency increase is not the only issue in wheelchair driving, though. As usual, we also measured Intervention Level. It can be observed that in collaborative control mode, Intervention Level was even slightly higher than in human control, meaning that he stopped less time, as expected from less safeguard layer triggering. Also, not only Joystick Variation was lower in collaborative control mode, but also less noisy and related to points where decisions had to be made, rather than to frequent path corrections (Fig.7.23).

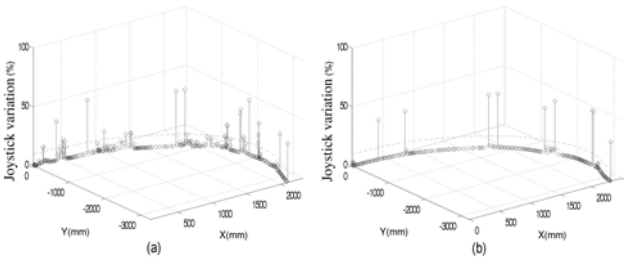


Fig. 7.23 Joystick Variation for volunteer 8: a) human control; b) collaborative control.

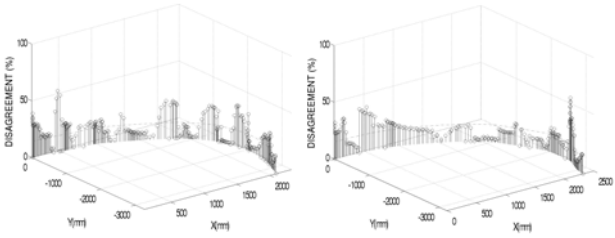


Fig. 7.24 Disagreement for volunteer 8: a) human control; b) collaborative control.

Finally, it can be observed that Disagreement was practically the same in standalone mode and collaborative control mode, i.e. it was mostly related to lack of practice in wheelchair control or familiarity with the environment rather than with discomfort with wheelchair assistance. Furthermore, it can be observed in Fig. 7.24 that Disagreement in collaborative control mode was clearly lower as soon as K_H goes up to 0.75, as expected, because the wheelchair output was closer to human commands, yet these were still corrected by the robot and, hence, wheelchair control seems to be easier for the user.

Results with the rest of our volunteers were very similar to the presented case: all of them managed to finish the trajectory in K_H modulated collaborative control mode, even those who could not do it alone. This is the case, for example, of volunteer 2, affected by right hemiparesis, with a mild cognitive disability (MMSE=17.3) and a significant physical one as well (Barthel=70). Even though she could not maneuver to get into the kitchen on her own, Fig. 7.25.a shows how she managed to finish the trajectory in collaborative mode and, despite her sharp steering commands, and even kept a high efficiency -with some directness problems- most of the time. In fact, she retained a K_H equal to 0.75 half of the time and never went down to 0.25. Other volunteers yielded a K_H equal to 0.5 most of the time, yet achieved an almost perfect trajectory in terms of the defined efficiencies. This is the case, for example, of volunteer 5 (Fig. 7.25), affected by Guillian-Barre, but with an excellent MMSE (30) and a Barthel index equal to 82. She could perform better than volunteer 2 or 8, yet she did not achieve a K_H equal to 0.75 until the end of the path. Volunteer 5 managed to finish the path on her own, though, so we could check that she improved her global efficiency from 74.36 in standalone mode to 80.5 % in collaborative mode, mainly due to a 5% increase in smoothness and a 12% in directness. Her joystick variation decreased from 2.19 to 1.74 and Disagreement also went down from 10.61 to 9.96, even though this reduction was not really significant as explained. Her Intervention Level was approximately 87% in both cases.

In brief, we could conclude after these tests that the proposed system increases driving efficiency for persons with disabilities, providing assistance in a continuous way, yet adapting the amount to the needs of the user. Results point out that users tend to feel more comfortable with the wheelchair when this kind of control is applied and, when asked, they feel that it is easier to drive like this. This is coherent with the usability metrics we obtained through the tests. The pulse oximeter

employed is fairly comfortable and can be used while moving, yet the information it provides is not enough to state that someone is nervous or not. Still, we checked that changes in K_H affected positively driving efficiency, as high pulses seem to be related to areas where driving is more complex.

7.4 As Time Goes by

Thus far, we have gone from having a doctor at hand to wearing a biometric device all day, but most times none of these options is feasible, so the question at this point is: can we still modulate the control function in absence of anything else? And, yes, we can, since thus far we have deployed the whole control architecture just at reactive level. The idea is pretty simple: human contribution to emergent control is based uniquely on what the person does at a given time instant, so we could average his recent performance to increase or decrease K_H depending on how well they've been driving. This approach has a serious challenge: how much time should we take into account to do this average? If t is too long, efficiency will be heavily filtered, so sudden drops of performance would not be adequately compensated. If it is too short, we would be close to non-modulated control most of the time. The answer is, of course, to make t adaptable. We want t to go back as long as the user has been performing consistently in average, but to increase if he/she improves and viceversa. This approach is fairly well known as Time Shifting Window based filtering and, in our case, K_H is calculated as:

$$K_H = \frac{\sum_{i=t_{dis}}^{t} \eta(i)}{t - t_{dis}} \tag{7.2}$$

t_{dis} being the last time instant previous to t in the trajectory where K_H showed a clear inflection point. In fact, K_H is related to the complexity of the environment and/or to the person condition -if affecting his/her driving skills- rather than to time, as we are adaptively filtering efficiency in terms of how persons face a situation. The effect of this filter is fairly intuitive: basically, a steadily changing η is related to

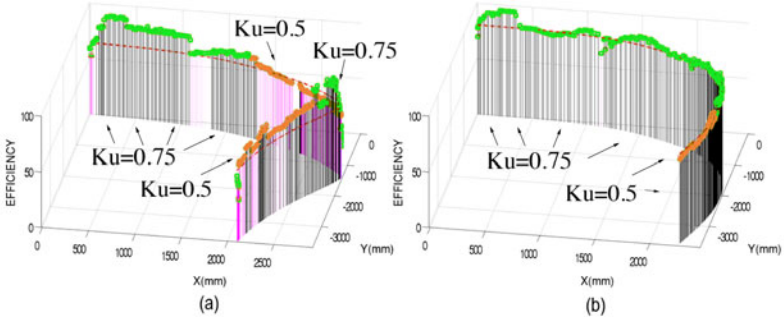


Fig. 7.25 Efficiencies in collaborative control mode with adaptive K for: a) volunteer 2; b) volunteer 5.

motion in difficult areas, where we want assistance to increase or decrease quickly. Punctual efficiency changes, though, correspond to local errors, that should not be reflected in the amount of assistance provided. The length of the window is basically controlled by how much K_H is holding in average with an acceptable variation. If someone has poor driving skills, after a short time span his/her K_H will become low and viceversa. Furthermore, if someone is very good at door crossing, but deals poorly with turns, K_H will clearly be larger in the first case than in the second one, as these situations can not be solved in a few seconds and, hence, K_H has time to adjust itself.

Naturally, using this formula, we could have a continuous variation of K_H, but doctors requested us once more to have just three values: 0.75, 0.5 and 0.25, corresponding to human higher control, equal contribution and machine predominance, respectively. The values are chosen according to the following criteria:

- If $(\bar{\eta_H} > 0.85)|(\bar{\eta_H} > 1.5 \cdot \bar{\eta_R})$, i.e. either the person is either doing very well or, at least, clearly outperforming the machine, $K = 0.75$.
- If $(\bar{\eta_H} < 0.85)\&(0.5 \cdot \bar{\eta_R} < \bar{\eta_H} < 1.5 \cdot \bar{\eta_R})$, $K_H = 0.5$.
- Else, $K_H = 0.25$.

7.4.1 Everybody Is Changing

This approach was also tested with volunteers in Casa Agevole (FSL) [175]. This time we tried an even more complex path: volunteers had to enter the house via the front door, followed by a narrow corridor. At their chosen point, they had to U-turn left, after leaving a cupboard on the right and always paying attention to the walls. Then, facing the opposite side in the main room, they had to move out of the house via a second door. The room for maneouver was quite restricted, but typical homes are usually like this, so it was interesting to check what would happen in daily-life-like conditions. Fig. 7.26 shows some captures of a random volunteer at key locations of the proposed path. It can be noted that there are no signals on walls or floor. As usual, we only provided general guidelines at the beginning of the test, like "enter the house by this door and get out by the other one". It is also important to note that moving backwards was not allowed, so turning too late in the trajectory could end up in a stuck-up situation. In this experiment, the system had a deliberative layer [179] that usually provided three local

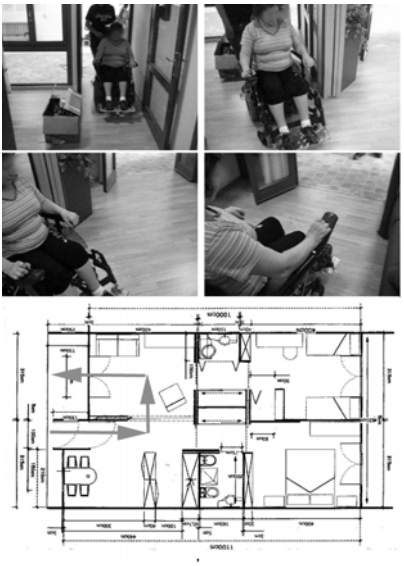


Fig. 7.26 Tentative path for experiment in Casa Agevole.

targets, approximately marked in Fig. 7.20 at the end of the three arrows. However, since paths were recalculated on a need basis, their locations may change and even additional local targets might appear if necessary.

First, we present an example with volunteer 2, a 68 years old lady affected by spinal cord injury. She was been chosen because she was already a volunteer in the previous tests, 5 months before, when modulation was still not used (see section 6.2.2). In her first tests in february 2009 she could not walk, but in june 2009 she came by foot with the help of a walker. In our new tests she had a MMSE index equal to 29.4, over 30, where 26 is accepted as average dementia threshold, i.e. no cognitive disabilities. Her Barthel index grew from 49 to 86 (over 100) in 5 months, meaning that she had recovered many physical skills. Indeed, this time, she performed clearly better than in february, where she had trouble with turns and managed to finish only one of three runs. K_H was not variable at the time, so february tests could be understood as a fixed K_H=0.5 case.

The path in february was approximately reverse to the one in Fig. 7.26, but it stopped before crossing the narrow door. Fig. 7.27 presents some results from february tests: a standalone benchmark run and a collaborative run. In the first case, the person received no assistance (except for a the usual safeguard mechanism). In the second case, the increase of efficiency at each point of the trajectory is overprinted in bright green over human performance. It can be observed that, despite the significant increase in efficiency, in this case the person was not capable of U-turning, mostly because she had severe complications with turns. For example, in the case in Fig. 7.27 it can be observed that delay in turning right led to sharp oscillations to correct the trajectory but, nevertheless, subject 2 failed to prevent the wheelchair from getting stuck too close to a cupboard. In the second case, collaborative control avoided some oscillations (see non-blue plot color), but assistance was not enough to correct the trajectory and avoid stucking up as well. Table 7.4 briefs efficiencies in february tests. It is important to recall that in collaborative mode, human actions also have an impact in robot efficiency, as the robot is not free to operate on its own. This impact could be positive (e.g. to avoid oscillations at doors) or negative, as smoothness could be affected by continuous compensation of the person's trajectory. Thus, robot's smoothness was not that good despite the benefits of a PFA. Yet, as this person had difficulties to turn, her worst feature was directness.

After experiments in february, we observed that almost every fail in finishing the trajectory could have been avoided if more assistance had been temporarily provided on a need basis, so we tested the proposed algorithm this time. Inpatient 2 physical skills had significantly improved since february. Still, we checked that assistance improved her performance. Furthermore, she reported to be quite comfortable with the wheelchair this time. Fig. 7.28 shows η_H, η_R and η_C respectively. We use the same color code, only the top of each efficiency value is colored green, orange or red for K_H equal to 0.75, 0.5 or 0.25, respectively. For example, it can be observed that there is a narrow area where PFA oscillations make K_H go green and $1-K_H$ go red (hence, a green K_H=0.75), as the person outperformed the robot for a while. At the second turn, it can be observed that the person steered late (loss of directness) and the robot induced a sharp turn (light blue area) to compensate. Yet, this time K

Table 7.4 Inpatient 2 Data

Test number		Feb'09	Feb'09	Jun'09
Control type		Standalone	Shared (K=0.5)	Shared (Kvar)
Global efficiency (%)	Robot	—	58.77	70.07
	Human	63.78	62.49	64.63
	Both	63.95	68.07	72.59
Smoothness (%)	Robot	—	42.31	51.15
	Human	54.88	73.57	63.18
	Both	55.09	66.2	67.93
Directness (%)	Robot	—	48.51	67.77
	Human	42.66	21.48	33.48
	Both	42.65	41.96	52.99
Safety (%)	Robot	—	85.69	91.29
	Human	94.07	92.66	97.18
	Both	94.2	95.99	96.88
Intervention Level	%	99.56	90.94	93.68
Disagreement	%	28.15	39.08	22.97
	dev	21.69	22.27	17.9
Joystick Variation	%	0.08	0.07	1.61
	dev	1.29	1.18	6.36
Inconsistency	%	4.19	7.11	8.37
	dev	4.19	7.11	9.45
Total Length	m	4.33	5.43	9.45
Total Curvature	degrees	101.1	128.8	175.06
Curvature	mean	0.01	0.01	-0.13
	dev	1.07	0.12	0.3
Completion time	sec	22.11	31.25	55.62

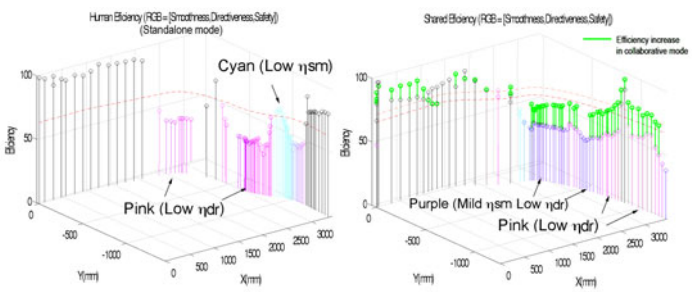


Fig. 7.27 Tests in february 2009 (K_H=0.5): a) standalone mode; b) collaborative mode.

did not grow because her directness had been consistently low in the most recent path section. Fig. 7.29,a shows the different trajectories achieved in june tests by inpatient 2 for K_H fixed to 0.5 and adaptive K_H. It can be observed that correction in the green K_H area allowed a shorter, more efficient trajectory in this try. we can

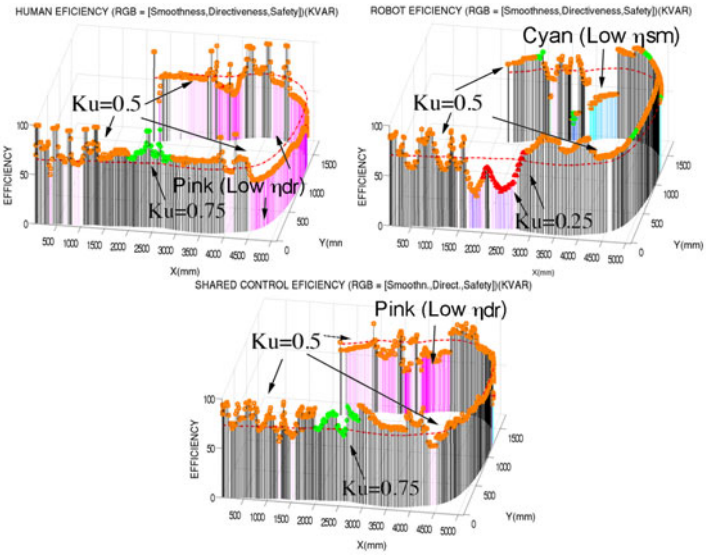


Fig. 7.28 Efficiencies for human, robot and collaborative control with adaptive envelope.

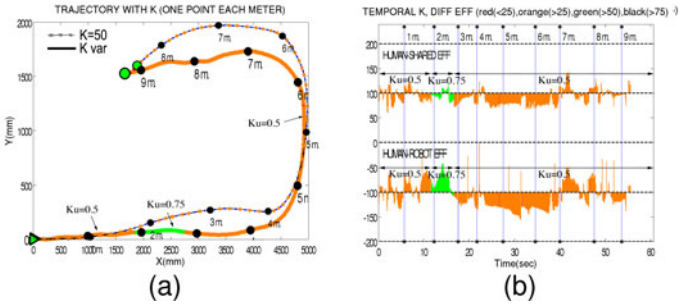


Fig. 7.29 a) Trajectories for K_H variable and K_H equal to 0.5; b) Substraction between and human-collaborative and human-robot efficiency for adaptive K_H.

observe in Fig. 7.29 b how human commands were clearly closer to collaborative control than to the robot's, specially in areas with high K_H values.

Naturally, inpatient 2's skills to U-turn in june were not simply due to our new approach, but rather to her rehabilitation therapy in the hospital. Still, it can be checked that the system worked as expected and this person reported that she felt more comfortable this time. Nevertheless, it is interesting to present results for a person who clearly required more assistance. Fig. 7.30 shows efficiency in standalone mode, K_H fixed to 0.5 and adaptable K_H for inpatient 5, affected by Guillain-Barre provoking tetraplegia and also by a strong apraxia (10 over 10). It can be observed that she was not able to complete the path on her own because she found it very hard to steer the

Table 7.5 Inpatient 5 Probes Data

Test number		Jun'09	Jun'09	Jun'09
Control type		Autonomous	Shared PFA	Adaptive K_H
Global efficiency (%)	Robot	—	78.49	76.82
	Human	52.58	68.95	76.73
	Both	55.25	77.65	80.5
Smoothness (%)	Robot	—	66.44	62.84
	Human	52.35	69.27	79.38
	Both	51.75	73.26	77.56
Directness (%)	Robot	—	76.65	73.88
	Human	34.36	41.85	54.91
	Both	43.08	63.75	67.91
Safety (%)	Robot	—	92.52	93.7
	Human	70.91	95.63	96.06
	Both	70.91	95.95	96.17
Intervention Level	%	58.82	88.49	90.78
Disagreement	%	10.41	13.63	11.68
	dev	12.29	9.45	9.26
Joystick Variation	%	1.25	2.25	1.74
	dev	5.74	7.98	7.19
Inconsistency	%	5.83	7.33	7.17
Total Length	m	3.47	4.78	5.32
Total Curvature	degrees	272.28	98.72	97.09
Curvature	mean	-0.87	0.22	0.15
	dev	10.87	0.3	0.2
Completion time	sec	18.74	17.48	23.96

wheelchair correctly. Collaborative control with K_H equal to 0.5 helped her to turn earlier, but since two turns were required in a fairly narrow space, once again she was unable to maneuver when she got too close to the armchair. Adaptive K_H presented two advantages: first, oscillations in the first door did not affect this inpatient anymore and, since she could drive fairly well in a straight line, she gained control over the wheelchair through most of the trajectory. Second, a better approach to the turn area, plus an increase in assistance, allowed her to turn correctly both times. It was not even necessary to decrease K_H to 0.25, as the robot approached the turn area from a better position thanks to human support. Unfortunately, after two turns the person lost some directness and trajectory needed to be significantly corrected at the end, but yet she still managed to gain a K_H equal to 0.75 for a while. It must be recalled at this point that the robot is not necessarily performing bad when K is high, but rather that the person is doing well, so she does not need so much assistance. In fact, even though inpatient 2 performed quite well this time, her K was mostly 0.5, i.e. she required help most of the time and only gained control when the robot performed poorly. In most cases, though, people managed to keep a high K

through large parts of the trajectory, meaning that a fixed K_H would have provided an unnecessary excess of assistance.

Evaluation of results with all volunteers pointed out that, in fact, they retained control over the wheelchair in any maneouvre they perform well, whereas K_H went to 0.5 in difficult areas. It rarely went to 0.25 because continuous assistance prevents users from falling into difficult areas, except for persons with mild to severe disabilities. Also, as PFA is used to control the robot and test areas were full of furniture and fairly narrow, we also checked that the robot contributes less when PFA is not doing well, making it easier for users to compensate its effects.

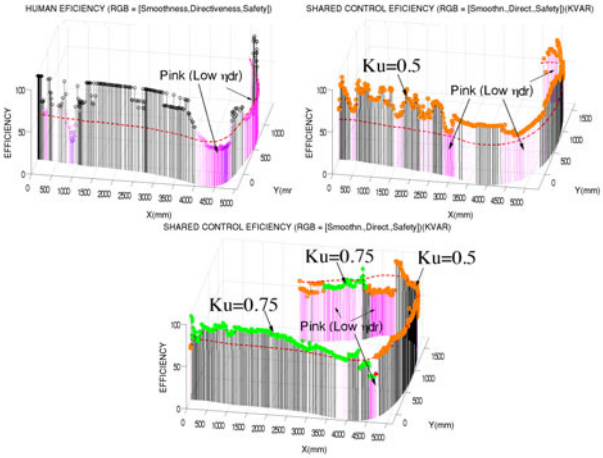


Fig. 7.30 Efficiency for standalone, collaborative control with fixed K_H and collaborative control with adaptive K_H.

Fig. 7.31 presents Intervention Level, Joystick Variation and Disagreement along the path for fixed and adaptive K_H respectively. It can be observed that Intervention Level is more dense in the second case, meaning that the user was actively cooperating all the time. Furthermore, locations where the person dropped the joystick, marked with dots at the plane, corresponded to decision points in the second case, whereas their location was more erratic for a fixed K_H. In both cases, there were less of these points than in standalone mode. This is also coherent with Joystick Variation, which was less noisy and smaller when K_H was adaptive. This is specially interesting when the inpatient failed to finish the first path, where it can be observed that joystick motion became rather erratic in a try to get out of the stuck situation. Finally, although Disagreement was similar in average in both cases, it can be observed that it was lower than average (discontinous red line) most of the time in the second case, except at the end of the trajectory, where a close turn led to higher robot assistance. When K_H was fixed, though, Disagreement was usually above the average, meaning that the person did not relate that well with the outcoming actions.

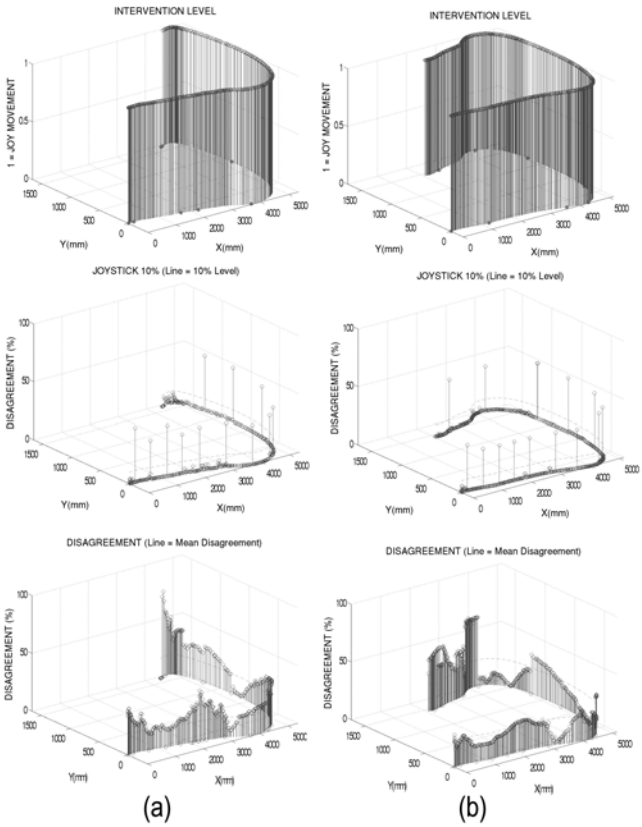


Fig. 7.31 Intervention Level, Joystick Variation and Disagreement for inpatient 5: a) K_H fixed (0.5); b) adaptive K_H

7.4.2 Way of the Samurai

Up to this point, it could be argued that users in our tests were physically disabled, but cognitively well so, most of the time, they contributed positively to collaborative control, except in maneuvers that they could not perform. Hence, in order to check how the system would operate in extreme, we tied the joystick to the wheelchair body so that it always pointed ahead and let the wheelchair follow the same trajectory than in tests with users. It needs to be noted that this is not a wheelchair standalone mode, but a collaborative mode with a dummy user who can only follow a straight direction. In this case, the user always had a high smoothness because it never tried to turn. Also, until a turn was required, it had a good directness too, because it was good at keeping a direction. At turn areas, directness would decrease drastically. Safety, however, would be ill preserved, as the dummy user would not mind about obstacles in the way.

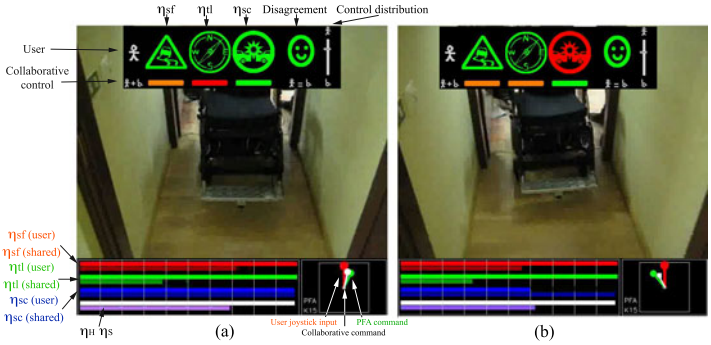


Fig. 7.32 a-b)Video captures of collaborative control (dummy user).

In this case, we will use live video frames to show how the system behaved (Fig. 7.32). The bottom of each frame is augmented with the values of η_{sf}, η_{dr}, η_{sm} and η, for user and collaborative control (upper and lower bars, respectively). Also, on the right of efficiencies, we can see the joystick -in dummy case, it was always "move ahead"- and collaborative control commands. Also, on top of each frame we have a qualitative measure of how user and collaborative control are performing: green, orange and red for efficiencies over 70%, 35-70% and below 35%, respectively. Disagreement is represented by a smiley icon if it is low, a neutral one for a mild value and a sad one if it is high. Finally, on the right of Disagreement, we can observe how much user and PFA are contributing to control in a slider. This is not a representation of K_H, but of the whole contribution of user and robot to motion after efficiency weighting and normalization. All these features are outlined in Fig. 7.32.a, a capture at the beginning of the trajectory that, in combination with Fig. 7.32.b shows us the effect of PFA oscillations in performance. It can be observed that the wheelchair entered the corridor slightly closer to the wall on its right, so PFA suggested to steer to the left. The collaborative command reduced the proposed turn and, hence, Disagreement was low. Yet, it can be observed on top of the

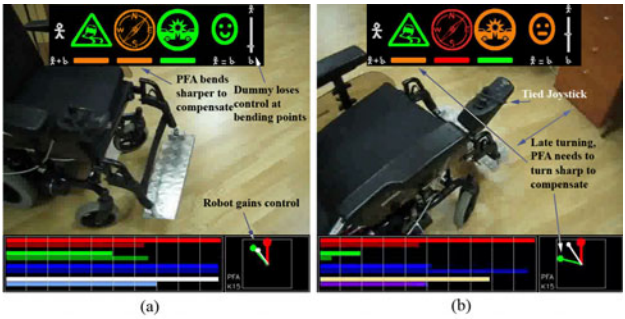


Fig. 7.33 a-b)Video captures of collaborative control (dummy user).

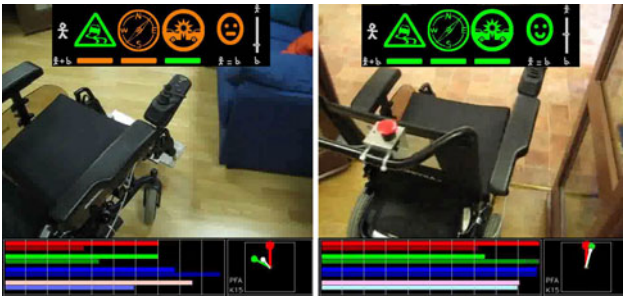


Fig. 7.34 a-b)Video captures of collaborative control (dummy user).

frame that our dummy user was driving better than the robot at the corridor because its commands did not oscillate. Furthermore, this slight turn made the vehicle get closer to its left wall, so PFA suggested to steer to the other side, even though the joystick insisted on moving ahead. Collaborative control was at this point closer to the joystick commands, so the wheelchair managed to move out of the corridor.

The proposed trajectory was easy for our dummy until it was time to turn left, an action that it could not perform. In this case, user's directness became lower and lower as soon as the robot decided it was time to change direction. At the beginning, user and robot commands were not that different, so Disagreement was low. However, as soon as turning became more urgent, Disagreement grew, user's directness dropped to red and PFA received more control, effectively turning. Unfortunately, this turn was too slow and left the wheelchair heading towards the wall on the right (Fig. 7.33 a). Obviously, the tied joystick suggested to head forwards but, at this point, the dummy user's efficiency was low enough for user and PFA to have a similar contribution to control, so the mobile steered steadily towards the main entrance. Due to the delayed turns, the wheelchair was facing the armchair near the door, so Disagreement was still mild: the joystick kept a direct trajectory (collision) and PFA suggested to move away from it, only this time the robot received more control because the dummy user had not only a low directness but a low safety as well. As soon as the wheelchair was facing the door, though, Disagreement decreased again and the wheelchair safely crossed it (Fig. 7.34). At door crossing, the dummy user defeated PFA, so it gained control over the system.

Fig. 7.35 a shows η_S in the presented test. It can be observed that, despite dummy control, it was close to 100% most of the time, except at a few locations. However, K_H was equal to 0.25 all the time, meaning that the robot had more control than the user all the time. Fig. 7.36 shows typical situations from the commented experiment, where responses to input locations have been clusterized into classes. The robot is always heading forward (0 direction), obstacles are represented as circles and the goal is marked with an X. Fig. 7.36 a shows a typical example of corridor navigation, where the dummy user compensated oscillations and the resulting trajectory was improved. Fig. 7.36 b shows the contrary case: a bending location where the dummy user proposed, as usual, to move ahead, and it was up to the robot to steer correctly.

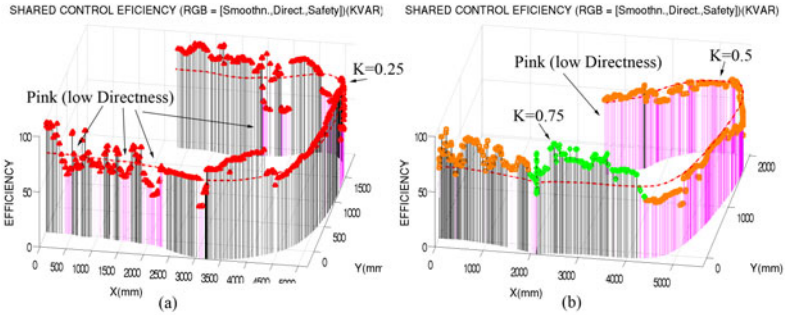


Fig. 7.35 η_S for: a) dummy user; b) blindfolded user.

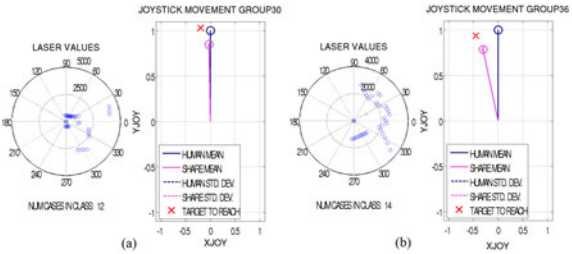


Fig. 7.36 Command clusters in dummy mode: a) narrow corridor; b) bending point.

7.4.3 X-Treme Testing!

At the end of our experiments, there were still a few things we wanted to test. The key point was that some users had reported that the joystick got stuck when they tried to move the wheelchair in a wrong direction, e.g. against an obstacle. In fact, our joystick was a commercial Meyra model with no haptic capabilities at all. Yet, we suspected that speed reduction caused by the combination of what the robot wanted to do and what the user was commanding when they are in direct opposition could be perceived by these people as a difficulty to push a joystick that is already in its limits. Naturally, Disagreement reduction via CBR learning had drastically reduced these cases, but we were actually wondering if this could, in fact, be useful for driving. Could we possibly use this false haptic sensation to help people with visual disabilities? We felt that we had pressed our luck too much, though, so we went for someone who could not say no to these tests: ourselves. And for a couple of days, in front of the very perplexed medical staff of FSL, most members of our team, plus a couple of guys who just happened to be walking nearby and were not familiar with the environment, proceeded to drive CARMEN blindfolded [174].

The test consisted of following the path in previous section and it was strictly forbidden to give any kind of vocal hint during navigation: the user was expected to manage on his/her own to complete the trajectory. Our goal was to try to decide when to turn with the help of collaborative control. The idea was very simple: a low

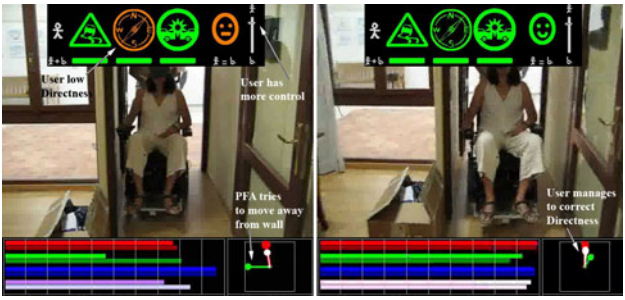


Fig. 7.37 a-b)Video captures of collaborative control (blindfolded user).

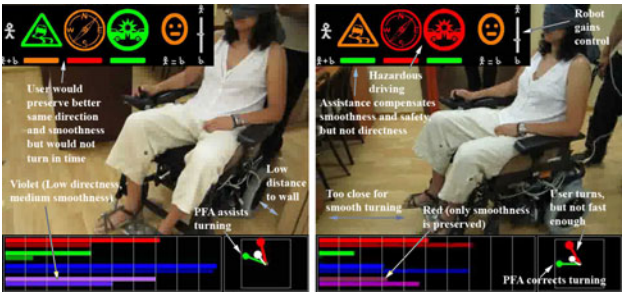


Fig. 7.38 a-b)Video captures of collaborative control (blindfolded user).

directness leads to a low η_C and Disagreement grows. The user should be able to notice this, because emergent motion would be different from the joystick command. Also, a high Disagreement provokes noticeable speed reduction. In fact, most users reported afterwards that they felt as if the joystick was harder to push -even though it was not haptic- if they went in the wrong direction. Instead, if users went with the flow, the wheelchair moved faster. From this point of view, collaborative control is similar to prompting. Fig. 7.35.b shows an example with a blindfolded user. Unlike in the previous case, this user drove better than a dummy[1], so K_H changed from 0.5 to 0.75. However, directness after the first turn was not good because the user did not know exactly where she was and either underdid or overdid the turn. Hence, η_C was pink the rest of the path.

Figs. 7.37 to 7.39 show different stages of this paths. It needs to be noted that people did not purposefully try to fight collaborative control, but rather to move as fluently as possible. Hence, Disagreement tends to be low most of the time. In any case, the safeguard layer would prevent collision into obstacles. The first stage of the path in Fig. 7.37 is a typical case of collaborative control. It can be observed that PFA tended to oscillate as usual, yet the user drove the wheelchair in a straight way. Disagreement was high, but just because oscillations made robot commands

[1] Or so she claims.

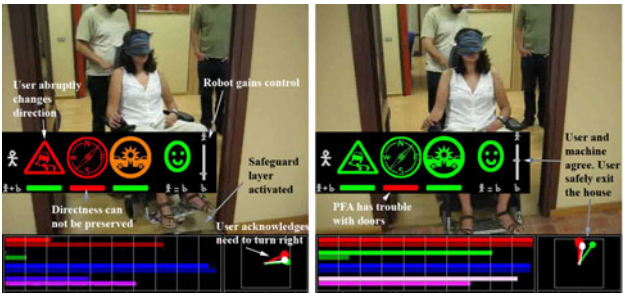


Fig. 7.39 a-b)Video captures of collaborative control (blindfolded user).

a bit erratic. This is also reflected in the higher amount of control rewarded to the user, that made emergent commands very similar to hers. It is interesting to observe that efficiency was close to 100% practically all the time, meaning that collaborative control was efficient in all three local factors.

The user faced her first problem when she needed to decide when to turn to the left. If she started to turn too early, she might have come too close to the left wall and further maneouvres might have become too hard. However, if she steered too late, she might have gone too close to the wall in front of her to turn safely. It can be noted in Fig. 7.38,a that Disagreement got higher and directness dropped, as expected. Now, emerging commands became a compromise between user and PFA and, also, motion was slower. When the user noticed this, she started to turn, but too smoothly. Hence, in Fig. 7.38,b she got close to the armchair on the right. It can be observed that Disagreement was still high and, since that her safety was low as well, speed decreased even more. The user reacted to this speed reduction by steering left, to try to agree with the wheelchair. However, she overturned and ended up facing the doorframe (Fig. 7.39,a). In this case, the safeguard layer stopped the wheelchair and the user realized where she was. Hence, she consistently steered right, exactly as the robot suggested. Disagreement, consequently, decreased and the wheelchair steadily moved in the correct direction. As soon as she was facing the door opening, resistance against straight motion became lower and the user successfully moved out of the house (Fig. 7.39,b).

Fig. 7.40 shows the effect of collaborative control in human commands in the commented experiment. Fig. 7.40,a presents a quite homogeneous cluster of 44 commands corresponding to the corridor. It can be observed that PFA prevented the user from getting too close to the right wall, but only reduced speed slightly, whereas in Fig. 7.40,b, where the user should be turning faster but was not doing so, speed was severely affected. Fig. 7.41,a shows how Joystick Variation was mostly low, meaning that the user did not change directions sharply, except at bending points. Also, Disagreement (Fig. 7.41,b) was mostly related to these locations, and also to commented problems faced by the user at the end of the path. There was also some Disagreement at the corridor due to PFA oscillations.

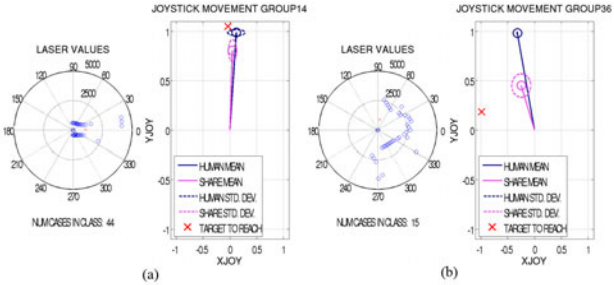


Fig. 7.40 Command clusters in blind mode: a) narrow corridor; b) bending point

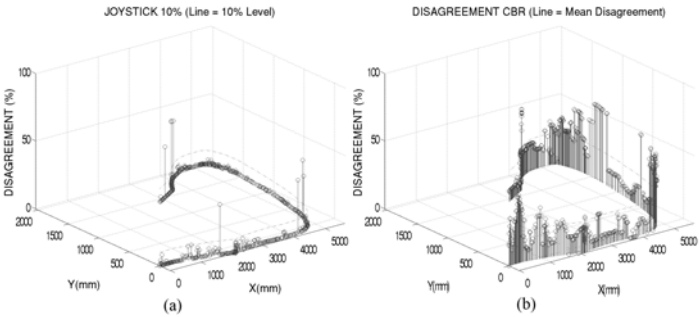


Fig. 7.41 Blind mode: a) Joystick Variation; b) Disagreement

7.5 Full Closure

Finally, our approach to collaborative control via efficiency based assistance modulation allowed *everyone* to finish the proposed trajectories, as long as there was a running deliberative layer to provide local targets, if necessary. Our final algorithm can be briefed as follows. Collaboration is based on estimating how well user and robot are doing at a given time instant to combine their motion commands in a weighted way, according to a purely reactive control scheme. Weights are a function of robot's and user's efficiency so that assistance is adapted to the user's needs. In order to gain some inertia against punctual errors and noise, an envelope is added to increase the contribution of either human or machine on a need basis. This envelope changes according to the temporal average efficiency between the current time instant and the last significant efficiency discontinuity. The system was fully tested in Casa Agevole with volunteering inpatients, presenting physical and sometimes cognitive disabilities. In all cases, collaborative control increased efficiency and all volunteers managed to finish a mildly complex trajectory despite their lack of experience with similar systems.

Reported improvements in the collaborative mode were supported, once more, by an ANOVA. In this case, when we compared η_H with η_C, F was equal to 9.3699,

and the *p-value* was equal to 0.0022. Thus, we can conclude that user and machine affect each other positively and, hence, cooperate for good. An unexpected outcome of the tests was the discovery of a pseudo-haptic feedback due to the user's tapping into the wheelchair speed space. This effect can be used to drive blindly, but also to help people with severe cognitive disabilities to recall their way.

Results proved that the amount of assistance received by users was adapted to their condition and also to the complexity of the maneouvre they were performing, yet they always had a contribution in emerging motion. Modulation improved users' acceptance and solved some situations where a specific user's disability prevented him/her from finishing trajectories. According to the medical team in the experiments, this is a positive feature to avoid loss of residual abilities and frustration. The system scored very well in their usability tests. Future work will focus on adding high level layers to define patterns and trajectories that link the proposed system to Activities of Daily Living (ADL).

Chapter 8
Good Night, Good Luck

Forty-two! - yelled Loonquawl. - Is that all you've got
to show for seven and a half million years' work?
I checked it very thoroughly
Deep Thought, The Hitchhiker Guide to the Galaxy

So, a couple of years after CARMEN was delivered in FSL, here we were with a fully working, tested system and several megas of data gathered through weeks of experiments that, fortunately, proved every hypothesis presented thus far. All in all, CARMEN was a success among users and doctors and it ranked the highest among all tested assistive devices -Rolland, i-Walker, Spherik- in terms of usability. So just conclusions and future work remain before curtain call ...

8.1 Don't Tell Me What I Can't Do

After so many tests, the amount of data we had gathered probably had hidden major information that we had not used yet. In fact, up to this point we had analysed what people could not do to calculate how much assistance they needed. However, the reverse can also be true: we can calculate what persons can do in terms of the assistance they need. This is no wordplay: if data gathered from a short collaborative driving period can be used to decide what someone can't do, we could work proactively, rather than in a reactive way. Being extremely optimistic, we could even extrapolate results from a person to another with a similar diagnosis and, if we still clap and believe in fairies, we might have a shot at diagnosis assistance after analyzing how someone drives. All in all, this looked promising enough to give it a try.

8.1.1 It's a Small World!

In chapter 5, we already ventured that reactive navigation could be represented by a reduced set of situations. At this point, we already had evidence that this was true.

C. Urdiales: Collaborative Assistive Robot for Mobility Enhancement, ISRL 27, pp. 181–196.
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In [106], in order to achieve collision avoidance in troublesome scenarios, the authors proposed a Divide and Conquer strategy where any complex scenario could be reduced to a set of relatively simple situations. Situations had to: i) be complete, i.e. fully describe all possible obstacle configurations, and robot and goal locations; and ii) be exclusive, i.e. given an obstacle configuration and a robot and goal locations, there is only one situation that represents it. A binary decision tree was used to determine these nuclear situations, where inputs of the tree were the obstacles and the robot and goal locations and the output was the situation. The tree was traversed using binary decision rules based on two concepts: security zone and free walking area. The security zone was obtained by defining a security distance d_s around the robot and checking if there were obstacles inside. The free walking area related the robot and its goal by searching for the direction free of obstacles that would get the robot closer to the target in the current situation. Taking this into account, they got five criteria:

- Safety criterion: High Safety (HS) means no obstacles in the security zone; Low Safety (LS) means there are.
- Goal within the free walking area criterion: High Safety Goal in Region (HSGR) means we are HS and the goal location is within the free walking area.
- Free walking area width criterion: If we are not HSGR but we are HS, High Safety Wide Region (HSWR) means that the free walking area is wide. High Safety Narrow Region (HSNR) means we that it is is narrow.
- Goal within the free walking area criterion: If we are LS, Low Safety Goal in Region (LSGR) means there are obstacles within the security zone, and the goal location is within the free walking area.
- Dangerous obstacle distribution criterion: If we are LS, but not LSGR, Low Safety 1 side (LS1) means there are obstacles within the security zone, but only on one side of the discontinuity (closest to the goal) of the free walking area. Low Safety 2 sides (LS2) means there are obstacles within the security zone on the two sides of the discontinuity (closest to the goal) of the free walking area.

The authors concluded that their set of situations was exclusive and complete to cover all the possibilities among the obstacle distribution and robot and goal location [106]. These situations are represented in Fig.8.1.

If these situations cover everything a person may locally face, we could state that someone who can cope with every one of these situations is perfectly able to navigate on his/her own. This is not a binary decision: even though the number of situations is limited, the number of solutions to each is not. Each person faces one situation or another in a different way, depending on how they drive, how used they are to the device and, more important in our case, what kind of disability they have. Indeed, we defined metrics in chapter 4 to decide how well we deal with a given situation. Thus, if we take enough navigation data from a given user and split it into the 6 classes in Fig.8.1, a person contributing to all 6 of them with efficient solutions is perfectly apt to navigate without assistance. If someone has no contribution to a class or all solutions provided are poorly efficient, they just require assistance when the related situation is detected/expected. Furthermore, if a person

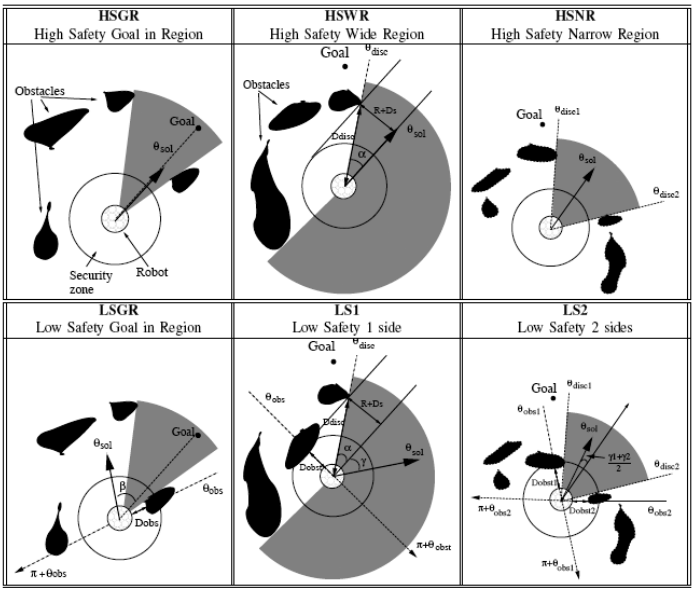


Fig. 8.1 Predefined situations and actions [106]

consistently proposes the same wrong solution to a given problem, this error might be correlated to his/her diagnosis.

8.1.2 A Touch of Class

After two years of experience, we can say it is a safe assumption that not even the healthiest person can achieve a flat 100% efficiency at every faced situation. Also, there are so many factors affecting performance that it is very difficult to decide when a person is apt to handle at a given situation or not. Fortunately, though, we do not need to. In fact, it is easier to just split the set of every trace we have recorded into clusters, so that every user has a presence in the results, including all people in the research team who ever tried the wheelchair. This sample space includes around 100 persons, both healthy and with a wide range of physical and cognitive disabilities. We clustered this space into the commented 6 situations. At this point, it did not matter what the user did, but just what situation he/she faced. It needs to be noted that each person typically faced the same situation many times during the experiments, so, in fact, classes included a huge number of solutions, whether efficient or not. Then, we calculated the prototype of each class Cluster prototype (CP)(i) as follows:

$$CP(i) = \frac{\sum_{j=1}^{N(i)} \eta_j c_j}{N(i)} \tag{8.1}$$

$N(i)$ being the number of cases c in class i and η_j the efficiency of case c_j. It can be observed that this average tends to be close either to the most efficient cases in the cluster or to the most frequent ones. Hence, our prototypes would be the best action that the larger number of people was able to produce for the situation at hand. Prototypes CP would be our reference to state that someone is efficient or not when solving a given situation.

Obviously, the right solution to one of the previous situations could not be calculated as the average solution of the elements of the class, because some solutions were good, but some were definitely bad choices. A possible solution would be to discard all cases whose efficiency was lower than a given threshold so only efficient cases contributed to the average solution. However, there can be more than one way of solving the same problem efficiently and, sometimes, added vectors neutralized each other. Imagine, for example, that there is a single obstacle in front of us and the goal is behind it. It would be equally advisable to steer right or left, whereas moving ahead would probably not be a wise choice. If we add both heading vectors and they are equally efficient, that is exactly what we would get. In order to avoid this problem, a second clustering was applied to every class to split it into subclasses only depending on case outputs. It was not necessary at this point to take sensor readings into account, because cases already belonged to a class that depended on the locations of the obstacles with respect to us. After this process was finished, there were several *CP* related to each situation that might have different efficiency. In some cases, different CP could have similar efficiency, specially when a situation could be solved in different ways (HS) or when there were multiple bad choices for the situation at hand (LS). Efficient CPs became our baseline to cope with situations, whereas bad CPs were expected to be related to specific disabilities.

Fig. 8.2 shows the resulting clusters for a prototype user after clustering all the data gathered in our experiments in standalone mode for every user in every test. Data was collected from more than 70 volunteers, plus all our testing. It can be observed that there are no HSWR nor HSNR situations, because all experiments were performed indoors, in mildly narrow areas, and people with good cognitive and physical skills tend to keep their goal in sight unless necessary. In our representation, the cluster section radius is equal to our user's average η_H to solve that particular situation. Its color corresponds to our efficiency RGB code. Finally, its area is proportional to the frequency of that situation in our experiments.

It can be observed that, in fact, our prototype user solves most situations quite efficiently, because most colors are bright and their radius is close to 1. Most cases corresponds to Low Safety Goal in Region (LSGR) clusters -as expected in indoor tests- that can usually be solved moving forwards or with minor steering. In these cases, our prototype user's efficiency tends to be pink, meaning that moving in narrow areas leads to minor loss of directness, probably to move away from nearby obstacles, even when it is unnecessary. The best possible situation -wide area ahead on the left- is close to white. LS1 and LS2 situations barely appear and are solved less efficiently by our prototype user, with major loss of directness (pink sectors) and, sometimes, loss of smoothness too (deep violet sectors). HSGR situations are solved with different skill, ranging from very low -only safety is preserved- to high -

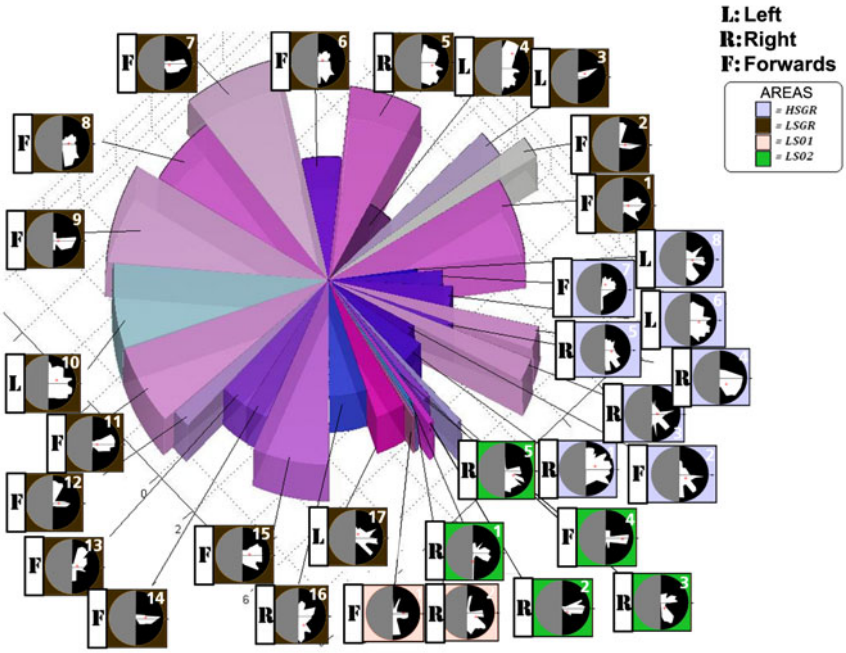


Fig. 8.2 Average user according to our experiments

minor loss of directness-, typically depending on how wide the area free of obstacles ahead is.

We need to recall that our prototype user has been extracted from real inpatients' data presenting a wide range of disabilities. As commented, we lean towards the best, most frequent decision they make to solve each given situation, but a healthy individual could possibly achieve better results. An alternative could be to create a prototype user for each specific disability rather than mixing them all, but this would require medical knowledge to spot the initial data set.

8.1.3 Piece of Cake!

Our prototype user can be used for benchmarking in real experiments. The simplest approach is to just subtract the prototype efficiency at solving each particular cluster from the a real user's graph. Some users can not solve a given situation at all. In these cases, we leave that area in white. Let's take, for example, volunteer 1 from section 6.2.1 (good cognitive and physical skills), 2 from section 6.2.2 (good cognitive and low physical skills), 10 from section 6.2.3 (low cognitive and physical skills) and 17, from section 7.2 (very low cognitive and physical skills). Fig. 8.3 shows the difference between those users and our prototype. Each sector is colored according to the user's efficiency in standalone mode. The difference can be positive -if the user is better than average at solving that particular situation- or negative, otherwise.

In some cases, users did not find all the situation, because they did not follow exactly the same trajectory. In other cases, users were not able to solve a given situation, so they do not have cases in its cluster.

We can observe that subject 1 (multiple sclerosis) solved the trajectory with 9 sectors, most of them LSGR. This was somewhat expected because experiments were carried indoors in a narrow environment. She also presents a LS2 cluster, meaning that, at some point, she drove herself to a very narrow spot, but she could solve it with a forward command. She was indeed very good with forward motion: we can observe that her forward clusters are above the prototype's and tend to white. At most, she lacked some directness, e.g. clusters 1 and 8. She also dealt quite well with left turns, which were not frequent in the experiments, but could be used to correct trajectories (cluster 10). However, we can observe that she only has two right turn clusters (16 and 5), even though there should be more in our particular experiment, which basically included forward motion and right turns. Furthermore, she was well above the prototype in sharp turns (16), but performed very poorly at fine turning (5). We can recall that this is very coherent with our observations from the experiment: subject 1 did not control well her right steering and this made her turn late. This also explains why there is a LS2 cluster that does not appear in other subjects.

Subject 2 (spinal cord injury) had a worse physical condition and, indeed, she presents a lower number of clusters (7). Also her efficiency is remarkably below the

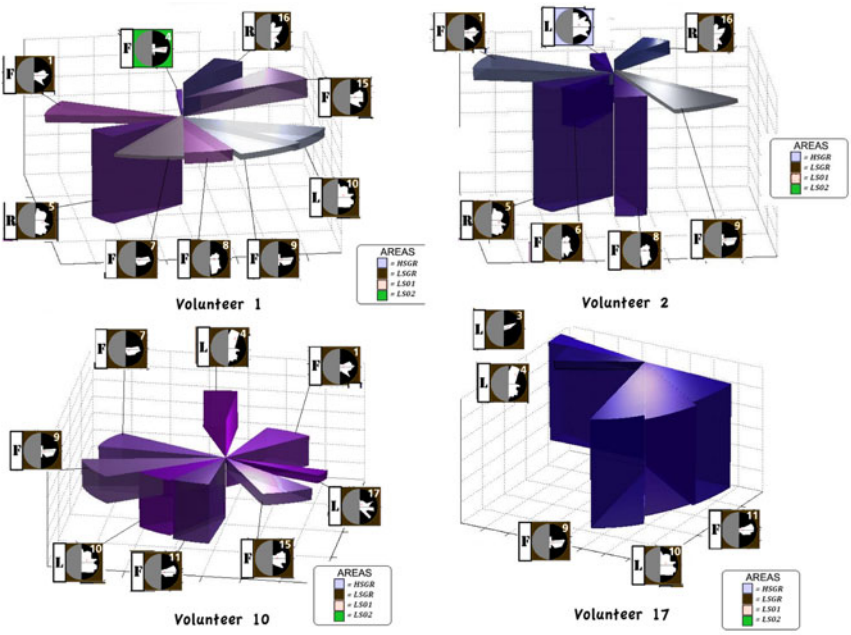


Fig. 8.3 Real users vs prototype user (standalone mode)

prototype's except for cases 1 and 9, which she solved very well. The other clusters are almost blue, meaning that only safety was preserved. Indeed, her only efficient movements were moving forwards in corridors and drastic steering. This explains well why she did not manage to cross the doorway, where she needed to maneuver with care.

Subject 10 (ischemic stroke (left hemisphere)) has a pink efficiency, i.e. lacked directness in practically every decision he made. Even though his differences with the prototype are lower than in some previous difficult cases, he never even tried to turn right, so it is not surprising that he could not cross the doorway in standalone mode, either. It might be interesting, from a medical point of view, to check why he never steered right, but it is out of our area of knowledge.

Subject 17 (hemiparesis-left aphasia mixta) was our worst case scenario, with extremely low physical and cognitive skills. She only presents 5 clusters and their value is well below our prototype. Furthermore, they are all blue, i.e. only safety is preserved, and, in this case, it could not be otherwise because the safeguard layer was always on. Like in subject 10's case, she present no right clusters, only her joystick commands were not smooth either. As in previous cases, she did not manage to cross the door.

It is also possible to predict, up to some point, what a given user is able to do or not in terms of these nuclear skills. For example, Fig. 8.4 shows the differences between subject 14 (Guillain-Barre, MMSE=23, Barthel=28) and the prototype user. We can observe that she has basically all the blocks she needs to build any kind of trajectory, except at very narrow places. However, she was not very good at direction keeping and sometimes turned sharply. In any case, since there is no real lack of driving skills, she should be able to complete any trajectory in our tests on her own, with a relatively low efficiency. If we check her statistics now (table 8.1) we easily realize that this was exactly the case. Her efficiency improved largely in collaborative mode and she reduced her completion time approximately a 30%, but still she managed to finish all paths in standalone mode.

Finally, the global shape and color of this pie representation provides information on the user's condition. Flat pies correspond to people close to the average. Asymmetries correspond to very specific disabilities and representations in intense colors, particularly blue, correspond to persons with major disabilities. Further study should provide more information to this respect.

8.2 That's All, Folks!

And now that we have come to an end, for anyone who did not make it here via the traditional lineal chapter-reading, a wrap-up section is in line. For all of you who patiently went through the whole text ... yay! bear with me a little longer, I promise we'll be done in a blink!

Table 8.1 Subject 14 Test Data

Test number		1	2
Control type		Autonomous	Shared PFA
Global efficiency (%)	Robot	—	66.15
	Human	58.54	52.03
	Both	58.71	69.1
Smoothness (%)	Robot	—	59.31
	Human	57.05	45.91
	Both	57.05	68.83
Directness (%)	Robot	—	47.45
	Human	28.58	22.85
	Both	28.77	44.02
Safety (%)	Robot	—	91.68
	Human	90.17	87.39
	Both	90.42	94.44
Intervention Level	%	72.57	84.26
Disagreement	%	31.45	34.23
	dev	20.5	18.26
Joystick Variation	%	3.24	2.61
	dev	6.66	7.24
Inconsistency	%	12.65	11.49
	dev	12.65	11.49
Total Length	m	5.49	5.58
Total Curvature	degrees	140.09	136.28
Curvature	mean	-0.76	0.21
	dev	19.24	2.33
Completion time	sec	52.85	36.46

8.2.1 The Murphy's Approach to Experiments with People

Even if this sounds like a mad genius cookbook, having the following information from the start would have saved us the time we used to learnt so many things via trial and error during our experiments. If experiments are focused on persons with disabilities, concerns come in pairs, so it is useful to keep some stuff in mind.

1. Simulation and reality in robotics are as close as the real world and the Matrix. You may test things a zillion times in your computer and real tests will never cease to amaze you. And, most times, not in a pleasant way. While simulation is absolutely necessary for starts, it is better to move to real tests as early as possible in research, even if you have to repeat things over and over again. So buy or build your robot prior as soon as possible. If this is impossible, try to get datasets from real experiments with a target population like yours and create emulations from there. Many research institutions like Placelab[1] provide this data for free.

[1] http://www.placelab.org/datasets/

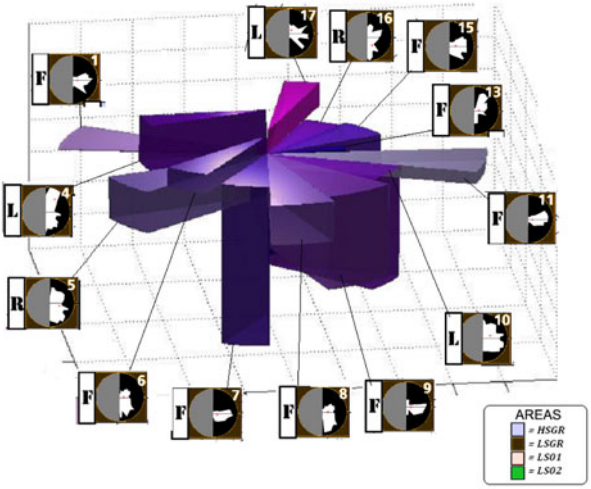


Fig. 8.4 Subject 14 vs prototype user (standalone mode)

2. Unless you are a powerful international business with big bucks for standardization, rather than build your robot from scratch, buy a conventional, standard-compliant wheelchair and build whatever you need on top. The same goes for biometrics devices or anything that needs to be manipulated by people. Otherwise, getting your tests to be approved is going to be quite challenging.
3. Experiments with PhD students and post-docs will only take you so far. In fact, they are usually too familiar with the system and know what to expect. Plus they usually do not match the target population. Also, it is a reduced and quite homogeneous population, usually in contact with each other. Of course, we researchers are expendable to make the first try with our devices -in a classic horror movie way- but as soon as we decide it is safe enough to actually let real people use it, just go for it. The best way to find a large enough heterogeneous population with disabilities is to make friends with a doctor in a rehabilitation hospital or to apply for a coordinated project with them and then ask as nicely as possible. Take into account that time is scarce in health business and you'll probably need at least two persons from the staff with you all the time, so learn as much as you can from the experience and keep in mind at all times that they do know more than you on health care: if a doctor tells you that head trackers are not good for people with spinal cord injury, don't build one!
4. If you got yourself a Hospital or Care center, remember they usually have an Ethical Commitee. This comes handy to know exactly the can dos and can do nots, but you will need to write very clearly what you plan to test at least 1 month in advance and take into account every possible variation for approval in their next meeting.

5. If you are planning to publish your results anytime soon, there are only two choices: compare yourself to existing systems[2] or use standard metrics to present results, so that anyone can compare with respect to those metrics. There are many different metrics in wheelchair navigation and some of them could not fit your problem at all, but a deep study of whatever is at hand and reported in other works is usually fruitful.
6. Tests are never as fast as they were expected to be, plus errors happen. Some user may finish tests in 10 minutes and another may take half an hour. There are meals when you least expect them and clinical sessions tend to get in the way. Your best option is to work with inpatients, i.e. people who are spending some time at the hospital rather than in and out in the same day. Thus, if a person can not do the tests today, there is always tomorrow. A robotic researcher might think that if a person leaves, there is always another, but caregivers invest a lot of time in calculating disability indexes -e.g. Barthel, MMSE, CIRS ...- for this people, getting them to fill usability questionnaires -e.g. PIADS, QUEST...-, getting their -or their families'- consent to participate in tests and be filmed ... Not being able to do a test with a set volunteer is usually catastrophic in terms of invested time.
7. The simpler, the better. Non fancy interfaces tend to be much appreciated by people who would rather be concentrated into not colliding their vehicle in a $60m^2$ apartment than in trying to figure out which button to push after that awesome 3D animation that pops each time you want to change directions ... There are several tests to check usability in the field, e.g. [73][148]. Use them at least in initial experiments to refine your interface. The closer your interface is to a conventional one -that people are used to- the easier it will be for them to accept it.
8. Stay on the safe side. Do not try to go for an ultra-efficient way of solving things until you can grant safety in every situation you can think of[3].
9. Store everything, and I mean *everything* you can get from the experiment in raw format. Sometimes, there is this operation you forgot to include in your processing algorithms that renders results completely useless, sometimes you think of something different you would have liked to calculate three weeks earlier, sometimes someone just asks you for a piece of data you never even realize could be meaningful ... you get the drift: DVDs are cheap and revamping experiments can be unaffordable.

8.2.2 Your Everyday Experiment to Do List

☐ Determine what your system can do *safely*
☐ Discuss with doctors what tests should consist of and which people should participate
☐ Lay contingency plan for everything you expect not to work ... or to work
☐ Choose the most fitting set of standard metrics you can find

[2] Getting people to lend you their very expensive existing systems for an unknown period of time to prove that yours works better is, for some reason, quite tricky.
[3] And try to be imaginative to this respect, people in tests usually are.

☐ Bring replacements for anything you can, e.g. laser, WLAN card, onboard PC ...
☐ Check periodically the wheelchair basics, i.e. wheel pressure, battery condition, assembly pieces ...
☐ Write down whatever information you can get from the doctors on each volunteer, e.g. condition, disability indexes ...
☐ Ask volunteers to fill a standard usability questionnaire
☐ Ask volunteers for permission to be filmed and do not forget to blur their faces afterwards in the videos
☐ Annotate your data with whatever catches your attention during tests, e.g. driving preferences, comments ...
☐ Store all data in raw format. You can process it later anyway you like
☐ Be extra-careful to keep all gathered data (medical, traces, questionnaires, videos...) correctly indexed
☐ Discuss any medical issue you observe with doctors while they are at hand
☐ Back-up any data you gather at the end of the day[4]

8.2.3 A Simple Plan

Assistance, like many vital things in life, is often required in ADL, but an excess is not welcome. In fact, it's not easy to find out how much assistance someone needs: too much may lead to frustration and loss of residual capabilities; too little may make it impossible for a person to achieve certain goals. Specifically, in the field of assistive wheelchairs, approaches have converged to the so called shared control approach. Traditionally, shared control has been based on switching control between robot and person, either automatically -when a hazardous situation is detected- or manually -when the user decides to activate one behavior or another to perform tasks that he/she finds particularly difficult-. In extreme cases, the system may simply stop the wheelchair in case of danger -Safeguard layer- or, completely maneouver the wheelchair to a destination point without input from the user -autonomous navigation-.

The main drawbacks of the commented approaches to shared control are that:

- There might be sharp control switches that are inconvenient both for the user and the robot, like an ABS system that keep going on and off.
- The user will never practise anything he/she finds hard to do, as the system is designed to do it for them.
- Specific disabilities that affect some skills and yet not others might be associated to an excess of assistance in some cases and lack some in others.

Think, for example, of memory. Years ago, anyone could remember a bunch of phone numbers, even though they had to write down the least frequently used ones in agendas. Nowadays, though, most people would lose contact with friends and

[4] And remember that back-ups in a single PC turn to back-down you when you least expect it.

family if their mobile phone unexpectedly crashed down. A mobile phone does not give you a hint, it simply returns the number you want to call to. It will be of no use, though, to tell you who is calling if the incoming number is not in the phone memory.

Instead, we chose to combine user and robot commands reactively, in a continuous way, so that they cooperate all the time rather than switching control from one to the other. We call this approach collaborative control, to outline that person and robot depend on each other and cooperate all the time. In collaborative control, both robot and person are modelled as reactive systems that provide motion commands to the vehicle all the time. Specifically, in our implementation the robot started using a PFA to calculate what it would do at each location, whereas the person provides commands via a joystick or any suitable HCI available. Both commands can be combined into a single one via vector addition.

The trick to combine those commands properly is to decide how much weight we give to the person and to the robot in this addition. Since the goal is to provide assistance on a need basis, the simplest choice at reactive level is to locally measure the efficiency of each of them in the situation at hand. The weight of their vectors and, hence, the amount of help the person receives, is proportional to their respective efficiencies. There are not so many factors that can be empirically measured at local level: typical efficiency features like distance to collision, total travelled length or trajectory time, *etc* are obtained at medium-large term. Basically, there are three significant factors related to efficiency that can be easily measured in a single time instant: safety, smoothness and directness. The first one is related to how close obstacles are, the second is obtained in terms of the angle between the current heading and the chosen one and the last is a function of the angle between the chosen direction and the goal one. They represent that trajectories that move far from obstacles, keep direction changes to a minimum and try to get to the goal as straightly as possible are preferrable to other ones.

We detected in our experiments that the robot always won in terms of directness. This happens because it knows exactly where to go at each point and its strategy is usually to go for it, whereas the person only has a general idea on trajectories: there is no *X* marking the spot. While this makes sense for persons with low cognitive skills that can not keep a direction course, it is not fair for persons with full cognitive capabilities, that should be able to decide whether they want to turn earlier or move one way or another. In order to avoid this problem, directness was measured differently for the robot and for the person. In the first case, it relates to the angle between the goal direction and the chosen one, whereas in the second, we try to just check if the person can keep directions by evaluating the angle between the chosen and the favored one in an adaptable time window. Tests with this new efficiency criteria gave persons more freedom to drive as they want, yet helped people with low cognitive skills still to drive in the correct direction, should there be one.

8.2.4 Minority Reports

After collaborative control was tested in our facilities[5] and we checked it was safe, it was submitted to the Ethical Commitee of FSL for tests with volunteers. Their medical staff kindly agreed to provide diagnosis and health indexes for all subjects in the experiments. From the engineering part, a double effort was made to find suitable, well established metrics to evaluate user's performance in all their aspects. We even handed in a few new metrics of our own to effectively measure the impact of this new approach to control: Disagreement and Inconsistency, representing how well the user and the wheelchair get along and how coherent the decisions of the user are. It was assumed from the very beginning that there was no canonical trajectory in these tests, but just general guidelines to reach a destination point, like *move towards the door and get in*. Tests were performed at a wing of FSL, and involved corridor driving and door crossing. All persons in the experiment managed to finish the proposed trajectories. Furthermore, collaborative control equalized their performance, as expected.

This apparently pointed out that the system helps more those people who need more help, so the system seemed to fulfill its goals. However, when results were evaluated later, we found out with some surprise that persons with better cognitive and physical capabilities consistently performed worse than subjects reported to be in a worse condition. A careful analysis of the results, plus a review of annotated comments on the users' performance when affected by this problem proved that, in these particular cases, Disagreement went up to the sky, meaning that persons who realize that they are receiving assistance try to avoid it, even if they need it, as help is only evident when the subject is driving clearly worse than the robot. Some persons even tried to do exactly the contrary they had been told to do to compensate for the robot help. Naturally, this effect appeared less when persons accepted they could not achieve a certain task on their own (low physical skills) or simply did not realize they were receiving help (low cognitive skills).

At this point, it seemed logical that robot assistance was not well accepted because it was too different from what the person would do if he/she were performing as usual, in the same way a body sometimes reject tissue acknowledged as foreign to the system. Thus, it we could make the robot drive like the user would do if he/she could, things should go smoother. The main problem here was that there is no canonical way of driving: each person drives his/her way, depending on many different factors. This problem is accentuated if persons have disabilities, as there may exist large differences between one user and another that are hard to predict a priori. Consequently, learning seems easier than modelling, and the best way to capture the specifics of each particular user is to learn by imitation. In this case, as navigation is handled at reactive level, it is fairly straight to simply couple what the user does at each particular situation with the input instance -obstacle and goal relative positions and current heading-, so that complex trajectories can be obtained from combination of simple, local cases. It would be like decomposing complex

[5] No undergrad students were harmed during the making of this book, but some seriously reconsidered their professional choices.

words into letters and them using them to create new words by using a few, simple, memorized rules.

In particular, CBR seemed a good choice to store these situations for future use in the shape of cases. Case adaptation was based on PFA to fill the gaps or improve existing case efficiency if necessary, for example, if the number of stored cases is very low. CBR may learn from own experience, meaning that the casebase is more complete when the system is used and robot navigation becomes more and more similar to the person. Also, if the person is improving by wheelchair practise or thanks to rehabilitation, the robot will progressively adapt to his/her improvement. On the contrary, if the person is suffering from a degenerative process and losing capabilities, the casebase can be frozen in time so that the robot drives like the subject did when his/her skills were highest.

Before the proposed CBR based collaborative system was tested in FSL, driving data from the different volunteers in previous experiments were processed to emulate how the robot would behave if it cloned them. Not only paths returned by the system were very similar to those used to create the casebase, but also similar to other paths not included in the casebase. For example, a casebase extracted from a path where a person drove in a corridor and entered a room was used to generate a path where the person exited the room and drove the corridor, instead. The resulting path was compared to a real one, captured from the very same subject, and both turned out to be pretty similar. Furthermore, paths generated by casebases from different volunteers had significant differences so it was concluded that driving features could be extracted via the proposed method.

New tests in FSL, this time in a more complex, house like environment Casa Agevole proved that our initial hunch was right: persons with good cognitive and physical skills improved their efficiency when CBR based collaborative control was used and, indeed, Disagreement was lower. It was also observed that CBR based collaboration was particularly useful for persons with good cognitive skills, as expected.

8.2.5 The Day the Wheelchair Stood Still

Our final system still presented some problems. First, when CBR is used, casebases have a limited set of cases, represented by prototypes, to solve all possible situations. As the wheelchair is navigating, at some point CBR switches from one case to the next for a better fit. Even though case differences may be neglectable from one point to the next, if they belong to different classes, their prototypes may be signifincantly different. Under these circumstances, subjects perceive sudden direction changes that make motion jerkier and uncomfortable. In order to avoid this problem, we decided to use a temporal window to smoothen transition between cases. More specifically, prototypes were modelled via a gaussian function before addition.

A second problem was that some people with very low physical or cognitive skills found it hard to finish complex trajectories despite provided assistance, specifically when there were actions they could not achieve on their own (see subject 17

in subsection 7.2). This problem was solved by modulating the amount of help in the collaborative control equation via an envelope. This envelope can be fixed by hand -according to medical advice-, in terms of biometrics -to check if the drived is stressed- or by averaging efficiency over a shifting time window, to decide how well people are coping with the situation at hand. In fact, it would be optimal to take all these factors into account to set the envelope value, but arbitration between involved factors is far from simple.

All in all, after all these final details were tied up, experiments turned out good. A deeper statistical study of these last experiments could be of interest to obtain sound results and check if obtained information can be used not only to help people but also to gain knowledge about their condition.

8.3 The Shape of Things to Come

Every end is also a beginning. As George Bernard Shaw stated, science never solves a problem without creating ten more[6] and work with CARMEN has not been the exception. For starts, the proposed collaborative control paradigm is not limited to robotics wheelchairs. During our experimentation stage, our research partners developed an assistive walker (i-Walker) that could benefit from collaborative control as well. Furthermore, any robot designed to be partially operated by a person could be a candidate to collaborative control. Think, for example, of surgery robots, exploration rovers, trolleys, etc. Our collaborative control system was designed modularly, in a layered way, so it can easily be added to any layer based control architecture. Specifically, we used DLA, a hybrid GPL architecture that we released in 2006 and supports both Linux and Windows OS. DLA can run in several machines and relies on sockets and shared memory for communications, so layers can exchange information with any ISO compliant system. The collaborative control layer is also going to be Open Software in brief.

It has been stated over and over all through the text that the proposed system is reactive, even though it relied on a deliberative layer developed in [163], also integrated within DLA. That layer was used by the robotic system to estimate a set of partial goals that our reactive module tried to reach in sequence. This list of partial targets changed dynamically to acommodate to whatever the user was doing during tests, but ultimately led to the final destination. It was also used to estimate directness for the robot. In free navigation mode, this layer was disabled, but during trajectory tests, it was used to assist people with cognitive disabilites to go in the correct direction and also to decide when they were outperformed by the robot in terms of goal-reaching. In our case, the deliberative layer simply performed localization and path planning tasks, but, ultimately, higher level knowledge is required to decide where trajectories should lead to in terms of the user's ADL. This is far from simple: who knows what a person might want to do at a given time? Fortunately, people, and most specifically people with disabilities, tend to have habits, that usually can be decomposed into more or less structured sequences of actions. If these

[6] In some cases, not only to scientists, mind you.

sequences can be recognized, at least partially, places related to these habits can be identified and send to the path planning layer, which will propagate them down in sets of partial targets. Naturally, this implies a heavy effort on activity recognition, and learning that remains to be done, plus a negotiation stage to determine the best course of actions that could be engaged by distributed software agents.

Finally, assistived navigation is an activity that generates a large amount of data in time, most of it with qualitative meaning and correlated to the user's condition and state. When a new person starts using one of these devices, he/she suffers from the classic cold start problem, meaning that he needs to get used to the device. In our case, we tried to make the device get used to the user instead, so convergence to standard use would be faster. Still, the robot needs some time for this adaptation. This is a perfect problem for a Reduce/Reuse/Recycle approach to data: if we manage to extract the basics of navigation from a given user's interaction with an assistive device, we could export it to seed the learning system of another person's device so he/she does not start from scratch if both present similar medical and personal conditions. This implies much work on generalization, learning and databases, with special care regarding security, as sensitive data is involved. We even expect that this could ultimately lead to a new generation of assistive devices [30] capable of social networking to search the best possible configuration for the users, not only via personalization but also by observing others' experience.

Glossary

A* algorithm. A heuristic path planning algorithm that reduces the problem complexity by favoring paths close to the shortest one between origin and destination. 36, 37

Adjustable Autonomy. Control function to estimate how much weight the decision of a given agent has in a cooperative multiagent system at each time instant. 33

ANOVA. In its simplest form ANOVA provides a statistical test of whether or not the means of several groups are all equal, and therefore generalizes Student's two-sample t-test to more than two groups.. 146, 185

aphasia. Acquired language disorder in which there is an impairment of any language modality. This may include difficulty in producing or comprehending spoken or written language.. 151, 192

apraxia. Neurological disorder characterized by loss of the ability to execute or carry out learned purposeful movements, despite having the desire to and the physical ability to perform the movements.. 70, 77, 79, 85, 91, 115, 166

automata. Derived from the Greek word *automatos*, "acting of one's own will": a self-moving machine, or one in which the principle of motion is contained within the mechanism itself (Encyclopaedia Britannica). 1, 2

Barthel. index. A medical indicator of the physical condition of a person regarding his/her ADL and ranging from 0 to 100. 70, 77–79, 85, 91, 92, 131, 140, 151, 166, 170, 173, 193, 196

Casa Agevole. Casa Agevole is a 60 m^2 house built within FSL in Rome, projected by architect Fabrizio Vescovo from SPCA. It has been designed to maximize living space and, at the same time, be compliant with existing standards for assistance.. 17, 119, 162, 166, 172, 200

collaborative control. Particular case of shared control in which person and machine have a weight in every decision at the same time. 17, 41, 44, 46, 48, 49, 63, 74, 79, 80, 83–88, 90, 93, 99, 105, 115, 120, 121, 125–129, 137, 140–142, 144, 146, 149–151, 154, 157, 158, 166, 168, 169, 173, 177–179, 181, 182, 184, 198, 199, 201

curvature. Magnitude related to how much a curve bends at each point. Corners in a shape would be peaks of its curvature function and straight segments would be zero curvature areas.. 44, 46, 53, 55, 77, 78, 81, 82, 86, 89

dead reckoning. Localization technique based on accumulating odometry in time without external correction. 27

deliberative. **(architecture)** Control paradigm based on keeping an updated world model, which is processed in order to take a decision via a planning algorithm. 31, 43, 44, 46

Digital Divide. Social gap created by new technology between those who are able to use it and those who can not.. 21

directness. Local efficiency parameter that reflects that a direct approximation to a target is the best choice in terms of trajectory length. 44, 52, 73, 77, 78, 81–84, 86–90, 92, 103, 104, 121–124, 126, 129, 131–133, 136–141, 143, 146, 153, 154, 157, 163, 164, 166, 167, 169, 170, 173, 174, 176, 178, 180–183, 191, 192, 198, 202

disability. Degree of difficulty or inability to independently perform basic activities of daily living. 68, 150

Disagreement. Local efficiency factor related to the angle difference between the direction proposed by an agent and the direction the vehicle actually takes. It seem to reflect stress and frustration, but also to control difficulties due to the vehicle mechanics and interface. 74, 77, 78, 85, 86, 89–93, 95, 121, 122, 124–129, 131–134, 136–138, 140–146, 153, 156, 157, 168–170, 174, 176, 177, 179–184, 199, 200

divergence. Spatial difference between the projection of the same point in a pair of stereo images. It is equivalent to the distance between such point and the camera. 25

EagleEyes. GPL interface system developed by Boston College for persons with extreme mobility challenges to operate a computer pointer. It comes in two flavours: gaze based control and skin electrodes.. 23, 25, 36

Eliza. One of the first AI programs based on a set of rules that it used to match the left hand side of the users' input. It received her name from Pygmalion's Eliza. 7

emergent. (behavior) Result of the combination of several reactive sense/action pairs together. 83, 84, 91

free walking area. Direction free of obstacles between robot and its target. 188

geometric map. A map that represents space in a geometrically accurate way. 28

Golem. Humanoid entity made of clay and annimated by the sacred word shem placed inside its head by a rabi to accomplish a given task. 4, 5

Guillain-Barre. An autoimmune disorder affecting the peripheral nervous system, usually triggered by an acute infectious process. It usually exhibits as an ascending paralysis noted by weakness in the legs that spreads to the upper limbs and the face along with complete loss of deep tendon reflexes.. 122, 175, 193

holonomic. Vehicle thay can move in any direction from the same point.. 44

hybrid. **(architecture)** Control paradigm based on combining a deliberative layer for planning and a reactive one for fast action, plus a middle layer to handle their interaction. 32, 33, 43, 46–48

Inconsistency. Efficiency factor related to the variation of the user's commands to solve a similar situation. It seems to be related to his/her cognitive skills. 74, 77, 78, 85, 86, 89–91, 121, 122, 124, 126, 128, 133, 134, 137–139, 141, 144, 153, 156, 157, 174, 176, 199

Intervention Level. Efficiency factor related to the percentage of time that the user operates the interface during a trajectory. It is related to his/her collaborative profile. 74, 78, 83, 85, 86, 89, 90, 121–126, 131, 141, 153, 157, 168–170, 174, 176, 177

Inverse Kinematics. Branch of robotics which deals with the study and application of the process of determining the parameters of a flexible object in order to achieve a desired pose.. 95

Joystick Variation. Efficiency factor related to the percentage of time that the user changes the joystick position more than a 5%. It is proportional to human workload in controlling the vehicle.. 74, 77, 78, 86, 89–91, 121, 123–126, 131, 132, 136, 140, 141, 153, 168, 169, 174, 176, 177, 184

kouros. An Archaic period hellenic statue representing a young male. 9

Markov Model. A stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event. 28

mecha. A japanese combat robot controlled either by a pilot on board or teleoperated. 6

multiple sclerosis. An inflammatory disease in which the fatty myelin sheaths around the axons of the brain and spinal cord are damaged, leading to demyelination and scarring as well as a broad spectrum of signs and symptoms. 122, 192

navigation. Act of actively moving towards a defined goal in a safe way. 14, 15, 17, 19, 20, 42, 46, 67

Neural Network. Adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. 98

occupancy grid. Geometrical environment representation proposed by Hans Moravec in the 80s in which space is split into a grid where each cell yields a value ranging from 0 to 1 equal to its probability of being occuppied. 28, 35, 37, 48

optical flow. Intensity gradient of a fixed point through a sequence of images. Related to the speed of that point in the field of view.. 25

P300. Evoked Potential: Involuntary response of the brain to an input of interest that appears with a 300 ms delay.. 24

partial target. In navigation, any significant location that the mobile must reach prior to the final goal.. 44

reactive. **(architecture)** Control paradigm based on associating a sensor instance to a fixed action into a pair. Emergent behaviors are the result of combining several of these pairs. 32, 35, 41, 43, 46, 81

Roadmap. Motion planning algorithm which solves the problem of determining a path between a starting configuration of the robot and a goal configuration while avoiding collisions. The basic idea behind roadmaps is to take random samples from the configuration space of the robot, testing them for whether they are in the free space, and use a local planner to attempt to connect these configurations to other nearby configurations. The starting and goal configurations are added in, and a graph search algorithm is applied to the resulting graph to determine a path between the starting and goal configurations. 29

robot. A re-programmable multi-functional manipulator designed to move materials, parts, tools, or specialized devices through variable programmed motions for the performance of a variety of tasks (*The Robotics Institute of America* (RIA)). 1, 4

safeguard. Shared control method in which the machine only receives control when a hazardous situation is detected. 34, 77, 84, 120, 123, 125, 131, 137, 139–141, 152, 154, 182, 192, 197

safety. Local efficiency factor that reflects that it is better to keep as far from obstacles as possible. 44, 52, 73, 77, 78, 81–84, 86–90, 92, 103, 104, 121, 124, 128, 129, 132, 136, 137, 140, 141, 143, 153, 154, 166, 168, 169, 174, 176, 178, 183, 192, 198

security zone. Area around the robot where there should be no obstacles for safe maneouvering. 188

sensor. A device that measures a physical quantity and converts it into a signal which can be read by an observer or by an instrument. 2

shared control. Control paradigm in which a person and a machine work together according to Adjustable Autonomy principles. 34, 35, 37, 41, 42, 45, 46, 63, 67, 197

shifting time window. Time interval that always contains the current instant. 44

smoothness. Local efficiency factor that reflects that it is better to change vehicle headings as less as possible. 44, 52, 55, 73, 77, 78, 81–90, 92, 103, 104, 121, 122, 124, 128, 129, 131–134, 136, 137, 140, 141, 143, 153, 154, 163, 166, 167, 169, 170, 173, 174, 176, 178, 191, 198

Spatial Semantical Hierarchy. Hybrid topological-metrical representation of the environment proposed by Benjamin Kuipers and build in a top down way. It relies on building a topological model via node insertion each time a significant input

instance is detected. Nodes are annotated with metrical information for dissambiguation after the structure is complete. Unexplored space is not represented. 29, 36

standalone. mode. Wheelchair operation mode in which control is exerted by a person without assistance. 79–81, 83, 91, 120–125, 127–129, 131, 134, 140–142, 146, 151, 152, 157, 168, 178

subsumption architecture. Method of decomposing complicated intelligent behaviour into many simple behaviour modules, which are in turn organized into layers. Each layer implements a particular goal of the agent, and higher layers are increasingly abstract. Each layer's goal subsumes that of the underlying layers, e.g. the decision to move forward by the eat-food layer takes into account the decision of the lowest obstacle-avoidance layer. As opposed to more traditional AI approaches subsumption architecture uses a bottom-up design. 32, 34, 36

teamworking. Interaction between several agents, physical and/or sofware, in order to achieve one or several common goals. 33

Time Shifting Window. Filtering technique based on averaging the values of a magnitude within a shifting interval that always contains the current time instant. 171

topological map. Map that has been simplified so that only vital information remains and unnecessary detail has been removed. 29

Unimate. First commercial robots created by Devol and Engleberger for industrial uses. 4

Visibility Graph. A real time motion planning algorithm. It uses a statistical representation of the robot's environment through the so called histogram grid. VFH takes into account the dynamics and shape of the robot, and returns steering commands specific to the platform. 29, 37, 39

Visual Complexity. Web site (*http://www.visualcomplexity.org*) devoted to visual representation of complex phenomena, large amounts of data, multidimensional spaces ... ranging from the degree of connectivity between Facebook users to musical correlation in current pop. 7

Voronoi diagram. Partitioning of a grid into convex polygons such that each polygon contains exactly one generating point and every point in a given polygon is closer to its generating point than to any other. 29, 37, 39

wearable. (device) A low invasive, wireless monitorization device that can be used for a continuous time period. 160

Acronyms

3T Three Tier. 32, 33, 37, 38, 48

AA Adjustable Autonomy. 33
ABS Anti-lock Braking System. 15, 34, 197
ADL Activities of Daily Living. 13, 14, 68, 70, 71, 75, 197, 202
AI Artificial Intelligence. 5, 6
AIBO Artificial Intelligence roBOt. 11
AKH Active Kinematics Histogram. 35, 38, 42
ALS Amyotrophic Lateral Sclerosis. 23
ANN Artificial Neural Networks. 100, 101
ATAT All Terrain Armored Transport. 6

BCI Brain Computer Interface. 23–25
bpm beats per minute. 73, 161
BSG Battlestar Galactica. 6
BT Bluetooth. 160, 161

CARMEN Carnegie Mellon Robot Navigation Toolkit. 30
CARMEN Collaborative Autonomous Robot for Mobility ENhancement. 16–18, 64, 78, 166, 181, 187, 201
CBR Case Based Reasoning. 17, 98–105, 107, 109, 111–118, 120–122, 124, 128, 129, 132, 135–138, 140, 143–147, 149, 151, 181, 200
CCD Charge-Coupled Device. 36
CEO Chief Executive Officer. 12
CGA Comprehensive Geriatric Assessment. 68
CIRS Cumulative Illness Rating Scale. 70, 78, 196
CMYK Cyan-Magenta-Yellow-Black. 8, 51
CP Cluster prototype. 190
CPU Central Processing Units. 20, 21

DLA Distributed Layered Architecture. 18, 37, 201
DNC Double narrow corridor. 51, 52, 54–59, 61, 62

DWA Dynamic Window Approach. 34, 36, 37, 39, 48

ECG Electro-Cardiogram. 159, 160
EEG Electro-EncephaloGraphy. 23, 24, 159
EGE European Group on Ethics. 64
EOG Electro-Oculographic Potential. 23, 25
ESP Enhanced Steering Performance. 20

FD Function disability. 68
FEW Functioning everyday with a wheelchair. 75, 76, 78
FSL Fondazione Santa Lucia. 16, 17, 63, 65, 68, 78–80, 107, 119, 121, 150, 158, 162, 166, 172, 181, 187, 199, 200, 214
FW Follow Wall. 51–62

GDS Geriatric Depression Scale. 69, 78, 79, 91
GPL General Public License. 18, 37, 201
GPS Global Positioning System. 27, 28
GSR Galvanic Skin Response. 161

HCI Human/computer interface. 17, 20, 21, 24, 38–40, 42, 49, 72, 76, 198
HOAP Humanoid for Open Architecture Platform. 5, 12
HRI Human/robot interface. 80
HS High Safety. 188, 190
HSGR High Safety Goal in Region. 188, 191
HSNR High Safety Narrow Region. 188, 190
HSWR High Safety Wide Region. 188, 190

IADL Instrumental Activities of Daily Living. 69, 77, 78, 131, 151
ICF International Classification of Functioning, Disability and Health. 68
ICS Intelligent Control System. 20
IEW Independence-Enhancing Wheelchair. 20
ISO International Organization for Standardization. 201

LR Learning Rate. 57, 58, 61, 62
LS Low Safety. 188, 190
LS1 Low Safety 1 side. 188, 191
LS2 Low Safety 2 sides. 188, 191, 192
LSGR Low Safety Goal in Region. 188, 190, 192

MDE MultiDimensional Evaluation. 69
MMSE Mini-Mental State Examination. 69, 77–79, 85, 90–92, 120, 122, 131, 140, 146, 151, 166, 169, 170, 173, 193, 196
MPT The Matching Person and Technology. 75, 78

NASA Nacional Aeronautics and Space Administration. 13
NC Narrow corridor. 51, 52, 55, 56, 58, 59, 61

NN Nearest-Neighbor. 102, 103

PD Pass door. 51, 52, 55, 56, 58, 59, 61–63
PFA Potential Fields Approach. 39, 42, 44, 46–48, 52, 81, 83, 84, 87, 88, 90, 92, 99, 102, 105, 108, 115, 121–126, 128–130, 132–134, 136, 137, 140, 141, 143–146, 149, 151, 154, 164, 168, 173, 174, 176, 177, 179, 180, 182–184, 198, 200
PIADS Psychosocial Impact of Assistive Devices Scale. 75, 77, 78, 196

QRIO Quest for cuRIOsity. 12
QUEST Quebec User Evaluation of Satisfaction with assistive Technology. 76, 78, 196

RGB Red-Green-Blue. 52, 121, 123, 190
ROS Robot Operating System. 30
RUR Rossum's Universal Robot. 3, 5, 9

SENARIO SEnsor Aided Intelligent Wheelchair NAvigation System. 19, 35, 37, 38
SHARE-IT Supported Human Autonomy for Recovery and Enhancement of cognitive and motor abilities using information technologies. vii, xi
SIAMO Sistema Integral de Ayuda a la MOvilidad. 19, 37, 39
SLAM Simultaneous Localization and Mapping. 20, 28, 38
SPA Sense-Plan-Act. 31, 32, 37
SPP serial port profile. 161
SRM Stimulus Response Modeling. 35, 38
SSH Spatial Semantic Hierarchy. 36

TAMP Tufts Assessment of Motor Performance. 71, 78
TLX Task Load Index. 75, 76, 78
TOF Time of Flight. 25

VAHM Vehicule Autonome pour Handicapes Moteurs. 19, 35, 38
VCR Video Cassette Recorder. 16
VFH Vector Field Histogram. 35, 38, 42, 48, 92
VFM Valutazione Funzionale Mielolesi. 71, 78
VOA Velocity Obstacle Approach. 35, 38

WHO World Health Organization. 68
WST Wheelchair Skills Test. 71, 78

Glossary of Symbols

α_{dest} Angle between the command and the direction towards the next goal. 45
α_{dif} Angle between the robot heading and the command vector. 44
α_{min} Angle between the command and the combined repulsion of surrounding obstacles. 44

C_{dr} Constant to set the relative importance of directness on navigation. 45
C_{sf} Constant to set the relative importance of safety on navigation. 44, 45
C_{sm} Constant to set the relative importance of smoothness on navigation. 44, 45

D_c Distance to collision. 73
d_s Security distance around the robot. 188
D_s Distance to stop. 73

η Reactive wheelchair navigation efficiency. 44, 45, 87, 128, 129, 134, 171, 178
η_{dr} Reactive efficiency regarding directness. 44, 45, 88, 178
η_H Reactive human efficiency while driving a wheelchair. 44–46, 63, 81–84, 86, 88, 121, 123, 124, 126, 127, 133, 136, 141, 151, 153, 156, 174, 185
η_R Reactive robot efficiency while driving a wheelchair. 44–46, 63, 83, 84, 86–88, 121, 126, 128, 133, 136, 141, 151, 156, 174
η_C Collaborative robot efficiency while driving a wheelchair. 44, 46, 57, 83, 84, 86–88, 121, 126, 133, 134, 136, 141, 154, 156, 174, 181, 182, 185
η_{sf} Reactive efficiency regarding safety. 44, 45, 88, 178
η_{sm} Reactive efficiency regarding smoothness. 44, 57, 88, 178
$e(x)$ Amplification envelope. 150

F Friction to settle a particle system in equilibrium. 9

k_{att} Constant to adjust the attraction of a goal in a Potential Field. 47
K_H Value to modulare human contribution to collaborative control. 150, 151, 154, 156, 162, 164–177, 179, 181, 182
k_{rep} Constant to adjust the repulsion of an obstacle in a Potential Field. 47

M_{atr} Attraction matrix between particles based on their likeness. 9
M_{rep} Repulsion matrix between particles based on their differences. 9

$N(i)$ Number of cases in a class i. 190

ρ Curvature function of a path. 53

T_c Time to collision. 73
t_{dis} Most recent time instant in which the wheelchair driver showed a consistent increase/decrease in efficiency. 171
T_s Time to stop. 73

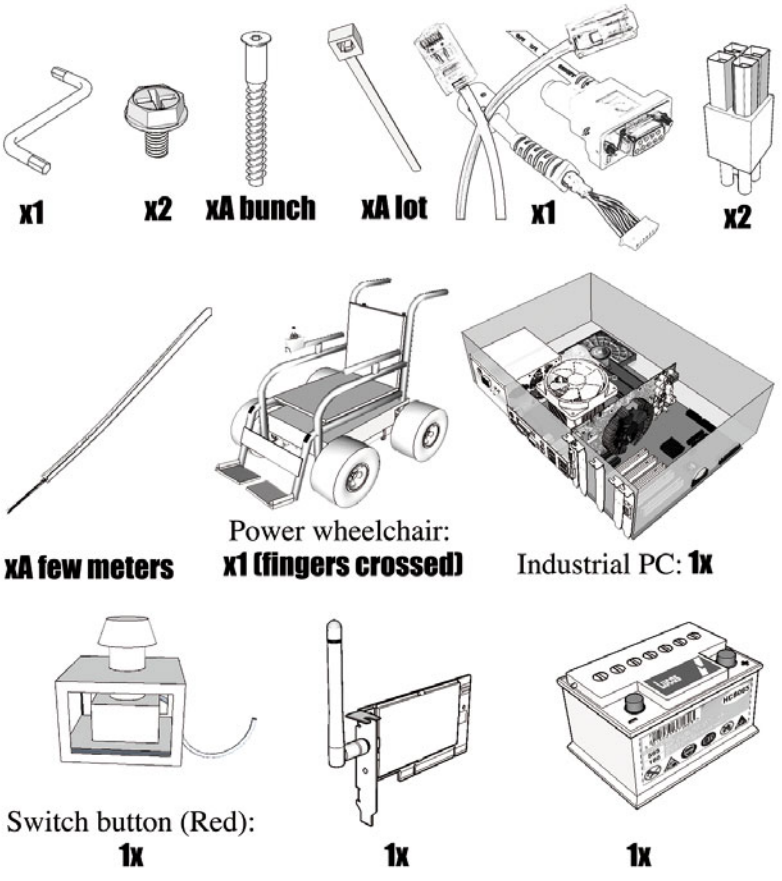
U_{cs} Case similarity threshold. 105
$U_g(q)$ Attraction force in a Potential Field at location q. 47
$U_o(q)$ Repulsion force in a Potential Field at location q. 47

$\mathbf{v}_H$ Human command vector. 46, 151
$\mathbf{v}_R$ Robot command vector. 46, 151
$\mathbf{v}_S$ Collaborative command vector. 46

Appendix A
Build Your Own Assistive Wheelchair in 11 Simple Steps

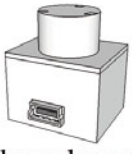
According to my calculations, the robots won't go berserk for at least 24 hours.
Oh, I forgot to carry the one.
- Professor Frink, the Simpsons

KÄRMĚN
?
ISIS
Design or quality


x1
x2
xA bunch
xA lot
x1
x2
xA few meters
Power wheelchair:
x1 (fingers crossed)
Industrial PC: 1x
Switch button (Red):
1x
1x
1x

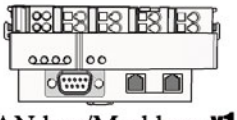
DC to DC converter: **x1**

Motor power controller with CAN IF: **x2**



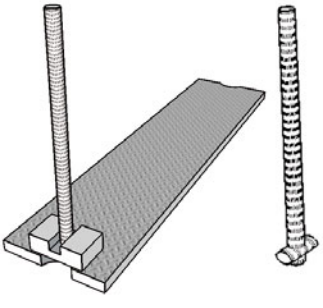
Hokuyo laser: **1x**

CAN bus router: **x1**

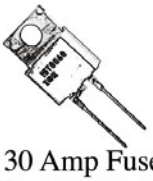


CAN bus/Mod bus: **x1**

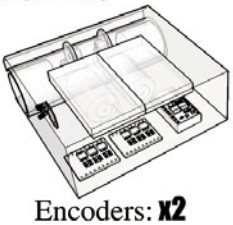
Plastic tape: **xA few kms**



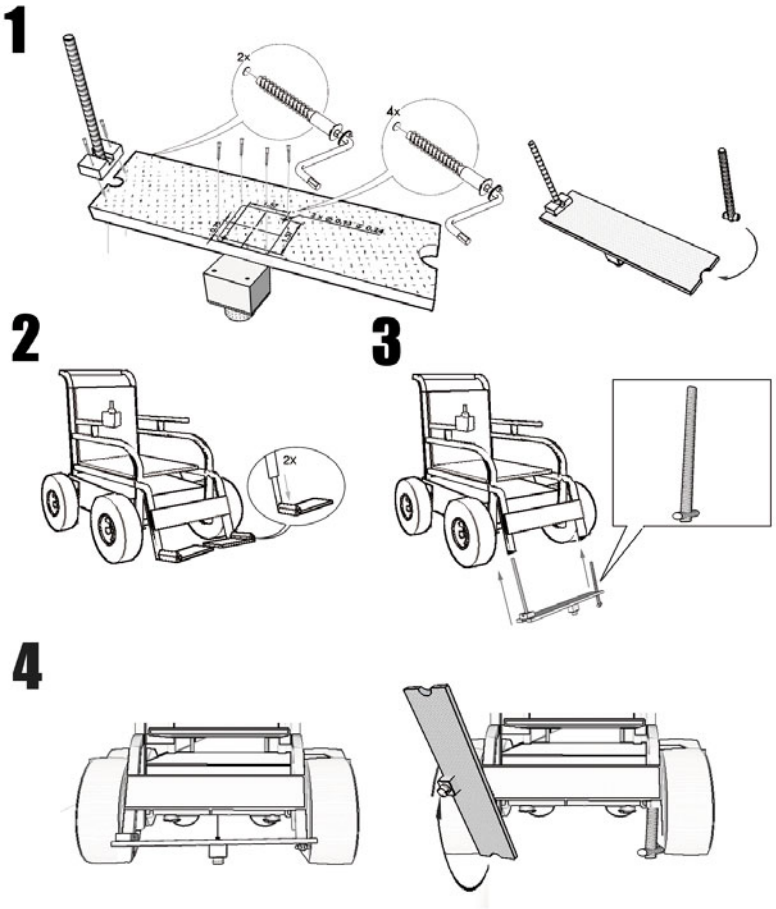
Metal customized pieces: **x1**

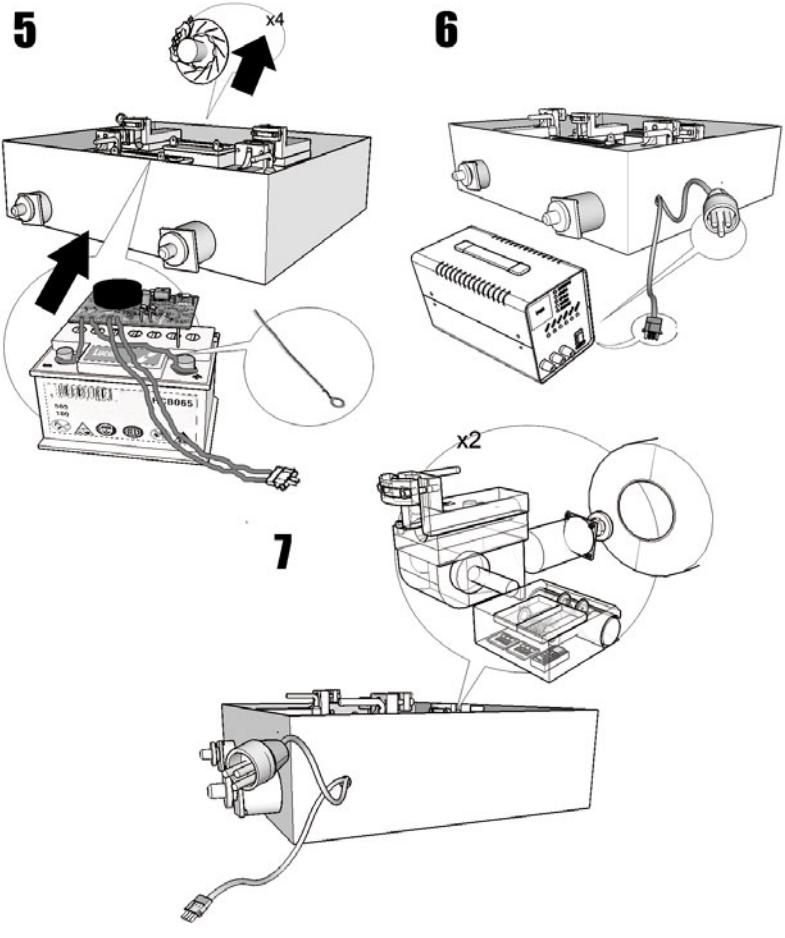


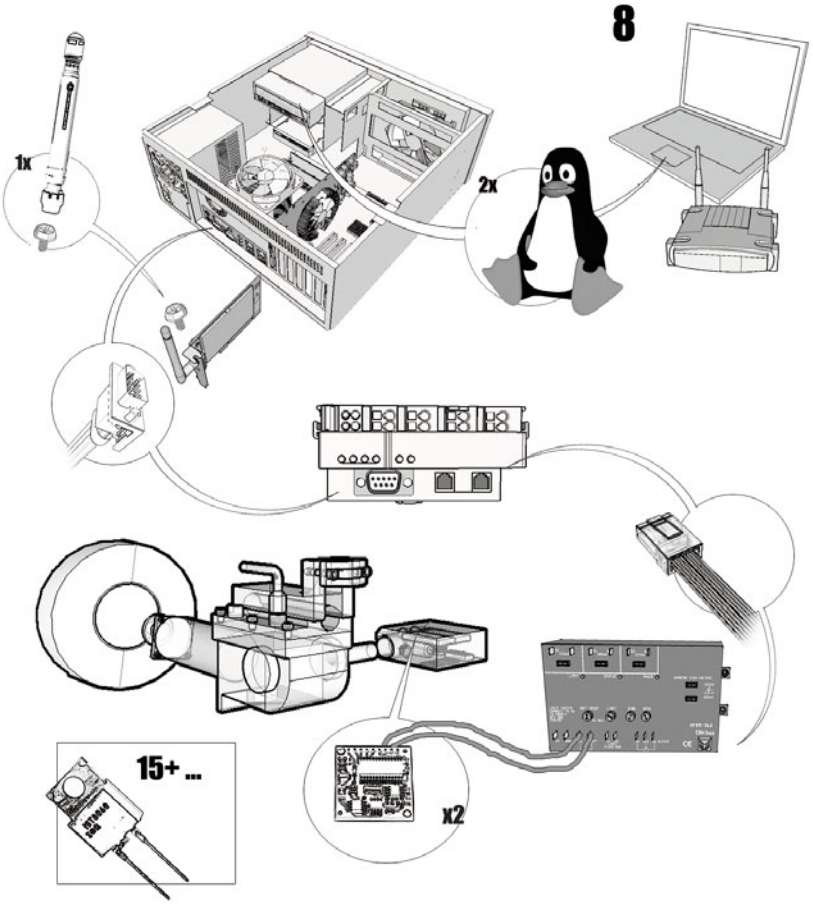
30 Amp Fuses: **xKeep 'em coming!**

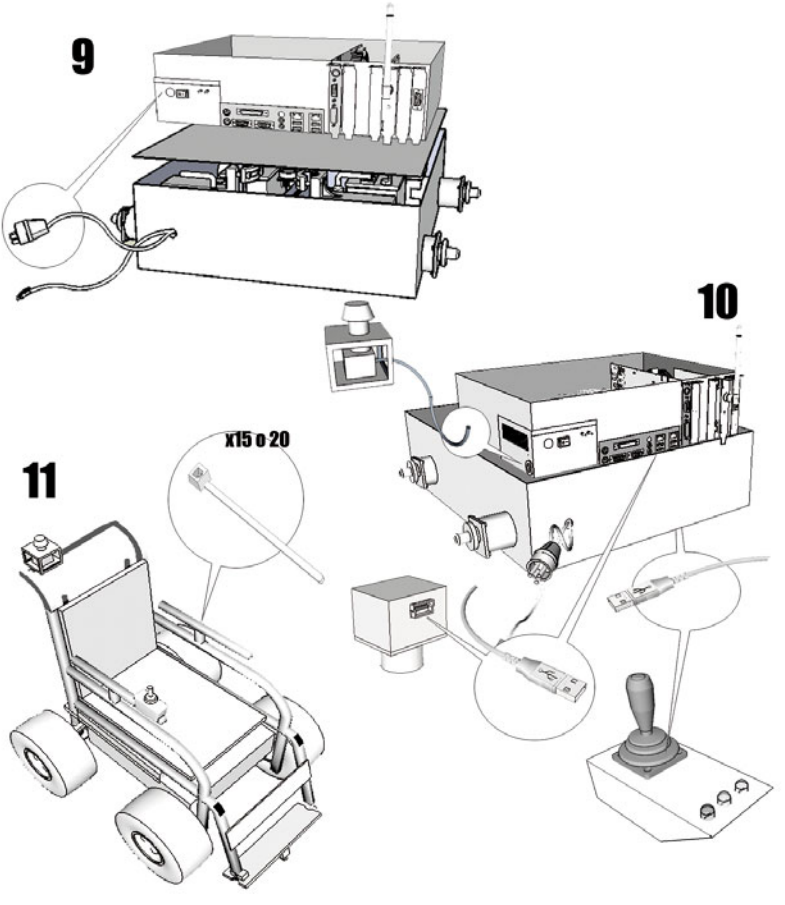


Encoders: **x2**


1
2x
4x
2
2x
3
4


5
x4
6
x2
7


8
1x
2x
15+ ...
x2


9
10
11
x15 o 20

Appendix B
Target Population

Patients were cynical and not responding and we couldn't bring 'em back-
They were cyanotic and not responsive.
When I want a lot of medical jargon, I'll talk to a doctor.
You **are** *talking to a doctor.*
- Mal & Simon, Firefly

This work focuses on increasing autonomy in terms of mobility through the use of assistive technologies. This work has tried to target a wide population in terms of functional, social, and clinical features. This population includes:

- Mild functional impairment: older and/or disabled populations are made up by individuals who present widely different and heterogeneous functional profiles. Considering the more prevalent diagnosis in this group of persons (stroke, Parkinson's disease, Alzheimer's disease), impairments range from extremely mild (people able to walk with a cane or affected by such a mild memory loss that allows them to live on their own) to extremely severe (persons bedridden or completely unable to understand a simple order). In the first case we are in the realm of prevention, in the second in that of palliative care or institutionalization. People with mild functional impairment those in the middle area of impairment are expected to have the best results through the use of proper assistive technology and are the target of the assistive intervention.
- Possibility of changing functional profile: mild disability is characterized by the possibility of increasing the functional level according to proper assistive or rehabilitative interventions. Users of a flexible assistive device can benefit from its adaptation so that it could help to improve their condition as a result of rehabilitation treatment, or can prevent the decrease of their autonomy as a result of intervening conditions or diseases.

A population defined by these characteristics is representative not only of the numerical majority of older and/or disabled persons, but, above all, by a wide range of population who can best benefit of the use of a highly flexible assistive device.

The simultaneous presence of cognitive and mobility impairments has a multiplicative effect, worsening global function more than expected by the sum of the

single conditions. An exploratory classification of increasing cognition/mobility interaction:

- Mobility problems depending on major physical impairment (hip fracture, spinal cord injury,)
- Mobility problems depending on major brain damage with motory diagram loss (stroke with apraxia, agnosia, and/or neglect)
- Mobility problems depending on major brain damage with motory diagram loss, decreased attention span, and altered capacity of finalizing action (dementia)

To obtain the best results in terms of self-dependency as defined above, the best interaction between user and assistive device has to be obtained, and this interaction has to be realized as soon as possible. As in rehabilitative sets, results not only depend on means, but on timing as well: individuals must start using their assistive devices in a post-acute condition, referring to the event which modified their previous functional state. In fact, in this situation the users have more possibilities to learn to properly use the devices to supply their needs. Therefore, we decided to select the users in a post-acute scenario, where they are trained to recover through rehabilitative treatment.

All this evaluation, as well as selection of volunteers, has been provided by the staff of FSL, as specialists in geriatrics and rehabilitation [4]. They were also present for the whose duration of the experiments in this work and supported data evaluation and medical conclusions [171].

B.1 Initial Self Made Questionnaire

Table B.1 Self made questionnaire

		Subject ID:
1. Age:		
2. Sex: ☐ Man	☐ Woman	
3. I drive: ☐ Bicycles	☐ Motorbikes	☐ Cars
4. My pulse is: ☐ Bad ☐ Very good	☐ Not too bad	☐ Good
5. I usually wear glasses: ☐ Yes	☐ No	
6. I play video games: ☐ Never ☐ Almost daily	☐ Rarely ☐ Daily	☐ Weekly
7. My relation to robotics is: ☐ None ☐ A lot	☐ Little	☐ Enough

8. Mark the difficulty of each test (1 min., 5 max.):			
FW test	NC test	DNC test	PD test
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
9. Mark your grade of control for each test (1 min., 5 max.):			
FW test	NC test	DNC test	PD test
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
10. Mark your grade of stress for each test (1 min., 5 max.):			
FW test	NC test	DNC test	PD test
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

B.2 Barthel ADL Index

1. The index[1] should be used as a record of what a patient does, not as a record of what a patient could do.
2. The main aim is to establish degree of independence from any help, physical or verbal, however minor and for whatever reason.
3. The need for supervision renders the patient not independent.
4. A patient's performance should be established using the best available evidence. Asking the patient, friends/relatives and nurses are the usual sources, but direct observation and common sense are also important. Direct testing is not needed.
5. Usually the patient's performance over the preceding 24-48 hours is important, but occasionally longer periods will be relevant.
6. Middle categories imply that the patient supplies over 50 per cent of the effort.
7. Use of aids to be independent is allowed.

B.3 Psychosocial Impact of Assistive Devices Scale

PIADS[2] is a 26-item, self-rating questionnaire that is designed to measure a person's perceptions of how assistive devices affect quality of life. The PIADS describes user experiences along three dimensions: competence, adaptability and self-esteem. Each word or phrase in the questionnaire describes how using an assistive device may affect a user. Some might seem unusual but it is important to answer every one of the 26 items putting an "X" in the appropriate box to show user perception.

B.4 Minimental State Examination (MMSE)

The MMSE[3] or Folstein test is a 10-minute 30-point questionnaire test used to screen cognitive function. This examination is not suitable for making a diagnosis but can be used to indicate the presence of cognitive impairment at a given point in time and to follow the course of cognitive changes in an individual over time, thus making it an effective way to document an individual's response to treatment. The MMSE is far more sensitive in detecting cognitive impairment than the use of informal questioning or overall impression of a patient's orientation. It samples various functions including arithmetic, orientation, registration (immediate memory), short-term memory (but not long-term memory) and language functioning.

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[1] Copyright Information: The Maryland State Medical Society holds the copyright for the Barthel Index. It may be used freely for non-commercial purposes with the following citation: Mahoney FI, Barthel D. "Functional evaluation: the Barthel Index." Maryland State Med Journal 1965;14:56-61. Used with permission. Permission is required to modify the Barthel Index or to use it for commercial purposes.

[2] http://www.piads.ca/

[3] It was introduced by Folstein et al. in 1975, it is copyright from the Psychological Assessment Resources (PAR). Permission to include or reproduce an entire test or scale in any publication or on any website not granted.

Before administering the MMSE it is important to make the patient comfortable and to establish a rapport with the patient. Praising success may help to maintain the rapport and is acceptable, but persisting on items the patient finds difficult should be avoided. Scores of 25-30 out of 30 are considered normal; 21-24 as mild, 10-20 as moderate and <10 as severe impairment.

People from different cultural groups, or of low intelligence or education, may score poorly on this examination in the absence of cognitive impairment and well-educated people may score well despite having cognitive impairment. The MMSE may not be an appropriate assessment if the patient has learning, linguistic/communication or other disabilities (e.g. sensory impairments).

B.5 Modified Cumulative Illness Rating Scale (CIRS)

CIRS is one of the existing tools to measure comorbidity. It measures the chronic medical illness burden while taking into account the severity of chronic diseases. It was developed and was later revised to reflect common problems of elderly people and renamed the Cumulative Illness Rating Scale for Geriatrics (CIRS-G). More recently, the validity of this latter CIRS version with only slight modifications, was demonstrated as an indicator of medical burden that predicted 24-month mortality when acute conditions were included.

There are two scales: cumulative illness rating scale severity and CIRS-c cumulative illness rating scale. Each system is rated as follows:

1 = NONE: No impairment to that organ/system
2 = MILD: Impairment does not interfere with normal activity; treatment may not be required; prognosis is excellent (examples: skin lesions, hernias, hemorrhoids)
3 = MODERATE: Impairment interferes with normal activity; treatment is needed; prognosis is good (examples: gallstones, diabetes, fractures)
4 = SEVERE: Impairment is disabling; treatment is urgently needed; prognosis is guarded (examples: respectable carcinoma, pulmonary emphysema, congestive heart failure)
5 = EXTREMELY SEVERE: Impairment is life threatening; treatment is urgent or of no avail; prognosis is grave (examples: myocardial infarction, cerebrovascular accident, gastrointestinal bleeding, embolus)

B.6 GDS: Geriatric Depression Scale

The Geriatric Depression Scale[4] (GDS) is a 30-item self-report assessment designed specifically to identify depression in the elderly, developed in 1982 by J. A. Yesavitch et. al.

It uses yes/no answers, simpler than scaled responses. Answers are scored with one point and assigned to a scoring grid. A score of 10 or 11 or lower is the usual

[4] http://www.stanford.edu/ yesavage/GDS.html

threshold to separate depressed from nondepressed patients. However, a diagnosis of clinical depression should not be made on the GDS results alone. Although the test has well-established reliability and validity, responses should be considered in conjunction with other results from a comprehensive diagnostic work-up. It is generally recommended as a routine part of geriatric assessment.

A short version of the GDS containing 15 questions has been developed. The GDS is also available in a number of languages other than English.

B.7 Instrumental Activities of Daily Living (IADL)

The Lawton IADL scale was developed by Lawton and Brody in 1969 to assess the more complex Activities of Daily Living (ADLs) necessary for living in the community independently. Because IADL function is usually lost before ADL function, assessment of IADLs may identify incipient decline-physical, cognitive, or both-in an older adult who might otherwise appear capable and healthy.

The Lawton IADL scale takes 10 to 15 minutes to administer and contains eight items, with a summary score from 0 (low function) to 8 (high function). Responses to each of the eight items in the scale will vary along a range of levels of competence-from independence in performing the activity to not performing it at all. Each ability measured by the scale relies on either cognitive or physical function, though all require some degree of both. The scale is generally not useful for older adults in long-term care facilities, where residents perform few IADLs without assistance.

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