Chapter 11
Challenges in Assistive Living Based on Tech Synergies: The Cooperation of a Wheelchair and A Wearable Device

Nikolaos G. Bourbakis

Abstract The direct medical costs for falls only—what patients and insurance companies pay—was $34 billion [*Center for Disease Control and Prevention, 2013*]. The necessity for continuous monitoring and assisting of persons in risk, and the increasing prevalence of chronic conditions among our aging population present great challenges to our healthcare system. These costs are also expected to surpass $54 billion by 2020 (http://www.cdc.gov/ncipc/factsheets/fallcost.htm, in 2007). In addition, the larger healthcare providers offer low quality services. Thus, making a robotic machine "lifting-up" elderly persons or persons with disabilities from a sitting position and transferring them to the bathroom is a very challenging scenario that urgently require innovated solutions. Thus, advanced technological achievements based on robotic nurses and wearable health monitoring devices may represent the up-coming hopeful and desirable solutions. Thus, the challenges here are based on the importance of IT-Engineering solutions to healthcare needs. In addition these challenges offer a paradigm on the already growing personalized/person-centered healthcare and the role of 'smart homes' and 'smart beds' for independent living and self-management of chronic conditions. While the importance of such care is recognized, not many efforts have been pursued to develop low-cost (and inconspicuous) technologies. Thus, the chapter presents issues for the development of a novel synergistic interactive intelligent framework-model between intelligent wearable health-monitoring devices (WS) and intelligent robotic wheelchairs (IRC) for assisting people (HS) in risk at smart homes, improving safety and quality of life, and reducing healthcare cost. In particular, it will focus on two challenging scenarios (lifting-transferring) reported above providing concepts but at the same time maintaining the generality of this synergistic model. The challenges are related with a new generation of intelligent synergistic models of inexpensive, unobtrusive intelligent wearable sensors, monitoring devices, intelligent robotic assistants, and surveillance methodologies. In addition, the healthcare advanced research technologies and educational training is expected to transform the way physicians and nurses provide care and the way of people at risk will safely stay at their homes. Concurrently, they will offer a ground for new research directions for engineers to contribute in

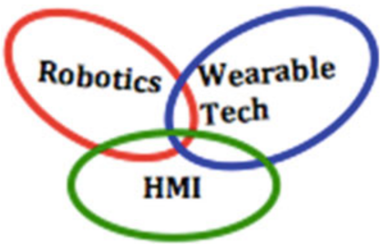
N. G. Bourbakis (✉)
Wright State University, Dayton, OH, USA
e-mail: Nikolaos.Bourbakis@wright.edu

G. A. Tsihrintzis et al. (eds.), *Advances in Assistive Technologies*, Learning and Analytics in Intelligent Systems 28, https://doi.org/10.1007/978-3-030-87132-1_11

healthcare applications. In addition, commercialization of these devices will certainly transform our healthcare monitoring systems for a large population, and transform the living conditions of people at need.

11.1 Overall Description of the Challenges

Those in risk and the elderly often require diligent monitoring to detect healthcare problems, when they are most-easily treated. Unfortunately, members of those populations can be either unable or disinclined to detect (or communicate) the existence of critical changes in their own health. A common solution for human healthcare professionals is to closely monitor patients directly or via crude patent's data collection devices. Of course, that solution does not scale economically. In addition, due to the high cost of medical care for groups (elderly, paraplegic and in general people in risk) and at the same time the lack of large number of qualified healthcare providers, the robotic nurses and health monitoring devices represent the most effective and desirable solution. Moreover, the continuous monitoring for people-in-risk and elderly offers safety. These people are vulnerable to crimes (theft, homicide, mistreatments, etc.). The continuous remote monitoring offers them a "protection" that may drive the suspects away. Thus, we envision a future in which people at risk are provided with inexpensive (in long term), intelligent robotic nurses and unobtrusive wearable devices in a smart infrastructure that automatically monitor and detect critical changes to their health and to offer first response help.



In response to this vision, here we present a synergistic intelligent framework, which will offer safe and efficient service to a Human Subject (HS) for one well focused healthcare challenging scenario that involves the intelligent interaction (HMI) between two systems (a robot-chair (IRC) and a wearable health monitoring device (WS)). This scenario is: *lifting a HS from a sitting position, transferring him/her to the bathroom.* To achieve this objective (scenario) we will address some of these innovative challenges:

Challenge-1: It will transform an existing power-wheelchair (which has a laptop, a screen, two cameras, a microphone, two speakers, range sensors, GPS, two robotic-arms) into *a novel and intelligent robotic-chair (IRC) by embedding methods with* *intelligent capabilities in order to make decisions and learn when and how to assist people (cognizant).* How: *These intelligent capabilities will come from challenging novel subtasks performed by IRC like lifting people, detecting, tracking, grasping, extracting, detecting body positions, and interacting with humans* [1–16]. *Based on the existing knowledge there is no such an IRC with the intelligent capabilities;*

Challenge-2: There are several wearable sensor-based devices, *but no one has intelligence prognosis capabilities and voice interaction (IVI) between HS and Wearable devices* [17–19]. *The wearable device with its IVI will reliably monitor (reflective) the HS body bio-signals for detecting not only sensor-based measurable symptoms after de-noising, but also a variety of important non-measurable symptoms (pain, cough, nausea,* etc.*).* An existing wearable device can be transformed *into a novel intelligent device to learn HS' health-history and interactively respond to a range of commands relevant to HS health condition.* How: *The novelty of WS is coming from the learning capabilities to interactively understand sentences incompletely spoken by HS, due to noise or to HS difficulty of speech to express his/her non-measurable symptoms.*

Challenge-3: The integration of WS, the IRC and the HS into *an interactive framework-model (reflective, protective and knowledge-rich) is a challenging issue and has to be tested on realistic scenarios not only for proving the concepts (exchange health information, decision-making, assist the human user, monitoring bio-signals, extract body signatures (patterns), but also to evaluate the process by offering safety and monitoring healthcare for people in need;* The novelty of this task is based on *the synergistic interaction of two intelligent assistive devices for effectively assisting human-users at need.*

11.2 Background and Significance

The demographic imperative for the US and many other industrialized countries is that the number of elderly people-at-risk will increase dramatically over the next 50 years. Many older adults will become chronically ill and frail, and over 50% predicted to have at least some cognitive impairment. There are two major challenging reasons to keep them safe at home for as long as possible: (1) home is where most people want to be, and (2) institutionalization is extremely expensive. As an example approximately 33% of persons over 65 and 50% of persons over 85 experience a fall each year [20–22]. The injuries associated with these falls can have serious consequences. Especially, following hip fracture, 50% are unable to live independently, 25% will die within six months, and 33% die within one year [20, 22]. In one study [23], hospital admissions due to fall-related injuries (of any type) carried the highest risk for disability. The percentages are as follows: 79.4% of the falls having some disability, 45.2% led to chronic disability, and 58.8% are related with nursing home admission. The costs associated with falls amongst the elderly are staggering. Expenditures associated with hip fractures alone exceed $10 billion annually [21].

Overall, this cost to treat fall injuries in people age 65 or older in 1994 was $27.3 billion (in 1996 dollars) and, by 2020, the cost is expected to reach $43.8 billion (in 1996 dollars) [24, 25].

Wearable Health Monitoring Devices (WS)

Technology solutions to people at risk, lifelong or acquired with age, have demonstrated numerous advantages. Among them, wheelchairs with sensory capabilities have provided mobility for millions of people with physical impairments. However, the long-term reliance on the upper limbs for mobility and in performing daily activities has led to increased repetitive strain injuries (RSI) and chronic pain. Upper limb RSI pain is indeed very common in manual wheelchair users. Specifically, carpal tunnel syndrome occurs in 49 to 73% of them [26, 27]. Also, rotator cuff tendinopathy and shoulder pain occurs in 31 to 73% of wheelchair users [28, 29]. Consequently, advances in sensor communication and IT have enabled health care providers to monitor and manage chronic diseases and to detect potentially urgent or emergent conditions [30]. Therefore, we are now in a position to reliably detect and prevent RSI injuries. This can be accomplished by monitoring the patient in one of two possible ways [31]: (a) Employ ambulatory monitors that relay on wearable sensors and devices which record physiological signals; (b) Sensors embedded with the home to collect behavioral and physiological data unobtrusively. The acceptance and positive psychological impact of these monitoring technologies have been confirmed in our studies that have already been included for people with dementia and other chronic conditions [3, 32–49].

Autonomous Wheelchairs and Robotic Nurses [50–79]

It is well known that the cost of human providers in serving people with disabilities or elderly is steep. Indeed, several reports such as the "2010 Computerized Nursing Facility Cost Report "and the "SPRC-Cost-of Providing Specialist Disability Services", [41–88] verify these high costs. In addition, human support degrades over time and is subject of distraction and abuse. Thus, researchers, engineers and practitioners have the recent years focused on autonomous wheelchairs with intelligent capabilities. Even, robotic-nurses with capabilities to lift or assist the people-at-risk have been considered. Several research groups at MIT, CMU, UPitt, UG, UBC, UTA, Purdue U, CART-WSU have actually developed autonomous or semi-autonomous wheelchairs for assisting people with disabilities. These wheelchairs already carry laptops, cameras, join-sticks, touch-screens, range sensors (laser, sonar, other) and sophisticated algorithms for path planning, navigation, human-device interaction (voice communication) map generation, etc. At the same time several companies and Universities in Europe (Germany, Italy) and Japan (Honda, Toyota) and S. Korea have already developed robotic nurses to assist the needs of people with disabilities and elderly.

11.3 The Associated Research Challenges

As it stated above, the effort here aims to address of a smart, synergistic and interactive model between the HS and the Assistive Devices. In particular, this model is composed of three components: an IRC, a WS and a HS. To prove the importance of this synergistic model, we present only one novel scenario, where the synergy of IRC and WS is important and necessary for the wellbeing of the HS. This scenario emphasizes the novel synergistic interaction and not the improvement or perfection of each robotic sub-tasks:

Scenario: *"A human user is laying on his(her) bed or sitting on a comfortable chair and he(she) needs to visit the bathroom. We assume here that the human user needs help to stand-up, sit on the IRC, which will transfer him/her towards the bathroom"*.

The scenario is composed by 3 major challenging tasks. Thus, we present the important components (or subtasks) of each task needed for its feasibility and successful implementation. Also, we show how these components (or subtasks) work together in a synergistic way under a complex scenario to achieve the goal. Some of these subtasks are unique and some others play an important complementary role. On the overall, the synergy is novel and based on challenging decision-making and unique interfacing of these subtasks in order successfully and safely to accomplish the goal(s).

11.3.1 Main Innovative Tasks

In this section we briefly present the main challenging tasks and their association for the successful implementation of the project, Fig. 11.1. For each of these tasks we also provide experimental results to show feasibility for their implementation.

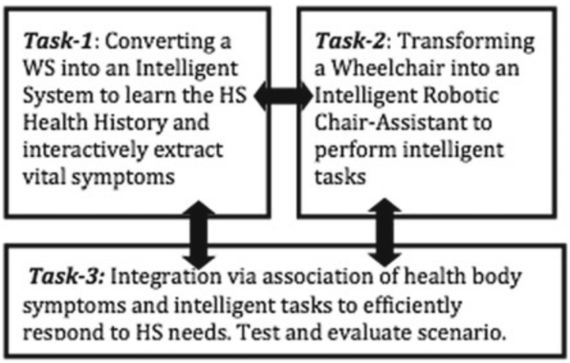


Fig. 11.1 The three main tasks and their associations for the implementation of research project here

11.3.1.1 Challenge-1: A Wheelchair as an Intelligent Robotic Chair (Irc)

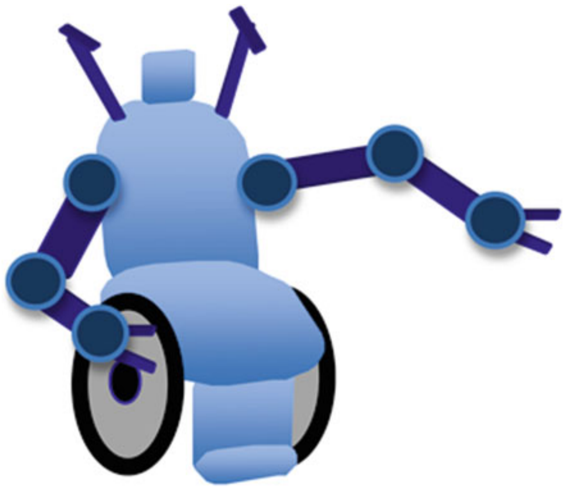
A. ***The Robotic Wheelchair as a Testbed***

There are several research efforts involving the improvement of power-wheelchairs [75, 76]. Here the unique challenge is not on the power wheelchair (laptop, two cameras, a microphone, an ear-speaker, range sensors, a computer screen, a GPS, two robotic arms) as shown in Fig. 11.2, but on the synergy of wearable sensors, robotic parts and cutting-edge-intelligent methods to advance a wheelchair into a robot-assistant to people-at-risk. In particular, in this challenge-1 an existing power-wheelchair (Fig. 11.2) will transformed into an intelligent robotic assistant by developing *intelligent algorithms* (*computational component*).

There are also researches using robotic arms to assist humans with special needs. In this case, although there is available expertise in robotic-arms design it is better for someone to buy two arm-hands from the market to eliminate the time of building them (Fig. 11.3). Thus, the main challenging research issue here is the intelligent algorithms to efficiently synchronize the IRC components and actions to safely service the HS. Another challenging point is the amount (in pounds or kilograms) that the IRC arms can lift or assist during standing-up and walking stages. From experience,

Fig. 11.2 The available IRC with a laptop placed under the seat. The view of a HS holding the "robotic-arms"

Fig. 11.3 The graphical view of the IRA with two arms and two cameras



the lifting will be near 80 lb without the IRC loosing its balance. For assistive modes this amount is manageable for pooling, lifting and assist standing stages [89, 90].

B. ***The IRC Innovative and Intelligent Capabilities***

Under the challenge-1, existing interface intelligent methods (sub-tasks) have to be modified or new to be developed in order to achieve compatibility among the IRC intelligent capabilities (like *autonomous Navigation, Tracking, Grasping, Body Recognition/Tracking, Learning Patterns of Behavior*) and effective Human-Machine-Interaction (HMI) (like *health monitoring, assistive lifting,* etc.). An additional challenge is the interactions between Human-Subject and IRC based on Voice or simple Gestures. Although there is a long list of research subtasks to be achieved, most of the research labs have already in house these standalone methodologies. Thus, the challenge here is to appropriately interface these methods to work as a sequence achieving goals. These sub-tasks will give to IRC intelligent capabilities needed for the successful completion of the scenarios presented here. Below we describe these sub-tasks for this challenge "Standing-up, Turning around, Sitting-down on the IRC":

*B1. The Robotic arm-hand gentle Grasping (**Gr**)*

In the robotic field researcher have developed various robot arm-hands [91, 92]. The sophistication of these robotic arm-hands has reached an acceptable level of sensitive grasping. For example there are robotic arm-hands that can handle eggs without break them. Also there are robotic arms used in cooking in smart kitchens. Thus, for the robotic-hand grasping here a neural net model will be used to control the robotic arm-hand to grab certain objects [90, 93]. For this grasping subtask, two robotic-arms can be bought from the market by reducing the time for design and developing new ones. Thus, the expertise on grasping methods with neural nets and fuzzy algorithms will be used to modify the existing robotic arms to be suitable for gentle grasping interactively coordinated by the HS, [90, 93]. For the robot arms

Fig. 11.4 It graphically shows the initial and intermediate states of the IRC positions to assist a human subject (orange color) to stand up from the sitting position (chair, green color), to turn around and sit down

grasping, touch sensors will be used to measure the force (pressure) that HS applies on the robotic arm. The pressure is a critical parameter for the IRC to judge if it is safe to lift the human subject from a sitting position or assist him/her to sit back to the place that was sitting.

B2. Novel Assistive Lifting ***(AL)*** *for Standing* ***(St)*** *and Walking (****Wa****) (major novel sub-task)*

Figure 11.4 graphically shows some of the states (body and IRC positions) of the robotic arms, when the IRC assists a Human user to stand-up from a chair. More specifically, the IRC will go close to the human user following either a command from HS *("help me to stand up" or "help me to walk", or "help to go to the bathroom" or for rehab exercises"*) or making a decision under urgent conditions. In the scenario (stand-up), the IRC will use the cameras to create stereo-vision images, detect the HS (where most of its time IRC will track HS movements) and determine the distance to travel in order to reach a position from which it will extend its robotic-arms to safely reach the HS. The HS has to grab the rob-arm and synchronize his/her effort with the robotic-arm movement upwards (*a neural net can be used to learn the human subject's responses and the robot assistant adjustments*). This will result the HS to reach the standing position. Thus, for the walking to the bathroom, the HS will hold and follow the IRC and command it to go there.

B3. Novel Learning Patterns of Body Signatures, ***BP****)* [2, 4, 94, 95]

In this case presents extraction, tracking and representation of a human performing an action by using local global graphs and stochastic Petri-nets (SPNs). In Fig. 11.5 presents the extraction of the human body and the association of different positions that describe an activity. Here 3 non-consecutive image-frames are presented for demo only, (Fig. 11.6). In these image-frames, the segmented human is colored with different colors to demonstrate the main parts of the body (head, (blue), arm (red), hand (green), and legs (yellow)).

From each image-frame the main parts of the segmented human body are extracted, represented and interrelated using the L-G graph. The Stochastic Petri-net (SPN) graph can be used to associate these body-parts in these frames to determine the changes of the states that took place. Between the first and the second frame, the token activates or causes the activation of the head to "look at" a certain direction, at the same time the arm is moving up and the legs change position. The SPN graph graphically presents and connects these changes. The same happens between the second and the third frames, where the SPN graph connects the body-parts using the affect of the previous token. The important issue here is that the SPN graph provides

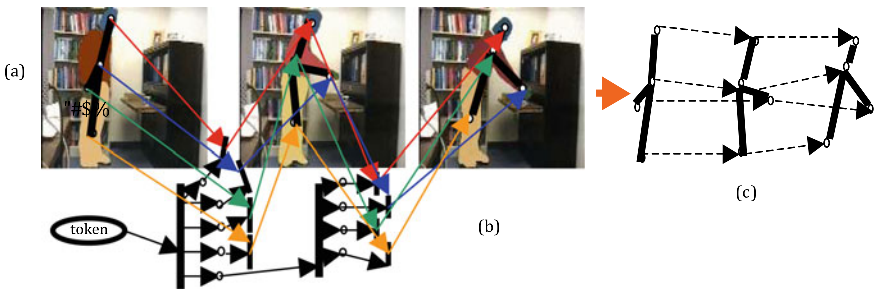


Fig. 11.5 A sequence of body positions. **a** The detection and extraction of the body posion using a skeleton approach; **b** The L--G graphs are represented by with thick and thin lines respectively on the segmented image frames (left) and on the right a sequence of L--G graph-patterns extracted and associated. The color lines the same body-regions in different positions in time; c) the SPN sequence of body positions

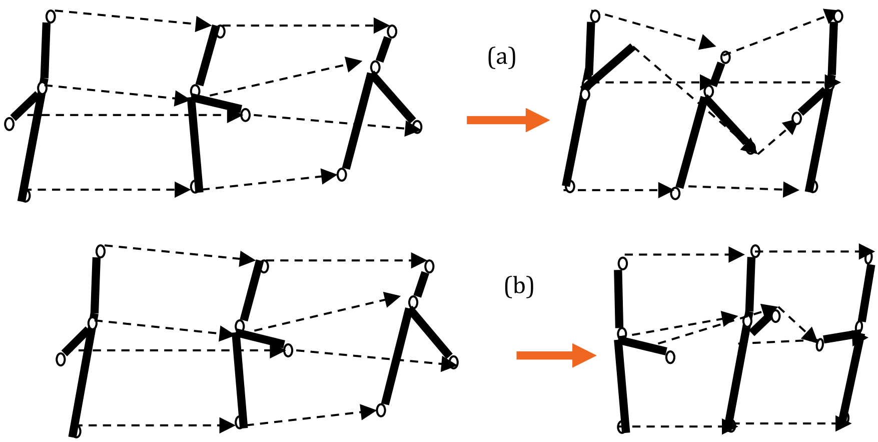


Fig. 11.6 In brief, **a** A sequence of states for drinking (or behavioral pattern); **b** a sequence of carrying a cup. Note here that the uses of three body L-G graphs is only for demonstration of the idea. In reality these are dozens or hundreds of image-frames and so the same number of L-G graphs for body-patterns

the ability of synchronizing the actions performed by the body-parts and creates the body behavioral patterns or signatures in time.

Predicting (Anticipating)and Associating Body Positions: Here in Fig. 11.6 also presents an extension of the previous example by anticipating (predicting) the next states of behavioral patterns. In particular, Fig. 11.6a shows a starting behavioral pattern and the possible next states of the pattern (or signature) for the scenario *"the man drinks water"*. Figure 11.6b shows the same starting behavioral pattern but with different next states of a pattern that lead to the scenario, *"the man takes the cup and returns to his desk"*. The prediction in a pattern will be determined by the higher probability of occurrence of the states that compose a pattern, according to the frequency of repetitions of that pattern in certain time (or according to an external *"token"* that might trigger an appropriate sequence of states). Note here that these or similar sequences of patterns (in more detailed representation) will be associated with heath conditions.

11.3.1.2 Challenge-2: The Intelligent Wearable Health Monitoring Device

A. ***The Wearable Monitoring Device***

A WS uses a variety of sensors to continuously monitor body bio-signals (**MB)** and evaluate the HS health conditions. It is known that bio-signals patterns and/or states may be presented in the various types of physiological parameters and vital signs measured by wearable biosensors, as symptoms [96, 97]. However, for a more accurate estimation of a user's health condition and the diagnosis of many diseases (if not the most), several other symptoms need to be taken into consideration [98, 99]. These symptoms, like cough or malaise, are either not measurable at all or they cannot be estimated without using invasive methods, e.g. as in the case of determining electrolyte levels in the body. Thus, these symptoms, once detected or quantified, provide important information, which together with the measured vital signs provide a more comprehensive description of what is referred to as the clinical presentation. Thus, the clinical representation under proper interpretation may lead to a specific diagnosis. However, in order to get feedback from the patient about the possible existence of these non-measurable symptoms the WS has to have speech recognition/synthesis capabilities and interactively ask the patient himself has to describe them. For this case a set of sensors can be used.

Figure 11.7 depicts the vital signal generated from our WS model [48]. Physiological biosensors constitute the front-end components of the system and will be integrated with textile communicators embedded into clothes as described above [100–105].

A Body Area Network (BAN) will be also employed for exchanging sensor data [106, 107]. In the latter case, the collected measurements will be amplified, filtered and digitized at the sensor nodes. The transmission from the sensors will be done via the BAN and collected at the central node. In the former case, there is the option where physiological signals can be transmitted in analog forms and then be digitally processed at the central node. Figure 11.8 gives a comprehensive overview of most of the physiological parameters and the most common symptoms that need to taken into consideration and properly evaluated to derive a specific diagnosis. This list is not exhaustive and it does not include findings, which can only be obtained from thorough clinical examinations and tests like MRI, CT scan, chest radiology and other medical and laboratory examinations typically performed in a hospital.

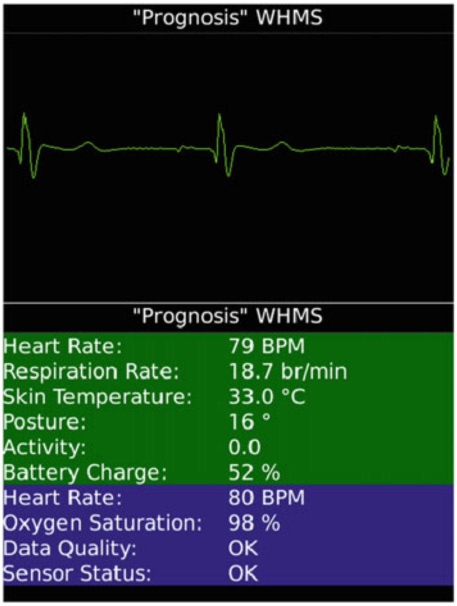


Fig. 11.7 WS sensors output sent to the physician for final approval

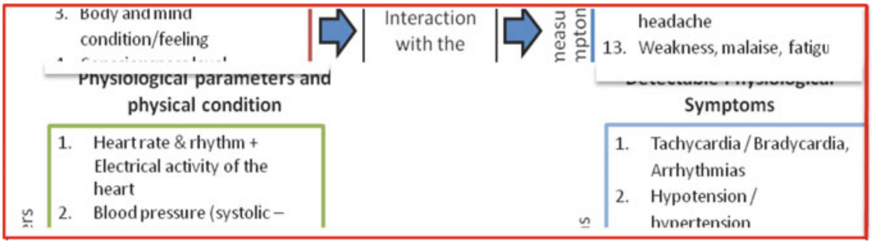


Fig. 11.8 It shows physiological parameters, health symptoms & biosensors for WS devices

B. ***WS Transformation (Learning and Novel Interaction)***

A key subtask is to intelligently upscale a wearable device is the installation of (a) “Speech Recognition/Synthesis” software; (b) A “health-history database”; and (c) “Training/learning scheme” Fig. 11.10. That is, the WS central node responsible for several possible subtasks [Prognosis]: (1) collecting various types of physiological data from the biosensors (see Fig. 11.8) applying further DSP on the signals (e.g. for feature extraction), (3) comparing the extracted features from the body-signals with the ones in the “Healthy History Database” using to provide a valuable decision support, (4) generation of alarm signals for the user, (5) displaying the estimated health status and/or collected data on the node’s screen, (6) transmitting medical data to a remote base station (e.g. hospital or cell phone of a supervising physician) or even a dispatched ambulance and (7) generating sensor's control signals for initializing measurements or setting up parameters such as sampling interval and A/D frequency).

A novel feature of a WS system is the ability to receive feedback from the patient through voice (or through writing on the central node's keypad). Once implemented, this functionality could enable the user to provide system-feedback regarding ***symptoms*** *(coughing, nausea, malaise, back or chest pains* etc.*) that cannot be measured through standard non-invasive biosensors*. The feedback regarding these symptoms could enable the detection of a wide variety of health conditions.

Alarm signals, measured physiological data and feedback from the patient can be exchanged with the IRC and securely transmitted through the cellular network or the Internet to the medical center or to dispatch ambulance. As the healthcare center keeps the long-term detailed medical history of the patient, the received data and patient symptoms can be further evaluated to derive a more accurate condition estimate or even verify the detected health risk.

*The Health History Learning Scheme (**HHLS**)* is depicted in Fig. 11.9. Here, we show the steps needed to extract health history and save it in a database under the physician's approval [49, 108].

Here, the learning is based on a fuzzy-based neural net, a personalized filter and the Prognosis formal method that leads to possible "diagnosis" forwarded to the physician for approval or correction.

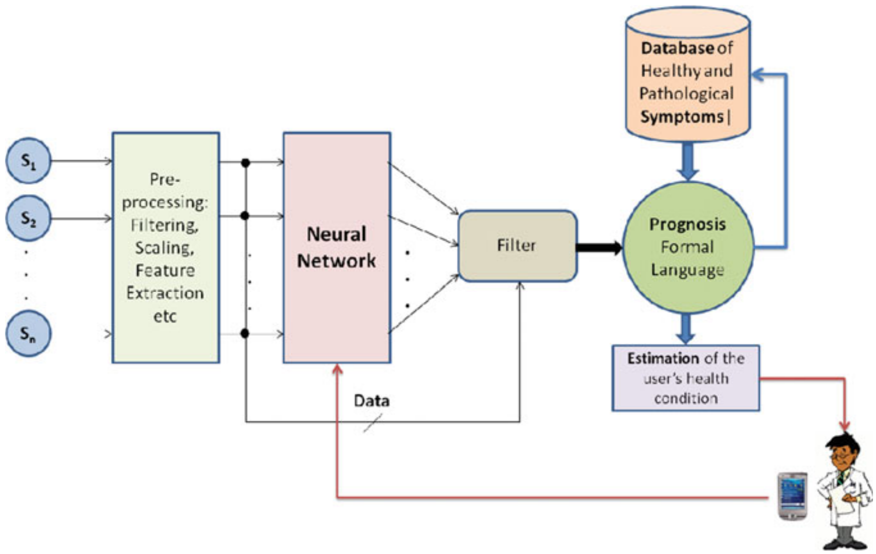


Fig. 11.9 The Health-history learning scheme for the WS

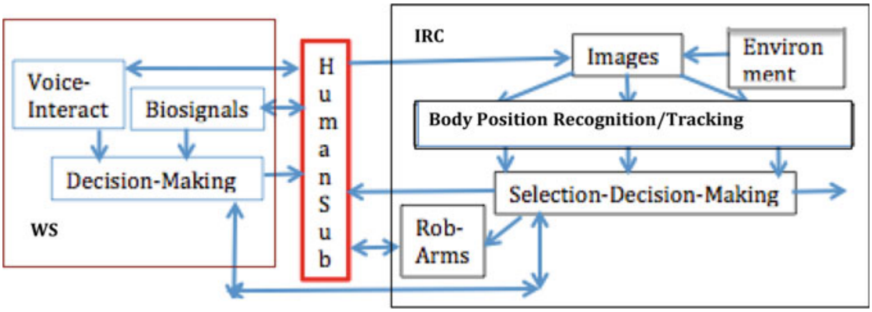


Fig. 11.10 The interaction among HS, IRC and WS

11.3.1.3 Challenge-3: The Novel Synergistic-Interactive Framework-Model

Under this task deals with to integration of the methodologies associated with the IRC and WS devices and at the same time to create a framework model of collaboration with the IRC, WS devices and the Human Subject (HS) [40, 86, 109]. The integration of the HS, IRC, WS and their operational subtasks are based on the development of an efficient interactive communication scheme. Figure 11.10 graphically shows the operational subtasks of the WS and IRC and the way that are connected or interacted internally and with each other. More specifically, the WS interacts with the HS to extract not only bio-signals (measurable symptoms), but also verbal symptoms as indicated in Figs. 11.7 and 11.8.

Then, it makes decisions (or prognoses) for the health condition of the HS. At the same time, IRC captures images from the environment and the HS and process them to recognize its own position in the 3D environment and the body position of the HS. Then it associates these pieces of information to determine its new position or actions, like to extract the navigation path (strategy) to be followed. In addition, IRC makes decisions to assist the HS by activating the robotic arms as shown in Fig. 11.4. A set of requirements has to be developed for the interactions between assistive devices and three different HMI schemes. The first scheme is for the HS + IRC interaction, the second scheme is for the HS + WS interaction and the last is for the efficient communication and information exchange between IRC + WS. Note that the WS and IRC will use the intelligent schemes mentioned in the tasks above for decision making, tracking and learning.

To facilitate the HS-IRC-WS interaction, the WS must have a verbal interactive scheme by giving to HS the option to ask (command) the operation of the robotic arms, when needed. In particular, the HS will have the option to ask the WS-IRC simple questions regarding to his/her conditions. As a response to these commands the WS passes them to IRC, which will operate the robotic arms in a slow but steady motion to assist the HS. For instance, the HS commands the IRC-WS **"help me to stand-up"**. Thus, the WS uses its voice recognition system to understand this command. Then it will pass this "command" in the form of sequence of subtasks to

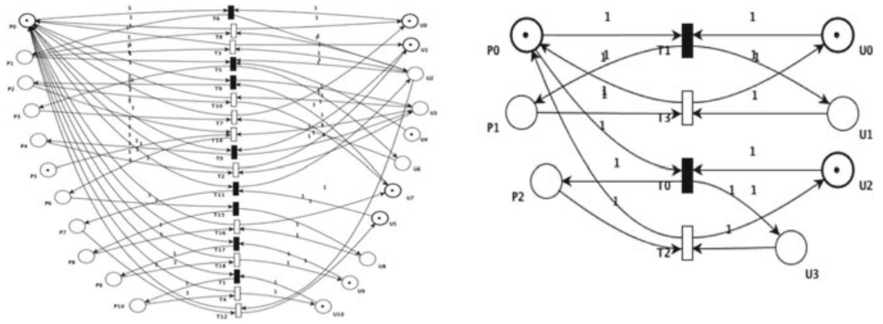


Fig. 11.11 The SPN Human-Device -Interaction scheme (left) available in house, [86], and its detailed representation of a small portion (right)

IRC. The IRC recognizes that sequence, checks the HS position again and gradually extends the robotic-arms to reach the HS. At this point the IRC uses its cameras to continuously track and monitor the HS body and hands positions to appropriately reach the pressure sensors at the end of the robotic-arms. The HS grabs the robotic arms at the position that the pressure sensors are. The IRC continuously monitors the pressure on the sensors and position of the HS hands and slowly raises its robotic-arms until the HS says "**stop**" or "**ok**", or the WS-IRC will ask the HS "**is it ok**". The explanations of such a subtask are graphically provided in the SPN scheme of Fig. 11.11. In a similar way we will study the synergistic collaboration (interaction) among HS-WS-IRC for other commands, like "**help me to turn around**" or **"help me to sit-down**", etc. Risky conditions, like, **"I cannot stand-up"** or the HS accidently releases the pressure on the sensors and IRC has to immediately react by grabbing the hands of the HS and assisting HS to sit-down by avoiding a possible collapse. Finally, such a synergy must be tested and evaluated in a collaborative framework of a small group of volunteers to secure its correct operation without harming the HS. Through this process. The model has to be trained to efficiently learn and adjust its responses according to the human subject's reactions.

A. ***Requirements for Interactions (RI)***

For this subtask a set of requirements of interactions are provided for the efficient communication of the HS with the IRC and WS systems. Some of these requirements are shown in Table 11.1.

B. ***Scenarios for Proof of Concept (Human Device Interaction)***

In Fig. 11.11 we show an SPN Human-Device Interaction model based on voice commands [40, 86] to satisfy the needs of certain scenarios that require communication between Human user and WS and IRC devices.

In the left side there are the states of various request (commands) and in the right side there are the machine interactions according to its status and capabilities. In the middle are the transitions that fire when the conditions of interactions are satisfied. This means that the same model will be appropriately modified to satisfy both HS +

Table 11.1 Interaction requirements

(1) The HS has always the highest priority for communication (commands) with the IRC and WS systems;
(2) Both IRC and WS have to periodically "ask" the HS for his/her health status. The HS and/or the physician will set the duration of that period;
(3) Both IRC and WS have to periodically exchange information regarding the health status of the HS;
(4) Both IRC and WS have to continuously check and exchange their status for ensuring their highest performance;
(5) Both IRC and WS have access and communication with the physician or a medical center providing the status of the HS, if needed;
(6) If any of the these two devices has a faulty operation, the other has to inform the medical center and the HS;
(7) In case of emergency, both devices have to collaborate to offer first response help to HS (if possible after MD "approval") and inform the medical center and the physician;

IRC and HS + WS interactions. Note that SPN stands for Stochastic Petri-net. The SPN model is well known in the literature, thus we provide no more information about it. A HMI–SPN model has been developed [86, 109] and appropriate modifications will be done to satisfy the **RI** of this project. Here, an example-scenario is offered for the HS + WS interaction for better understanding about the information extraction via questions (Table 11.2). WS will use this piece of information for a more accurate decision-making regarding the HS health status.

C. Scenario for Testing and Integration

Here, the idea is to use as a proof of concept the conduct of experiments in one innovative scenario described at the beginning of this chapter. Here we do not intend to study high risk and dangerous scenarios, as high-risk studies can be studied in a

Table 11.2 Example scenario

WS: < Detects a slight chest discomfort and some of his vitals start to go out of range>
WS: *Some of your vitals are out of regular range. Do you need help?* **HS**: *No*
WS: *Do you have any other symptoms?* **HS** *Yes*
WS: *Please describe your symptoms.* **HS**: *I have slight chest discomfort.*
WS: < the system does not acknowledge the user's phrase > *Please state your symptom again in a brief manner.* **HS**: *chest pain*
WS: < Recognizes the symptom > *Is the symptom intermittent or continuous?* **HS** *continuous*
WS: *Is the symptom instantaneous or persistent?* **HS** *persistent*
WS: *Is the pain radiating to your arms?* **HS**: *Yes*
WS: *Is the pain aggravated by movement or breathing?* **HS**: *No*
WS: *Are you experiencing any other symptoms, hemoptysis or sputum?* **HS** *No*
WS: *Describe your pain level on a scale from one until ten.* **HS**: *five*
WS: < decides that according to the user's answers and his recent vital signs the user could be in an alarming health condition > < notifies the medical-center by sending an alarm message via GPRS>

next phase. Thus, for the simple scenario presented here, various sequences of sub-tasks have to be performed, as they have been described above to show feasibility of this project:

Scenario: ***"A human user is laying on his/her bed or sitting on a comfortable chair and he/she needs to visit the bathroom. The hypothesis here is that the human user needs help to stand-up, turn around and sit down on the IRC to go to the bathroom".***

For this particular scenario, the IRC can provide support (using its robotic arms) to lift or assist the subject to stand-up. The IRC can also assist the HS to walk in the bathroom. Now, if a human provider is present, there is a quick response to this scenario. However, if there is no human provider or is busy with something else, a single device (WS) or a system (IRC) cannot provide a satisfactory quick response. In particular, for this scenario, the WS device cannot lift the HS and assist (assistive mode) him/her towards to the bathroom. The presence of the IRC therefore is necessary for this case. This scenario shows the need for both devices in a smart home environment. For people at risk the synergy of IRC and WS can improve and save lives, and at the same time reduce cost by reducing the time needed for a human provider to be present in such a group home. Table 11.3 itemizes the tasks required of the IRC.

Table 11.3 Required tasks of the IRC

1. *IRC recognizes the HS voice request to "go to the bathroom"* (***Voice Recognition***);
2. *IRC searches the room to locate the HS (if needed), although IRC will track the HS around the room if needed to "know" the HS location* (***Body Recognition/Tracking***);
3. *IRC moves towards to the HS location* (***Robot Navigation/Path Planning***);
4. *The IRC uses its synthetic-voice to inform the HS to be ready for assistance* (***Assistive Lifting***);
5. *IRC interactively (it talks to HS regarding the position of the robotic arms) extends its robotic-arms on the "right" position for the HS to grab them* (***Assistive Lifting***);
6. *IRC asks the HS if (s)he is ready to stand-up* (***Assistive Standing***);
7. *IRC interactively assists the HS to turn around* (***Assistive Turn Around***);
8. *IRC interactively assists the HS to sit on IRC seat (Assistive Sitting);*
9. *IRC asks the HS if (s)he is ready to move towards to the bathroom* (***Assistive Walking/Predicting Body walking behavior and Patterns***);
10. *IRC continuously inspects (monitors) the free navigation space for safety and collision avoidance* (**Navigation/Planning**);
11. *IRC assists the HS to take the "correct" position near the toilette* (***Tracking/Assistive Lifting***);
12. *IRC lows its robotic-arms interactively to assist the HS to seat on the toilette* (***Assistive Lifting/Tracking***);
13. *During these steps, WS continuously checks the HS health signs (especially the blood pressure) for alarming the IRC for a possible incident; Also, IRC continuously checks the HS body and her/his face for possible indications of uncomforted situation;*

11.4 Discussion

This chapter offers ideas for a challenging project with a profound social impact, but at the same time deals with the human machine efficient interaction that is also a challenging issue for the machine to respond in the same way that humans do. A brief description was given for a set of tasks to be performed under safe conditions (although risk issues can be evaluated) using only one novel scenario in an indoor environment. Thus, the success of such project will lead to the development of more efficient HMI in this very important area for the people in need.

The impact of these challenges presented are profound at many levels. It will advance discovery by promoting new technologies and models for quick first response of medical conditions for assisting people in need at their homes. This will be done through the interactive-collaborative synergy of monitoring sensors via wearable devices and intelligent robotic assistants based on power wheelchairs. It is expected that many research sub-projects and new directions will grow out of this idea in an area of great need for our society. Examples of this kind are numerous and include: (1) significant overall healthcare cost reduction for people at risk by improvements in early prognosis; (2) significant device cost reduction by developing a new generation of low-cost "Robotic Assistants" and sensors to intelligently monitor & detect health conditions, (3) patient safety improvements by reducing risk for falls, and other injuries and in general improving quality of life; (4) enhanced knowledge of human behavioral/health patterns in complex environments to guide development of future medical devices and treatments.

Finally a bibliography, although not complete, is presented for those with interest to contribute to these very important social issues and projects.

References

1. N. Bourbakis, P. Kakumanu, P. Yuan, 3D Object Recognition using synthesis of views. J. Artif. Intell. Tools **18** (2009)
2. N. Bourbakis, A. Esposito, D. Kavraki, A case study of invariant meta-features for learning and understanding disable people's emotional behavior related to their health conditions, *IEEE International Symposium on BIBE-06,* Oct. 2006, WDC, pp. 357–369
3. N. Bourbakis, S. Tzafestas, Bioengineering for people with disabilities. IEEE Robot. Autom. **8** (2002)
4. A. Tsitsoulis, N. Bourbakis, A survey on human activity recognition methodologies. Int. Journal on AI Tools **22** (2013)
5. L. Zhang, Z. Wang, J.L. Volakis, Textiles Antennas and sensors for body-Worn applications. IEEE Antennas Wireless Propag. Lett. **11**, 1690–1693 (2012)
6. J. Aleotti et al., Perception and grasping of object parts from active robot exploration. J. Intell. Robot. Syst. **76**(3–4) (2014)
7. A. Cherian et al., Mixing body-part sequences for human Pose estimation. *CVPR 2014 - IEEE Conference on Computer Vision & Pattern Recognition*, Jun 2014, Columbus
8. M. Rohrbach et al. A database for fine grained activity detection of cooking activities, in *IEEE Conference CVPR* (2012)

9. B. Sapp, B. Taskar, MODEC: multimodal decomposable models for human pose estimation, in *IEEE Conference CVPR* (2013)
10. B. Sapp et al. Parsing human motion with stretchable models, in *IEEE Conference CVPR* (2011)
11. M. Dantone, J. Gall, C. Leistner, L. van Gool. Human pose estimation using body parts dependent joint regressors, in *IEEE Conference CVPR* (2013)
12. V. Morariu, D. Harwood, L. Davis, Tracking people's hands and feet using mixed network and/or search. IEEE T-PAMI **35**(5), 1248–1262 (2013)
13. K. Fragkiadaki et al., Pose from flow and flow from pose, in *IEEE Conference CVPR* (2013)
14. Y. Yang, D. Ramanan, Articulated human detection with flexible mixtures-of-parts. IEEE T-PAMI (2012)
15. R. Tokola, W. Choi, S. Savarese, Breaking the chain: liberation from the temporal Markov assumption for tracking human poses, in *ICCV* (2013)
16. J. Shotton et al., Real-time human pose recognition in parts from single depth images, *IEEE Conference on CVPR*, pp. 1297–1304 (2011)
17. A. Pantelopoulos, N. Bourbakis, A Survey on wearable systems for monitoring and early diagnosis for the elderly. IEEE Trans. SMC-C **40**(1), 1–12 (2010)
18. P. Bonato, Wearable sensors and systems. IEEE Eng. Med. Biol. **29**(3), 25–36 (2010)
19. S. Patel et al., A review of wearable sensors and systems with application in rehabilitation www.jneuroengrehab.com/content/9/1/21
20. J. West, J. Hippisley-Cox, C.A. Coupland, G.M. Price, L.M. Groom, D. Kendrick et al., Do rates of hospital admission for falls and hip fracture in elderly people vary by socioeconomic status? Public Health **118**(8), 576–581 (2004)
21. B.S. Robinson, J.M. Gordon, S.W. Wallentine, M. Visio, Relationship between lower extremity joint torque and the risk for falls in a group of community dwelling older adults. Physiother. Theory Pract. **20**, 155–173 (2004)
22. I. Melzer, N. Benjuya, J. Kaplanski, Postural stability in the elderly: a comparison between fallers and non-fallers. Age Ageing **33**(6), 602–607 (2004)
23. T.M. Gill, H.G. Allore, T.R. Holford, Z. Guo, Hospitalization, restricted activity, and the development of disability among older persons. J. Am. Med. Assoc. **292**(17), 2115–2124 (2004)
24. F. Englander, T.J. Hodson, R.A. Terregrossa, Economic dimensions of slip and fall injuries. J. Forensic Sci. **41**(5), 733–746 (1996)
25. I. Ktistakis, N. Bourbakis, *A survey on Smart Handed Wheelchairs,* IEEE Conference NAECON, Dayton, June 2015
26. I.H. Sie, R.L. Waters, R.H. Adkins, H. Gellman, Upper extremity pain in the postrehabilitation spinal cord injured patient. Arch. Phys. Med. Rehabil. **73**, 44–48 (1992)
27. H. Gellman, D.R. Chandler, J. Petrasek, I. Sie, R. Adkins, R.L. Waters, Carpal tunnel syndrome in paraplegic patients. J. Bone Joint Surg. [Am]. **70**, 517–519 (1988)
28. J.C. Bayley, T.P. Cochran, C.B. Sledge, The weight-bearing shoulder. The impingement syndrome in paraplegics. J. Bone Joint Surg. [Am], **69**:676–678 (1987)
29. Preserving Upper Limb Function in Spinal Cord Injury: A Clinical Practice Guideline for Health-Care Professionals: *Consortium for Spinal Cord Medicine, Spinal Cord Medicine; 2005.*
30. B.G. Celler, N.H. Lovell, D.K. Chan, The potential impact of home telecare on clinical practice. MJA **171**, 518–521 (1999)
31. I. Korhonen, J. Parrka, M. Van Gils, Health monitoring in the home of the future. IEEE Eng. Med. Biol. Mag. **22**(3), 66–73 (2003)
32. M. Alwan, S. Dala, D. Mack et al., Impact of monitoring technology in assisted living. IEEE Trans. Inform. Technol. Biomed. **10**(1), 192–198 (2006)
33. N. Bourbakis, A. Pantelopoulos Modeling a health prognosis generic wearable system using SPNs, *Proceedings IEEE Conference Tools with AI-09*, NY, Nov. 2009
34. A. Pantelopoulos, N. Bourbakis, A comparative survey on wearable biosensor systems for health monitoring, *Proceedings IEEE EMBS Workshop on Wearable Systems and Sensors*, Aug. 20–22, Vancouver, Ca., 2008

35. N. Bourbakis, A. Pantelopoulos, R. Kannavara, iMASS Project: The LG graph model for detecting and associating signatures in NRF signals, *Proceedings IEEE International Conference on TAI-08*, Dayton, Nov. 2008
36. N. Bourbakis, Prognosis: a language for monitoring and prevention, AIIS Inc. Technical Report, TR-06–2007, 4 p
37. N. Bourbakis, J. Gallagher, *DIAGNOSIS: A Synergistic Co-Operative Framework of New Generation Health Diagnosis Systems for People with Disabilities and the Elderly* (International Conference Circuit. Computer, Crete, Greece July, 2008), pp. 20–22
38. R. Kannavara, N. Bourbakis, An FPGA Implementation of the L-G Graph based Voice Biometric Authentication, *IEEE International Symposium on FCCM*, April. 2009
39. N. Bourbakis, A. Esposito, R. Kannavara, An Iris authentication FPGA scheme using 1D LG graphs, *International Workshop on MMI-09*, Vietri, Italy, 2010
40. A. Esposito, N. Bourbakis, N. Avouris, Y. Hatziligeroudis, (eds) Verbal and Non- Verbal H-H & M-H Interaction, *Springer* (2008)
41. R.C. Simpson, P. Daniel, F. Baxter, The Hephaestus Smart Wheelchair System. IEEE Trans. Neural Syst. Rehab. Eng. **10**(2), 118–122 (2002)
42. Q. Zeng, C.L. Teo, B. Rebsamen, E. Burdet, A collaborative wheelchair system. IEEE Trans. Neural Syst. Rehab. Eng. **16**(2), 161–170 (2008)
43. R.C. Simpson, Smart wheelchair a literature review. J. Rehabil. Res. Dev. **42**(4), 423–438 (2005)
44. R.L. Kirby, D.J. Dupuis, A.H. MacPhee et al., The Wheelchair Skills Test (version 2.4): Measurement properties. Arch. Phys. Med. Rehab. **85**, 794–804, 2004
45. V. Zalzal, R. Gava, S. Kelouwani, P. Cohen, Acropolis: a fast Protoyping robotic application. Int. J. Adv. Rob. Syst. **6**(1), 1–6 (2009)
46. A. Atrash, R. Kaplow, J. Villemure, R. West, H. Yamani, J. Pineau, Development and validation of a robust interface for improved human-robot interaction. Int. J. Soc. Robot. **1**(4), 345–356 (2009)
47. A. Pantelopoulos, E. Saldivar, M. Roham, A wireless modular multi-modal multi-node patch platform for robust Biosignal monitoring, *in Proceedings 33rd Annual International IEEE EMBC*, pp. 6919–6922 (2011)
48. A. Pantelopoulos, N. Bourbakis, A wearable health monitoring system for people at risk: methodology and modeling. IEEE Trans. ITB **14**(3), 613–621 (2010)
49. A. Pantelopoulos, N. Bourbakis, Fuzzy petri nets based decision making in human-device interaction with wearable health-monitoring system, *Proceedings IEEE International Conference Bodynets*, Corfu, Greece, Sept. 2010
50. Recently published articles from Computer Vision and Image Understanding, www.journals.elsevier.com/computer-vision-and-image-understanding/recent-articles/
51. C. De La Cruz et al., A robust navigation system for robotic wheelchairs. Control. Eng. Pract. **19**, 575–590 (2011)
52. P.S. Gajwani et al., Eye motion tracking for wheelchair control. Int. J. Inform. Technol. Knowl. Manag. **2**(2), 185–187 (2010)
53. H. Yanco, *Integrating Robotic Research: A Survey of Robotic Wheelchair Development*, MIT, AI Lab, holly@ai.mit.edu
54. H. Yanco, *Shared User-Computer Control of a Robotic Wheelchair System*, Ph.D. 2000, MIT
55. M. Hillman et al., *The Weston Wheelchair Mounted Assistive Robot-The design, Robotica* (2002) volume 20, pp. 125–132. © Cambridge University Press
56. C. Stanger et al., Devices for assisting manipulation: a summary of user task priorities. IEEE Trans, Rehab, Engr. **2**(4) (1994)
57. K. Kawamura et al., Trends in service robots for the disabled and the Elderly, VU, Center of Intelligent Systems, TN, kawamura@vuse.vanderbilt.edu
58. P. Trahanias et al., Navigational support for robotic wheelchair platforms: an approach that combines vision and range sensors, *IEEE International Conference on Robotics and Automation Albuquerque*, New Mexico - April 1997

59. W. Song et al., KARES: intelligent Rehabilitation robotic system for the disabled and the elderly, *Proceedings of the 20*th*Annual International Conference IEEE EMBS* Vol. 20(5) (1998)
60. S. Tzafestas, *Research on Autonomous Robotic Wheelchairs in Europe*, IEEE RAM, March 2001
61. E. Prassler et al., *A robotic Wheelchair for Crowded Public Environments*, IEEE RAM, March 2001, pp.38–45
62. W.-K. Song, Visual servoing for a user's mouth with effective intention reading in a wheelchair-based robotic, *Arm, IEEE Conf. Robotics and Automation Seoul*, Korea, May 21–26, 2001
63. Z. Bien et al., Development of a Wheelchair-based Rehabilitation robotic system (KARES 11) with various human-robot interaction interfaces for the disabled, *IEEWASME International Conference on Advanced Intelligent Mechatronics (AIM2003)*
64. H. Seki et al., Minimum Jerk control of power assisting tobot based on human arm behavior characteristic, *2004 IEEE International Conference on Systems, Man and Cybernetics*
65. R.M. Alqasemi et al., Wheelchair-mounted robotic Arms: analysis, evaluation and development, *IEEE/ASME International Conference Advanced Intelligent Mechatronics Monterey*, California, USA, 24–28 July, 2005
66. C. Balaguer et al., Live experimentation of the service robot applications for elderly people care in home environments, IST-2001, *balaguer@ing.uc3m.es*
67. C. Balaguer et al., The MATS robot, IEEE RAM, March 2006, pp. 51–58
68. K. Edwards et al., Design, construction and testing of a wheelchair-mounted robotic armopment, *EEE International Conference Robotics and Automation Orlando , Florida*, May 2006
69. C.-H. Kuo et al., *Human-Oriented Design of Autonomous Navigation Assisted Robotic Wheelchair for Indoor Environments*, 1–424–9713–4/06/©2006IEEE, pp.230235
70. M. Palankar et al., Control of a 9-DoF wheelchair-mounted robotic arm system ua P300 brain computer interface: initial experiments, *IEEE International Conference on Robotics and Biomimetics Bangkok*, Thailand, February 21 - 26, 2009
71. D.-J. Kim et al., Eye-in-hand Stereo visual servoing of an assistive robot arm in unstructured environments, *2009 IEEE International Conference Robotics and Automation*, Kobe, Japan, May 12–17, 2009
72. F.A. Cheein et al., Autonomous assistance navigation for robotic Wheelchairs in confined spaces, *32nd Annual International Conference IEEE EMBS Buenos Aires*, Argentina, Aug.31–Sept.4, 2010
73. P. Schrock et al., Design, simulation and testing of a new modular wheelchair mounted robotic arm to perform activities of daily living, *2009 IEEE 11th International Conference on Rehabilitation Robotics Kyoto International Conference Center*, Japan, June 23–26, 2009
74. T. Mukai et al., Development of a nursing-care assistant robot RIBA that can lift a human in its arms, *2010 IEEE/RSJ Int. Conference on Intelligent Robots and Systems* October 18–22, 2010, Taipei, Taiwan
75. V. Maheu et.al., Evaluation of the JACO robotic arm, *2011 IEEE International Conference Rehabilitation Robotics Rehab Week Zurich*, ETH Zurich Science City, Switzerland, June 29 - July 1, 2011
76. Z. Bien et al., Integration of a rehabilitation robotic system (KARES II) with human-friendly man-machine interaction units. J. Autonom. Robot. **16**, 165–191 (2004)
77. N. Bourbakis, I. Papadakis Ktistakis, M. Alamaniotis, L. Tsoukalas, An autonomous intelligent wheelchair for assisting people at need in smart homes: a case study, *Proceedings IEEE International Conference Information, Intelligence, Systems & Applications (IISA)*, July 2015, Corfu Greece
78. Costs of Falls Among Older Adults, CDC, Center for Disease Control and Prevention, http://www.cdc.gov/homeandrecreationalsafety/falls/fallcost.html
79. M. Oish et.al., Modeling and control of a powered wheelchair, *Proceedings Conference CANCAM*, 2011

80. R. Cooper, *Research and Development of Intelligent Wheelchairs (2000–2011), School of Rehabilitation*, Univ of Pitt, Pittsburgh, PA
81. N.I. Katevas et al., The autonomous mobile robot SENARIO: a sensor aided intelligent navigation system for powered wheelchairs. IEEE Robot. Autom. Mag. **4**(4), 60–70 (Dec 1997)
82. Persons with severe disabilities: a clinical survey. J. Rehab. Res. Develop. **37**(3), 353–360
83. Y. Murakami, Y. Kuno, N. Shimada, Y. Shirai, Intelligent wheelchair moving among people based on their observations. IEEE T-Neural Syst. Rehab. Eng., 466–1471 (2000)
84. R.C. Simpson, S.P. Levine, Voice control of a powered wheelchair. IEEE T-Neural Syst. Rehab. Eng. **10**(2), 122–125 (2002)
85. A. Pantelopoulos a wearable platform with off-the-shelf components for quality analysis of physiological data. *IEEE International Conference on Bodynets,* 2010, Corfu, Greece
86. R. Keefer, Lin, N. Bourbakis, The development and evaluation of an eyes-free interaction model for mobile reading devices. *IEEE Trans SMC: Human-Mach. Syst.* **43**(1), 76–91 (2013)
87. S. Tzafestas, *Advanced intelligent Systems* (Kluwer Publisher, 2001)
88. A Wheelchair steered through voice commands and assisted by a reactive fuzzy-logic controller. J. Intell. Robot. Syst. **34**(3), 301–314
89. N. Bourbakis, Kydonas—an autonomous walking robot. IEEE Robot. Autom. **5**(2), 52–59 (1998)
90. A.Tascillo, N.Bourbakis, A neural-fuzzy control of a robotic hand. IEEE Trans. Syst. Man Cybern. **29**(5), .636–642 (1999)
91. A. Tsitsoulis, N. Bourbakis, A methodology-model for extracting human bodies from single images. IEEE Trans. Humans Mach. Syst. (2015)
92. S. Tzafestas, *Introduction to Mobile Robot Control* (Elsevier Pub. 2013)
93. N. Bourbakis, A. Tascillo, An SPN-neuro planning methodology for coordination of multiple robotic arms with constrained placement. Int. J. Intell. Syst. Robot. **17**, 321–337 (1997)
94. N. Bourbakis, J. Gattiker, G. Bebis, Representing and interpreting human activity and events from video. Int. J. AI Tools **12**, 1 (2003)
95. N. Bourbakis, G. Bebis, A method for associating patterns of motion in events from video, *IEEE Conference on TAI-06*, WDC, Nov. 2006, pp. 187–196
96. A. Lymperis, A. Dittmar, advanced wearable health systems and applications, research and development efforts in the European Union, *IEEE Engineering in Medicine and Biology Magazin*e, May/June 2007
97. G. Tröster, The agenda of wearable healthcare, *Wearable Computing at the Electronics Lab ETH* Zürich, Switzerland, Review Proposal in IMIA Yearbook of Medical Informatics, 2005
98. D.A. Rund, R.M. Barkin, P. Rosen, G.L. Sternbach, *Essentials of Emergency Medicine,* , 2nd Edition, Mosby-Year Book Inc (1996)
99. L.M. Tierney Jr., S.J. McPhee, M.A. Papadakis, *CURRENT Medical Diagnosis & Treatment*, 45th Edition, McGraw-Hill (2006)
100. J. Habetha, The MyHeart Project – fighting cardiovascular diseases by prevention and early diagnosis, 28th *Annual Internatonal Conference, IEEE Engineering in Medicine and Biology Society (EMBS)*, August 30 – Sept. 3, 2006, NY City, USA
101. J.L. Weber, F. Porotte, MEdical Remote MOnitoring with cloTHes, *PHealth, Luzerne,* 31 Jan, 2006
102. K.J. Heilman, S.W. Porges, Accuracy of the Lifeshirt® (Vivometrics) in the detection of cardiac rhythms. Biolog. Psych. **75**, 300–3005 (2007)
103. Sensatex, Inc., *Development of the Sensatex SmartShirt*, *pHealth,* (2006)
104. K. Nikita et.al., Digital Patients and their impact on healthcare: personalized glucose-Insulin Metabolism model based on self-organizing Maps for patients with type 1 diabetes Mellitus, *IEEE International Conference BIBE-13*, Nov. 10–13, 2013 Greece
105. Z. Wang, L. Zhang, J. Volakis, Textile Antennas for Wearable radio frequency applications. J. TLIST **2**(3) (2013)
106. A. Milenkovic, C. Otto, E. Jovanov, Wireless sensor networks for personal health monitoring: Issues and an implementation. Comput. Commun. **29**, 2521–2533 (2006)

107. E. Monton et al., Body area network for wireless patient monitoring, telemedicine and E-health communication systems. IET Commun. **2**, 215–222 (2008)
108. M.-A.. Fengou et. al., Unsupervised clustering of patient-centric models to cluster-centric models for ubiquitous healthcare environment, *IEEE International Conference BIBE-13*, Nov. 10–13, 2013 Greece
109. N. Bourbakis, A. Esposito, R. Keefer, D. Dakopoulos, A multi-modal scheme for HCI between blind users and AT devices, *IEEE Conference on TAI*, Dayton, Ohio, Nov. 2008
110. B.S. Duerstock, Purdue Research Project "Enhanced Control of a Wheelchair-Mounted Robotic Manipulator Using 3-D Vision and Multimodal Interaction" to be appear in CVIU Journal

Further Reading

111. C.E. Smith, N. Papanikolopoulos, Research projects on vision-guided robotic grasping: theory, issues and experiments (1995–2005), University of Minnesota, CSE Dept
112. A. Bergland, T.B. Wyller, Risk factors for serious fall related injury in elderly women living at home. Inj Prev. **10**(5), 308–313 (2004)
113. E.M. Steultjens et al., Occupational therapy for community dwelling elderly people: a systematic review. Age Ageing **33**(5), 453–460 (2004)
114. T. van Bemmel, J.P. Vandenbroucke, R.G. Westendorp, J. Gussekloo, In an observational study elderly patients had an increased risk of falling due to home hazards. J. Clin. Epidemiol. **58**(1), 63–67 (2005)
115. C.A. Dyer, G.J. Taylor, M. Reed, D.R. Robertson, R. Harrington, Falls prevention in residential care homes: a randomised controlled trial. Age Ageing **33**(6), 596–602 (2004)
116. B.L. Cho, D. Scarpace, N.B. Alexander, Tests of stepping as indicators of mobility, balance, and fall risk in balance-impaired older adults. J. Amer. Geriatric Soc. **52**(7), 1168–1173 (2004)
117. L.Z. Rubenstein, D.H. Solomon, C.P. Roth, R.T. Young, P.G. Shekelle, J.T. Chang et al., Detection and management of falls and instability in vulnerable elders by community physicians. J. Amer. Geriatric Soc. **52**(9), 1527–1531 (2004)
118. S.E. Kurrle, I.D. Cameron, S. Quine, Predictors of adherence with the recommended use of hip protectors. J. Gerontol. Med. Sci. **59**(9), M958–M961 (2004)
119. B. Clarkson, K. Mase, A. Pentland, Recognizing user context via wearable sensors, in *Proceedings of the Fourth International Symposium on Wearable Computing*, Oct. 2000, pp. 69–75
120. M. Jones, T. Martin, Z. Nakad, A Service Backplane for E-Textile applications, *Workshop Modeling, Analysis & Middleware Support for Electronic Textiles (MAMSET),*Oct. 2002, pp. 15–22
121. S. Jung, C. Lauterbach, W. Weber, Integrated microelectronics for smart textiles, in *Workshop on Modeling, Analysis, and Middleware Support for Electronic Textiles*. MAMSET 2002, Oct. 2002
122. T. Martin, M. Jones, J. Edmison, J. Shenoy , Towards a design framework for wearable electronic textiles, *Proceedings of the Seventh International Symposium on Wearable Computers, White Plains,* NY, October 21–24, 2003, pp. 190–199
123. D. Marculescu, R. et al., Electronic textiles: a platform for pervasive computing. Proc. IEEE **91**, 1995–2018 (2003)
124. Z. Nakad, *Architectures for E-Textiles*. Ph.D. Dissertation, Dept. of ECE, Virginia Tech, 2003
125. E. Post, M. Orth, P. Russo, N. Gershenfeld, E-broidery design and fabrication of textile-based computing. IBM Syst. J. **39**(3 and 4) (2000)
126. T. Martin, E. Jovanov, D. Raskovic, Issues in wearable computing for medical monitoring applications: a case study of a wearable ECG monitoring device, *Proceedings of the 2000 International Symposium on Wearable Computers*, Atlanta, GA, October 16–17, 2000, pp. 43–50

127. D. Raskovic, T. Martin, E. Jovanov, Medical monitoring applications for wearable computing. Computer J. **47**(4), 495–504 (July 2004)
128. E. Jovanov, J. Price, D. Raskovic, K. Kavi, T. Martin, R. Adhami , Wireless personal area networks in Telemedical environment, in *Third IEEE EMBS Information Technology Applications in Biomedicine Workshop of the International Telemedical Information Society ITAB-ITIS* 2000, Arlington, Virginia, November 2000, pp. 22–27
129. K. Lyons, T. Starner, Mobile capture for wearable computer usability testing, *Proceedings of the Fifth International Symposium on Wearable Computing*, Oct. 2001, pp. 69–76
130. J. Steven, McPHEE and Maxine Papadakis, 2007 Current Medical Diagnosis and Treatment, *McGraw Hill*, 2007
131. G. Kalb, Fixing America's Hospitals. *Newsweek*
132. L. Gatzoulis, I. Iakovidis, Wearable and portable eHealth systems, technological issues and opportunities for personalized care, *IEEE Engineering in Medicine and Biology Magazine,* Sept/October 2007
133. P. Bonato, wearable sensors/systems and their impact on biomedical engineering. IEEE Eng. Med. Biol. Mag., 18–20 (2003)
134. U. Anliker, J. et.al., AMON: a wearable Multiparameter medical monitoring and alert system. IEEE Trans. Inform. Technol. Biomed. **8** (2004)
135. R. Paradiso, G. Loriga, N. Taccini, A wearable health care system based on knitted integral sensors. IEEE Trans. Inform. Technol. Biomed. **9**(3) (2005)
136. M. Sung, C. Marci, A. Pentland, Wearable feedback systems for rehabilitation. J. NeuroEng. Rehab. (2005)
137. C.D. Katsis, G. Gianatsas, D. I. Fotiadis, An integrated telemedicine platform for the assessment of affective physiological states, *Diagnostic Pathology*, 01 August, 2006
138. J. Rodriguez, A. Goni, A. Illarramendi, Real-time classification of ECGs on a PDA. IEEE Trans. Inform. Technol. Biomed. **9**(1) (2005)
139. C. Wen, M.F. et.al., Real-time telemonitoring system design with mobile phone platform. Measurement **41**, 463–470 (2008)
140. A.L. Goldberger et al., PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation **101**(23), e215–e220 [Circulation Electronic Pages; http://circ.ahajournals.org/cgi/content/full/101/23/e215]; 2000 (June 13)
141. PhysioNet at www.physionet.org
142. Fredrik Nilsson and Communications Axis, Intelligent Network Video: Understanding Modern Video Surveillance Systems, (*CRC Press* 2008)
143. B. Phillips, The Complete Book of Home, Site and Office Security, (*BH* 2006)
144. H. Kruegle, *CCTV Surveillance: Video Practices & Technology* (Amazon 2006) 2nd edition
145. Paolo Remagnino Sergio A Velastin, *Intelligent Distributed Video Surveillance Systems (Professional Applications of Computing)* (IEE 2006)
146. Z. Xiong, R. Radhakrishnan, A. Divakaran, Y. Rui, *A Unified Framework for Video Summarization, Browsing & Retrieval: with Applications to Consumer and Surveillance Video* (Springer 2005)
147. G.L. Foresti, P. Mähönen, C.S. Regazzoni, *Multimedia Video-Based Surveillance Systems: Requirements, Issues and Solutions* (The Springer International Series in Engineering and Computer Science, 2000)
148. O. Javed, M. Shah, *Automated Multi-Camera Surveillance: Algorithms and Practice (The International Series in Video Computing)* (Amazon 2008)
149. P. Remagnino, G.A. Jones, N. Paragios, C.S. Regazzoni, *Video-Based Surveillance Systems: Computer Vision and Distributed Processing* (Amazon 2001)
150. A. Pantelopoulos, N. Bourbakis, A formal language as a Detection and Prognosis model for a Wearable system, *Proceedings IEEE International Conference on BIBE-08, Oct. 2008*, Athens Greece
151. A. Moghaddamzadeh, N. Bourbakis, A fuzzy-like region growing approach for segmentation of colored images. PR Soc. J. Pattern Recogn. **30**(6), 867–881 (1997)

152. A. Mogadamzadeh, D. Goldman, N. Bourbakis, A fuzzy-like approach for smoothing and edge detection in color images. Int. J. Pattern Recogn. AI **12**(6), 801–816 (1998)
153. X. Yuan, A. Mogaddamzadeh, D. Goldman, N. Bourbakis, Segmentation of Colour Images with Highlights and Shadows using Fuzzy-like Reasoning. IAPR Pattern Anal. Appl. **4**(4), 272–282 (2001)
154. N. Bourbakis, P. Yuan, S. Makrogiannis, Recognizing objects using wavelets and LG graphs. PR Soc. J. Pattern Recogn. **40** (2007)
155. N. Bourbakis, P. Kakumanu, S. Makrogiannis, R. Bryll, S. Panchanathan, An ANN based approach for image chromatic adaptation for skin color detection. Int. J. Neural Syst. **17**(1), 1–12 (2007)
156. W. Li, G. Bebis, N. Bourbakis, Improving 3D recognition based on algebraic functions of views. IEEE Trans. Image Process. **17**(11), 2236–2255 (2008)
157. N. Bourbakis, Low resolution target tracking and recognition from a sequence of images. Int. J. AI Tools **11**(4) (2002)
158. T.R. Gowrishakar, N. Bourbakis, Specifications for the development of a knowledge-based image interpretation system. Int. J. Engr. Appl. Artif. Intell. **3**(1), 79–90 (1990)
159. P. Kakumanu, N. Bourbakis, Recognition of facial expressions using LG graphs, *IEEE Conference on TAI-06,* WDC, Nov. 2006, pp. 685–692
160. A. Esposito, N. Bourbakis, The role of timing on the speech perception and production processes and its effects on language impaired individuals, *Proceedings IEEE Symp. BIBE-06*, Oct. 2006, WDC, pp.348–356
161. N. Bourbakis, P. Patil, A methodology for visual detection-extraction of texture-paths in images, *IEEE Conference on TAI-07*, Greece, Patras, Oct. 2007, vol. I, pp. 504–512
162. N. Bourbakis, Automatic conversion of images into natural language text-sentences for visual impaired home interfaces, *IEEE International Conference on TAI-08*, Dayton, OH, Nov. 2008
163. J. Moore, *Computer-Controlled Power Wheelchair Navigation System* (VA Reference No. 01–021)
164. Z.B. Musa, J. Watada, Multi-camera tracking system for human motions in different areas and situations. Int. J. Innov. Comput. Inform. Control **4**(5) (2008)
165. S.M. Monk, M.T. Nanagas, J.L. Fitch, A. Stofli, A.S. Pickoff, Comparison of resident and faculty patient satisfaction surveys in a pediatric ambulatory clinic. Teaching Learn. (Medicine) **18**(4), 343–347 (2006)
166. J.L. Reynolds, A.S. Pickoff, Accelerated ventricular rhythm in children: a review and report of a case with congenital heart disease. Pediatr Cardiol. **22**(1), 23–8 (2001), Review
167. L.W. Lawhorne, Managing laboratory results in the nursing home setting. J. Amer. Med. Dir. Assoc. (2009)
168. D. Dakopoulos, N. Bourbakis, Wearable obstacle avoidance electronic travel aids for visually impaired: a Survey. IEEE Trans. Syst. Man Cybern. **40**(1), 25–35 (2010)
169. The European Pilot Project on Ambient Assistive Living, ICT based solutions for Prevention and Management of Chronic Conditions of Elderly People" pages 15, April, 2008
170. N. Bourbakis, S. Makrogiannis, D. Dakopoulos, A system-prototype representing 3D space via alternative sensation for visual impaired navigation. IEEE Sens. J. **13**(7), 2535–2547 (2013)
171. L. Rothrock, S. Kantamneni, C. Harvey, S. Narayanan, A re-configurable telerobotics system for human factors engineering education. Int. J. Model. Simul. **24**(4), 1–9 (2004)
172. N. Bourbakis, A traffic priority language for collision free navigation of autonomous mobile robots in unknown space. IEEE Trans. Syst. Man Cybern. **27**(4), 573–587 (1997)
173. S. Mertoguno, N. Bourbakis, A retina-like, low level vision processor. IEEE Trans. Syst. Man Cybern. **33**(5), 782–788 (2003)
174. A.M. Cook , J.M. Polgar, *Assistive Technologies: Principles and Practice.* St. Louis: Mosby/Elsevier (2008)
175. A.Y.C. Nee, K. Whybrew, A. Senthil kumar, *Advanced Fixture Design for FMS*. London: Springer (1995)

176. L. Segal, C. Romanescu, N. Gojinetchi, Methodologies for automated design of modular fixtures. *Proceedings of International Conference on Manufacturing Systems*, Iasi, Romania. pp. 151–156 (2001)
177. C.H. Xiong, M.Y. Wang, Y. Tang, Y.L. Xiong, On prediction of passive contact forces of Workpiece-fixture systems. Proc. Inst. Mech. Eng. Part B-J. Eng. Manuf. **219**(3), 309–324 (2005)
178. C.H. Xiong, M.Y. Wang, Y. Tang, Y.L. Xiong, compliant grasping with passive forces. J. Robot. Syst. **22**(5), 271–285 (2005)
179. S. Makrogiannis, N. Bourbakis, Motion analysis with application to assistive vision technology, *IEEE Conference TAI-2004,* FL, Nov. 2004, 344–352
180. N. Bourbakis, detecting faces and facial expressions for monitoring emotional behavior. Int. J. Monitoring Surveillance Res. Technol. **1**(2) (2013)
181. R. Patrick, N. Bourbakis, Surveillance systems for smart homes: a comparative survey, *IEEE Conference on Tools with AI-09*, Newark, NJ, Nov. 2009, pp. 248–252
182. A. Tsitsoulis, R. Patrick, N. Bourbakis, Surveillance issues in a smart home environment, *IEEE Conference on TAI-12 and International Symposium on Monitoring & Surveillance Systems*, Nov 2012, Piraeus, Greece
183. C.H. Xiong, Y. Rong, Y. Tang, Y.L. Xiong, Fixturing Model and Analysis. Int. J. Comput. Appl. Technol. **28**(1), 34–45 (2007)
184. Fundamentals of robotic grasping and fixturing © World Scientific Publishing Co. Pte. Ltd. http://www.worldscibooks.com/engineering/6610.html
185. L.S. Wong, *Robotic Grasping*, May 2008, Stanford University
186. Y. Jiang, M. Stephen, A. Saxena, Efficient Grasping from RGBD images: learning using a new rectangle representation, *International Conference on Robotics and Automation* (ICRA) (2011)
187. N. Bourbakis, *Artificial Intelligent Methods and Applications.* World Scientific Publication (1992)
188. N. Bourbakis, I. Papadakis Ktistakis, Design micro-robot structures for detecting humans under debris in disasters, *Proceedings IEEE Conference NAECON-11*, July 2011, Dayton, OH
189. Assistive Technologies Research Center, Wright State University, *Projects and Pu*bs 2003-present, http://www.cs.wright.edu/atrc
190. N. Bourbakis, A. Pantelopoulos, R. Kannavara, Mobile-health: continuous monitoring, bio-signals de-noising for processing and secure information exchange, book-chapter in Biomedical Telemetry. Wiley-IEEE, ed. K. Nikita (2013)
191. Advanced Remote Patient Monitoring Systems http://www.reportlinker.com/p01172037
192. Center for Technologies and Aging, *Technologies for Remote Patient Monitoring for Older Adults,* www.techandaging.org/RPMPositionPaper.pdf
193. A. Tsitsoulis, N. Bourbakis, A. A representation of the flow of images on a multiprocessor surveillance system. Int. J. Monitoring Surveillance Res. Tech, IGI Global Publisher, **1**(1), 1–21 (2013)
194. G. Vavoulas et al., The mobifall dataset: an initial evaluation of fall detection algorithms using smartphones, *IEEE International Conference on Bioinformatics and Bioengineering (BIBE)* 2013, Nov. 10–13, 2013, Chania, Greece
195. P. Kannus et al., Prevention of falls and consequent injuries in elderly people. The Lancet **366**(9500), 1885–1893 (2005)
196. J.A. Stevens et al., The costs of fatal and non-fatal falls among older adults. Inj. Prev. **12**(5), 290–295 (2006)
197. V. Vaidehi et.al., Video based automatic fall detection in indoor environment, *in Proceedings 2011 International Conference on Recent Trends in Information Technology (ICRTIT)*, pp.1016–1020, 3–5 June 2011
198. C. Rougier et al., Robust video surveillance for fall detection based on human shape deformation. IEEE Trans. Circuit. Syst. Video Technol. **21**(5), 611–622 (2011)

199. A.K. Bourke et al., Evaluation of a threshold- based tri-axial accelerometer fall detection algorithm. Gait Posture **26**, 194–199 (2007)
200. S. Fudickar et al., Fall-detection Simulator for accelerometers with in-hardware preprocessing, *in Proc. 5th International Conference on Pervasive Technologies Related to Assistive Environments*, Heraklion, Crete, Greece, June 6–8, 2012.
201. F. Bagalà et al., Evaluation of accelerometer-based fall detection algorithms on real-world falls, *PLoS ONE,* vol. 7, no. 5, e37062, pp. 1–9, doi:https://doi.org/10.1371/journal.pone.0037062 (2012)
202. F. Sposaro, G. Tyson, iFall: an Android application for fall monitoring and response, *in Proceedings 31st International Conference IEEE EMBS*, Mineapolis, Minasotta, USA, September 2–6, 2009
203. J. Dai et al., Mobile phone-based pervasive fall detection. Pers. Ubiquit. Comput. **14**, 633–643 (2010)
204. Y. He et al., Falling-incident detection and alarm by smartphone with multimedia messaging service (MMS). E-Health Telec. Syst. Netw. **1**, 1–5 (2012)
205. R.Y.W. Lee, A.J. Carlisle, Detection of falls using accelerometers and mobile phone technology. Age Ageing **40**, 690–696 (2011)
206. R. Vardasca et al., Clinical Needs and Implementation of health services in Ambient Assistive living, *2nd International Living Usability Lab Workshop on AAL Latest Solutions, Trends and Applications - AAL 2012; 01/2012 and IEEE T-SMC*
207. Medical and Biological Engineering in the Next 20 Years: the Promise and the challenges. IEEE T-Biomed. Eng. **60**(7) (2013)
208. M. Spanakis et al., Exploitation of patient avatars towards stratified medicine through the development of in silico clinical trials approaches, *IEEE International Conference BIBE-13*, Nov. 10–13, 2013 Greece
209. E. Maniadi et al., Designing a digital patient avatar in the context of the My Health Avatar project initiative, *IEEE Int. Conference BIBE-13*, Nov. 10–13, 2013 Greece
210. F. Chiarugi et. al., A cirtual individual's model based on facial expression analysis: a non-intrusive approach for wellbeing monitoring and self-management, *IEEE Int. Conference BIBE-13*, Nov. 10–13, 2013 Greece
211. X. Zhao et al., A Scalable data repository for recording self-managed longitudinal health data of digital patients, *IEEE International Conference BIBE-13*, Nov. 10–13, 2013 Greece
212. H. Wei et al., A Cross-platform approach for treatment of Amblyopia, *IEEE International Conference BIBE-13*, Nov. 10–13, 2013 Greece
213. I. Papadakis Ktistakis, N. Bourbakis, An SPN modeling of the H-IRW getting-up Task, *IEEE Conf. on Tools with AI*, Nov. 2016, S.Jose CA, USA
214. I. Papadakis Ktistakis, N. Bourbakis, A multimodal human-machine interaction scheme for an intelligent robotic nurse, *IEEE Conf. on Tools with AI*, Volos, Greece, Nov. 2018