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Flexible, Personal Service Robot for ALS Patients*

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***Abstract*— Diseases that cause motor impairment leave people dependent on the help of caregivers or new technologies for their daily tasks. Care robots could support these patients and help them gaining autonomy in some of their daily activities. In this paper, a robotic assistant is introduced based on Amyotrophic Lateral Sclerosis patients requests for care robotics. The presented use cases are derived from their feedback and integrated using a compliant lightweight robotic arm. The system has been developed to be used independently from the input device owned by the patient, which grants an easy access to the robot without any special training. The system is flexible enough to not harm the patient for tasks that involve physical human-robot interaction, and yet precise enough to manipulate different objects. Despite the increasing acceptance of care robots in the community nowadays, the robotic assistant is one of the few robot solutions that combines autonomous behaviors and teleoperated control.**

***Index Terms*— Service Robots, Physical Human-Robot Interaction, Physically Assistive Devices**

I. Introduction

The Amyotrophic Lateral Sclerosis (ALS) is a progressive neurodegenerative disease, which causes the death of neurons controlling voluntary muscles, and gradually prohibiting the ability to speak, walk, grasp objects, move, swallow and breathe. According to the ALS Association [1], ALS is the most common adult-onset motor neuron disease, with a predicted increase in population over the coming years [2].

As there is no known cure for ALS, the disease management focuses on treating the symptoms and providing supportive care to improve the quality of life and prolonging survival [1]. ALS patients require the help from others and can benefit from technologies for assistance or care.

A personal care robot is defined by the European Committee for Standardization as a service robot that performs actions contributing directly to improve quality of life, including certain tasks that require physical contact with the user [3], [4]. Thus, care robots could provide support to ALS patients, making the disease less stressful for both patient and caregiver [5], while increasing also patient's autonomy and intimacy.

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Fig. 1. An example of the implemented use cases for the robotic assistant: scratching a human arm with a brush, explained in Section III

In this paper, we introduce a personal care robotic solution for ALS patients, where the user can control a lightweight robotic arm with their preferred input devices to carry out different tasks, as can be observed in Fig. 1. In Section II, a brief description of the state of the art is given; followed by the architecture description in Section III, as well as a discussion of each implemented use case. Section IV elaborates on the lessons learned while testing with patients. Finally, we talk about future work and provide a summary in Section V.

II. Motivation and State of the Art

Numerous surveys and studies have identified the following use cases as the most required by disabled people [6]: help for eating and drinking; personal care, including washing, shaving, scratching, among others; general reaching and handling of objects, known or not.

Unsurprisingly, these solutions have been implemented in different service robots before, as Hersh [6] explains exhaustively in her work, whether in single tasks robots,

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which are designed to carry out a particular task (for example the Neater Eater or Neater Drinker [7], [8] designed to help people with limited mobility to eat and drink); or in multi-function robotic systems, which are designed to carry out several tasks as selected by the user.

Nevertheless, even now, only a few care robotics are available on the market despite the potential to support disabled people. For example, the system developed by Chen at al. [9] for a PR2 robot [10] uses a mixture of autonomous behaviors and shared control. Teleoperation by the users without any autonomous behavior is often used as control strategy. The multi-function robotic manipulator iArm (intelligent Assistive robotic manipulator) [11], a robot with 6 degrees of freedom and two-fingered compliant gripper, can be operated by a keypad, joystick or single button control. The EDAN (EMG-controlled Daily Assistant) [12], a robotic platform with 7 degrees of freedom and a five-finger hand with 15 degrees of freedom, can be operated using muscle signals on the skin surface instead of a joystick.

The robotic system here presented uses a commercially available robot, the Franka Emika Panda [13], with 7 degrees of freedom and torque sensors for compliance, and a two-finger gripper. It combines autonomous behaviors with teleoperated control. The hardware setup is shwon in Fig. 2.

The system here developed has included feedback from patients and caretakers at different stages throughout the project to understand their needs and expectations. The case study population consisted of 89 patients with ages from 33 to 82 years old [14].

Fig. 2. The robot assistant setup includes two depth cameras for object and face detection, the patient computer with the user interface as an application, and the robot arm. An eye tracking device is provided as one option for controlling the system.

III. Architecture and Implemented Use Cases

Physical human-robot interaction for care robots needs extra precautions, which do not need to be considered for classical industrial applications as they have no shared workspaces. For instance, for patients with reduced mobility, it is critical to consider unexpected and inadequate collisions, or how to avoid harming the user, guaranteeing as few risks as possible. Thus, all aspects of the manipulator design need to be considered: from hardware (beware of sharp edges, sensor malfunction, among others) to software (proper control architecture, robustness, adaptability, etc.).

Authors like Hersh [6] and Alami et. al. [15] have explained in great detail the importance of very high reliability for care robots, as users might not react as fast as needed if there is any problem, or are dependent on their care systems. ALS patients, for example, will perform tasks that require direct robot-skin contact. Therefore, reducing unpredictable behaviors and negative side effects resulting from physical human-robot interaction is critical.

The goal of this robotic assistant is to combine modern hardware – where compliant elements allow the robot to adapt continuously during the task execution – with a control software design that allows controlling the robot stiffness, and modifies its behavior to achieve its goals.

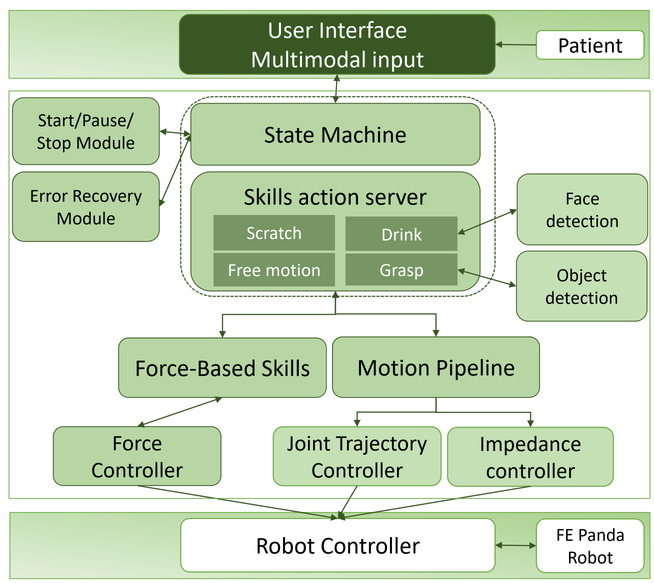

Fig. 3. The implemented hybrid and modular architecture with three interconnected levels, as described in the Section III.

A. *Robotic assistant architecture*

To achieve a robust control architecture, a deliberative based hybrid architecture [16] is implemented in the robotic assistant. Pure deliberative architectures, as explained by Laugier and Fraichart, are based in a “Sense-Model-Plan-Act” sequence and do not take into consideration any possible changes in the modeled world surrounding the robot. Instead, we also consider external feedback from the robot arm and cameras, which allows the system to be reactive while trying to accomplish the goals. Connecting all the components of this setup is done with the Robot Operating System [17], utilizing its cross vendor support.

The implemented architecture consists of three interconnected main levels, as can be observed in the Fig. 3; namely the user interface, the high-level control and the robot control. Both user interface and robot control are not of major concern for this paper, as they have been developed by other research groups[1].

The high level control here developed processes the requests from the user interface and transforms the user commands into goals to be achieved. There are four implemented use cases available in the user interface, and each of them is represented by a ROS action server (skill action server). Each action server requests the resources it needs to provide its skill, i.e. camera depth information, robot control, etc. This modular approach allows for each skill to be developed and executed independently, which also simplifies future additions. Collision recovery is also implemented in the high level control.

The skills include two types of motions: recorded trajectories, executed on a compliant controller; or movements with force-based models, learned and applicable anywhere in the work space. When using the recorded trajectories, the robot's stiffness can be adapted dynamically to the situation: stiff and precise for grasping, or flexible for physical human contact.

This research has focused around two categories of robotic assistance for ALS patients: manipulation of objects with physical human-robot interaction, and manipulation of objects in their environment.

B. Object manipulation and physical human-robot interaction

Within this category, two use cases are implemented: scratching a patient forearm with a brush, and approaching a drink to the proximity of their mouth.

Scratching a body part: One of the most frequently requested use cases is scratching, as it allows the patients to feel more independent, and regain more of their privacy. Unlike previous robot manipulators, an autonomous scratching skill is implemented, which is able to scratch the patient forearm while laying it on a pillow, for now relying on robot proprioception to detect human robot contact. Additional sensors for whole body recognition to allow for targeted contact with different body parts are currently under development.

The patients can select different scratching modes using the user interface. They can choose between different brushes, as well as intensity (point pressure applied by the brush within the safety limitations) or the duration of the scratching.

The main focus is to gain a better understanding of physical human-robot interaction, and how to approach the user reducing the risk of bruises or accidental lacerations. The control of the robot arm is a force sensitive compliance control, thus allowing minor positional errors while not exceeding force limits.

In the implemented setup, the robot first picks up the selected brush from the table, using taught trajectories and then slowly approaches the human arm, as observed in the Fig. 4. The stiffness of the robot adapts in the different steps of the motion, which allows the end-effector to make a soft initial contact with the human arm before starting the scratching motion. The robot sensors continuously check for physical contact between the brush and the human arm. This allows the robotic arm to adapt to positional changes of the limb. If contact is disrupted, the time limit exceeded or the execution is stopped by the user, the robot stops scratching, places the brush back on the table and returns to its idle position.

Fig. 4. One of the authors at the Demografiekongress 2018, where ALS patients had the opportunity to live test the implemented use cases and provide feedback for improvements on the system development.

Reaching for a cup and helping to drink: To help the user perform daily tasks like drinking or eating, the system requires visual feedback. For this purpose, depth cameras are used and image data is processed to define different targets of the end-effector. The drink assistance use case can be divided into two main components: the motion of the end-effector and the pose definition of the user's mouth.

First, it is necessary to redefine the end-effector of the system for this use case, as it grasps a cup with a fixed straw. The trajectory to grasp the cup is taught, and the motion towards the user's mouth is generated from the calculated pose for the center of the mouth in relation to the straw's tip.

To estimate the pose of a central point in the user's

[1]The ROBINA consortium is comprised by 8 partners, including Franka Emika as the developer of the robot controller and another research team from the FZI Research Center for Information Technology providing the user interface.

mouth, a external library is used to detect the face and its facial features using an RGBD camera. This library is the dlib's feature detector [18], which uses Histogram of Oriented Gradients (HOG) filters to recognize a human face, with a SVM classifier to detect facial landmarks using shape prediction. Initially, predicted pixel of the mouth are used to determine the mouth's central point. Additionally, the depth is then obtained as median depth value of all the sampled points. From this, the mouth's position in relation to the robot can be derived. In Fig. 5, both the approach with a straw and the mouth feature detection are shown.

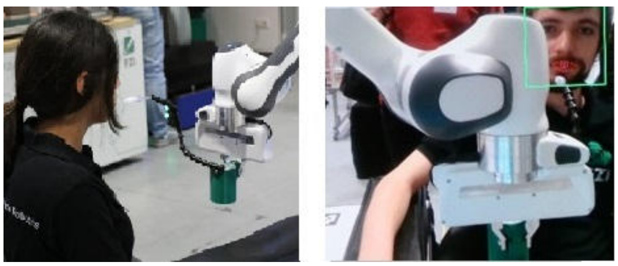

Fig. 5. Some of the authors testing the grasping and approaching a cup use case. The right image also shows the bounding box for the detected face and the mouth features.

C. Object manipulation in their environment

Based on patients' feedback, another two use cases are implemented: the ability to freely move the robot, including control of the gripper, to manipulate arbitrary objects; and the grasping of familiar objects using a neural network for object recognition.

Free motion and grasping: Free interaction with the environment is also crucial for increasing patient's autonomy. The robotic assistant provides the patients with direct control through iteratively triggering discrete motion commands. Although this represents a very basic form of control, it gives patients the freedom to manipulate objects beyond programmed functionality. In combination with a pipeline for autonomous grasping and shared control, we offer a twofold approach to cover basic object manipulation scenarios.

In the free motion scenario, we use impedance control with a low stiffness to enable soft interaction with hard surfaces, such as table tops. Patients command incremental motion, such as forward, backward, left, right, grasp among others. Although this appears cumbersome, it is crucial in taking a control loss of the patient into account. If anything happens between two commands the system must stop safely to avoid continuous, uncontrolled motion.

One of the advantages with this control interface is the ability to hand cognitive tasks over to the patient. Tasks, such as finding the right spots to grasp unknown objects, are classically complicated to solve. However, the ultimate goal is to provide a continuously growing set of object skills, which takes this need off the patients and shifts autonomy and task cognition towards the system.

Automatic object handover: Patients who can still control their upper limps, but don't possess the mobility and strength to reach far, profit from such a shared control to move objects. In this scenario, it is assumed a clear view on the setup for object detection is given, and that the objects are not covered and can be grasped from most sides. The object detection provides the objects' poses with respect to the robot. A skill is then triggered to approach and grasp the object. For this, a Cartesian force control is implemented on the manipulator with velocity proportional damping, such that target wrenches (forces and torques) can steer the robot gripper safely in Cartesian space.

Generating these control wrenches is done online within the skill model. The idea behind the skills is to turn motion planning into something that could be scaled in amplitude and would comply better with force sensitive control. These skills utilize the Open Motion Planning Library (OMPL) [19], which is common in robotics. During an offline preparation and on a purely object level (without robot and environment), the approaching motion is planned in form of paths from arbitrary starting poses of the gripper towards a dummy object. (classically in a spherical volume with radius 30 cm to the dummy to grasp). Through automatic generation, a massive number of goal directed paths is sampled. Then, the individual path points are transformed into goal-directed forces and torques for two succeeding points each, obtaining a normalized wrench field around the object primitive to be grasped. Note, that in contrast to a centric field, this field contains semantics, such as collision aware orientation before grasping, taking the gripper jaws into account. A supervised learning to train a feed forward neural network on this dataset is used to obtain a mapping from Cartesian poses to end-effector wrenches of the robot. Finally, when a skill is triggered during run time on the real system, the robot with the gripper essentially traverses these learned wrench fields [20].

The benefits of this approach are that the skills are scalable in force amplitude. Their execution can be slow and sensitive, without losing semantics. They can be interrupted and continued from many entrance points as long as we stay in the volume around the object that was used during training. Another advantage is that the robot does not build up forces as in impedance controlled motion. This point is crucial, since holding back the robot while it builds up forces to get to some moving target is possibly dangerous. Furthermore, a grasping force field for one skill is defined between two primitives, and allows to grasp objects of similar shapes alike, such as flat, box-shaped objects or cylindrical, standing objects.

Object detection for predefined object handling: As it is explained before, a robust object detection is beneficial for autonomous grasping and moving objects in the vecinity of the users. The implemented modular architecture of the system allows the integration of different algorithms. For example, in the demonstrator two state of the art implementations of neural networks are tested. YOLO [21] and Mask-RCNN [22] are integrated into the system, with the last one being the currently chosen network, due to its simplicity for training the network.

Mask-RCNN uses an RGB-image to detect bounding boxes and pixelwise masks around the objects. The neural network is pre-trained with available datasets such as COCO [23]. Afterwards, the weights of the network are adjusted with a custom dataset of the scene and the available objects.

The resulting bounding boxes are used in a post-processing step to get the final pose of the objects. For that, an edge detection inside the bounding box is performed and a coordinate system is aligned to the longest edge. This approach works well with the common shapes of household items, such as remotes or cellphones, and could be extended to different shapes as needed. Afterwards, the object's coordinate system is transferred into robot coordinates and used for the aforementioned force-based grasping, as shwon in Fig. 6.

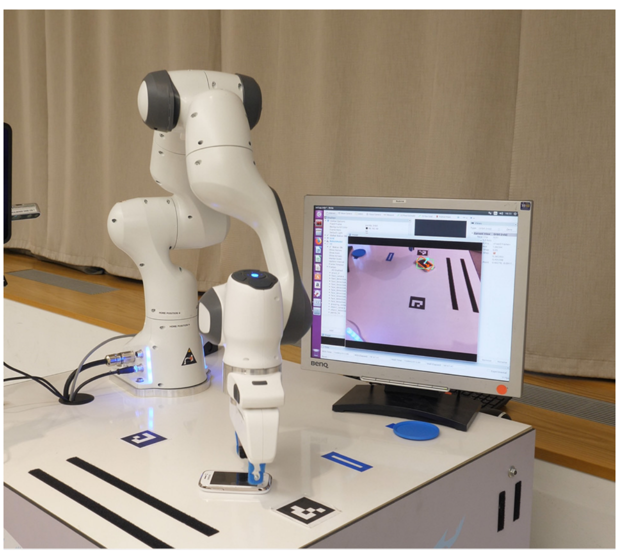

Fig. 6. Detection of the mobile phone (in the background) with Mask-RCNN and adaptive grasping.

IV. Live demonstrator

Our robotic manipulator is not only used in the robotics lab environment but also presented at different fairs throughout Germany. The ROBINA consortium displayed the live demonstrator at the Hauptstadtkongress Medizin und Gesundheit 2018 [24], the Demografiekongress 2018 [25], the Zukunftskongress 2019 - Mensch-Technik-Interaktion [26], and the Clusterkonferenz Zukunft der Pflege 2019 [27].

Fig. 7. A patient at the Demografiekongress 2018 live testing the robotic system.

As Hersh [6] explains in her work, a good robotic solution involves the end-users in all stages of design and development. Therefore, the feedback from patients has been fundamental for the development of our use cases throughout the project runtime, from the beginning in 2017 till today. As mentioned before, the implemented use cases were selected after surveying ALS patients and caretakers [14].

At the Demografiekongress 2018 in Berlin, a first testing with ALS patients was held in the uncontrolled congress environment, a drastic contrast to a robotics laboratory. In total, five different patients took part and tested the scratching and drinking use cases. The patients were in varying stages of the disease, from slight motor impairments to a near-complete loss of their motor functions in arms and legs. Despite the obvious motor impairment, they still have tactile perception and thus are sensitive to physical stimulus.

The patients' feedback enabled us to develop a safer robotic manipulator and to consider and include the actual needs of the patients.

For example, the users emphasized the value of scratching, as it increases their independence from caregivers. They were delighted to use the robot to scratch themselves without needing to depend on someone else. Importantly, they expressed interest in new technologies which can provide them with more autonomy in their everyday life, and the importance of being able to control the interface with their own computer and input devices without the need of extra training or readjustment.

V. Conclusions and Future Work

In this work, we have presented a new robotic assistant for ALS patients, which increases their autonomy, and helps them to regain part of their independence. This research is done taking feedback from the affected persons and their caregivers, their real needs and expectations about a care robot assistant into account.

All provided robot capabilities are easily integrated with existing patient's computer interfaces. The independence from any specific input device makes it possible to use the system without special training, even for patients with, in the late stages of ALS, substantial motor impairment.

Using a compliant robot, physical human-robot interaction is successfully achieved. However, this research will focus in the future on integrating, for example, more sensors to predict the full body pose of a user and improve skin-robot contact. For this purpose, force profiles for different body regions will need to be developed and additional safety considerations implemented, as stated by the ISO standards [3], [4].

Since object interaction is a great part of our daily lives, an expanded skill library will be necessary to support patients to substantially increase their autonomy. However, both supporting patients with shared control while maintaining their flexibility and freedom in choosing object-related actions with only a finite set of primitives remains a challenge for future research. Additionally, this research would also like to consider mobility of the robot arm, for example attaching it to a wheelchair, which has been also requested by the patients.

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