Individualised and adaptive upper limb rehabilitation with industrial robot using dynamic movement primitives

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***Abstract*—Stroke is a leading cause of serious long-term disability. Post-stroke rehabilitation is a demanding task for the patient and a costly challenge for both society and healthcare systems. We present a novel approach for training of upper extremities after a stroke by utilising an industrial robotic arm and dynamic movement primitives (DMPs) with force feedback. We show how pre-recorded and learned DMPs can act as basis exercises, that can be modified into individualized and adaptive rehabilitation exercises that fit with the patient's physical properties and impairments. We conclude that our novel approach allows for easy and flexible set-up of rehabilitation exercises and has the potential to provide the therapists and patients much easier interaction with such complex technology.**

I. Introduction

Stroke is a leading cause of serious long-term disability and reduces mobility in more than half of stroke survivors age 65 and over [1]. Rehabilitation after a stroke is a huge and demanding task for the patient and a costly challenge for both society and healthcare systems [2], [3], [4].

Several studies have shown that after a stroke, increased amounts of task repetition causes cortical changes and functional improvement [5], [6], thus, letting the brain re-learn to control the paralysed muscle groups [7], [8], [9].

Depending on the nature of the functional impairment, the patient is often unable to perform exercises without the help and physical support of a therapist. This decreases amount of task repetitions practically possible. In the Patient@home project we aim at making a robotic system which is able to rehabilitate the upper extremities. The system must be flexible enough to support and be adaptive to the many different impairments that people suffer after a stroke. One solution to this challenge is to provide the therapist with a standard set of rehabilitation exercises that can be individualized for each patient. This will make it less time consuming for the therapist to set up a specific exercise - e.g. seen in contrast to having to record each specific exercise for each patient.

Many other projects investigated the use of electromechanical and robotic devices for rehabilitation [10], [11], [12], however, those systems usually do not use feedback or modification of training movements during the training process and, therefore cannot adapt to particular needs of a specific person. Currently, within the field of robotics, *dynamic movement primitives* (DMPs, [13], [14]) are some of the most common choices for generation of robot motions, due to their attractive features such as generalization to new start-/end-points, robustness to perturbations, and ability to modify trajectories on-line by ways of learning and/or sensory feedback. Recently, the usage of movement primitives in rehabilitation and physiotherapy has been suggested by N. Hogan and D. Sternad [15].

Here, we present a novel approach for training of upper extremities by utilising an industrial robotic arm and DMPs with force feedback [16], where a set of pre-recorded and learned DMPs act as training exercises for individualized and adaptive rehabilitation exercises that fit with the patient's physical properties (e.g., short arms vs. long arms) and impairment.

II. Methods and Materials

Our setup consists of a UR5 industrial robot from Universal Robots, A Robotiq force-torque sensor, a PC for running the developed java control software and a tablet for running the web-application. Our robot control software is built upon the RobWork framework [17], which is a collection of C++ libraries for simulation and control of robot systems. We mounted a handle on the force-torque sensor allowing the user to grab hold of the robot. Additionally, gloves with Velcro and wrist support are used to support patients that do not have enough grip strength to hold on to the handle.

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First, a basic set of training trajectories (exercises) is recorded using the UR5 robot-arm. This set is based on standard exercises used at the neurorehabilitation department at Odense University Hospital, Denmark, and include supination and pronation of the forearm and wrist, as well as flexion and extension of shoulder and elbow as shown in Figure 1. Usually, these exercises are done along a table surface, such that the arm's weight is supported by the table. In this project, the robot replaces some of the support provided by the table, giving physical support to overcome both gravity and friction. The basic set of movement primitives chosen are 1) straight movement (translation) of the arm, 2) a rotation of the wrist, and 3) curved movement.

(a) Flexion extension (b) Pro-/supination (c) Rotation

Fig. 1. Images of three basic exercises.

Afterwards, these trajectories are encoded and learned by using a version of DMPs for interaction learning as proposed by [16]. We use force feedback in order to modify and adapt trajectories on-line. Note, that in our case a reaction to forces is not learned, but predefined manually.

Finally, learned DPMs are used for individualised training by

- changing start-/end- points of given movement primitive;
- combining primitives, e.g., translation of an arm with a rotation of a wrist;
- altering velocity profile of the movement;
- altering position profile of the movement based on robot-patient interaction by utilising force feedback.

III. Results

What is presented here is a series of results, that each count as foundational building-blocks in our overall approach to making a flexible and adaptive rehabilitation partner for individualised rehabilitation. Figure 2 a) shows how therapist and "patient" together define basic exercises, which are then recorded through the browser interface where from the therapist and patient can initiate recording and execution of training exercises. This interface is also used to allow the patient to later train using adapted / adapting versions of the originally recorded exercise.

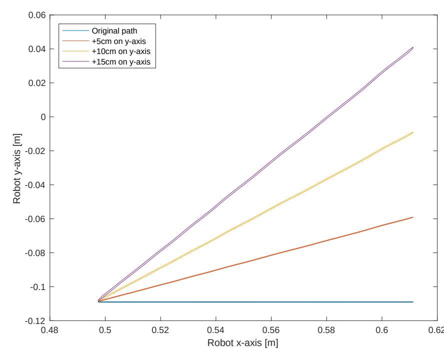
A. Changing of start- and end-points

Changing start- and endpoints is an important necessity, when configuring exercises for different types of patients and impairments. First, patients rarely have identical physical properties, which means range of motion is different. Second, different types of impairments means different types of patient

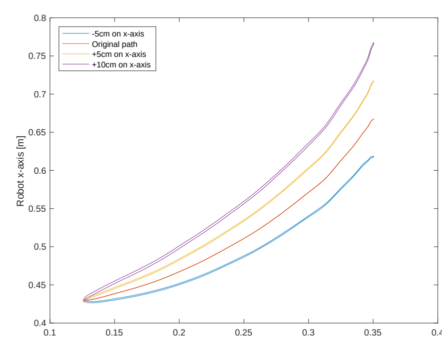
(a) Recording exercise (b) Patient training

Fig. 2. Setup of the robotic-arm for training.

arrangement during training - e.g. some patients can sit, while others have to be laying down. Therefore the physical placement of the robot arm in relation to the patient is almost never the same. Figure 3 a) shows how we are able to modify the standard flexion extension exercise displayed in Figure 1 a) displacing the endpoint along the y-axis, which would for instance be necessary if a patient is seated at another angle in relation to the robot. Figure 3 b) is displaying the same kind of scaling of the rotation exercise also shown in Figure 1 c).



(a) Flexion extension scaled



(b) Rotation scaled

Fig. 3. Generation of new movement trajectories by changing end-points.

B. Combining primitives

Often, patients train different types of movement separately before combining them. This could for instance be the flexion extension exercise displayed in Figure 1(a) and the pro-/supination exercise shown in Figure 1(b). Merging these two would lead to a forward translational movement while rotating the wrist, while chaining them would lead to an exercise with these two exercises performed in succession.

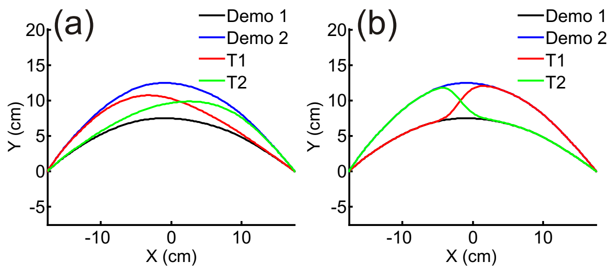


Fig. 4. Simulation results for merging of movement primitives: (a) a gradual transition from Demo 2 to Demo 1 (trajectory T1) or from Demo 1 to Demo 2 (trajectory T2), and (b) an abrupt transition. Demo 1/Demo 2 - learnt demonstrated trajectories, T1/T2 - generated new trajectories.

Simulation examples of generation of new trajectories by merging two basis motions (Demo 1 and Demo 2) are shown in Fig. 4. In panel (a) we show trajectories T1 and T2 which emerge from gradually shifting from Demo 1 to Demo 2 (trajectory T2) or vice versa (trajectory T1), whereas in panel (b) we show emerged trajectories from an abrupt transition. Also, other trajectories can be generated by merging trajectories with different weighing functions.

C. Altering velocity profile

Changing the velocity of an exercise is also key in rehabilitation. Usually, right after a stroke, patients can only move their impaired limbs very slowly - if at all. Building up speed goes hand in hand with building up strength or regaining muscle control, and therefore a robot training partner has to be able to detect and support this progress. Also velocity control is a necessary step in making natural force feedback using the robot force sensor. Figure 5 shows how we change the speed of the flexion extension exercise (Figure 1 a)). The red curve displays the robot back and forward motion at constant speed, while the blue curve shows the motion at varying speed.

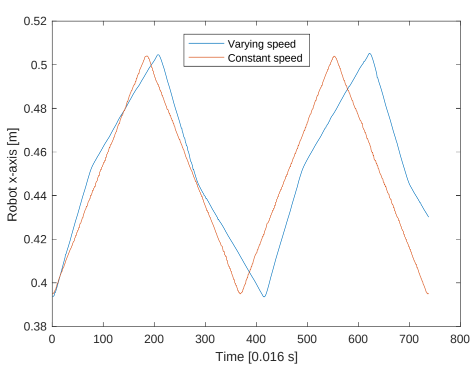


Fig. 5. Generation of trajectories with a varying speed.

D. Altering position profile

During rehabilitation patients often increase their range of motion - e.g. the number of degrees you can rotate around your shoulder joint. Increased range of motion is, like increased speed, a sign of progress in the rehabilitation process, and therefore the robot has to be able to acknowledge this progress - e.g. through its force sensing and adapt by increasing the range of motion accordingly. Using the robot force/torque sensor output we succeeded in first varying the speed of any given exercise with regards to the force applied - allowing the user to only follow the defined DMP path. Figure 6 shows how this is done in simulation. Experiments still have to be conducted on the real robot.

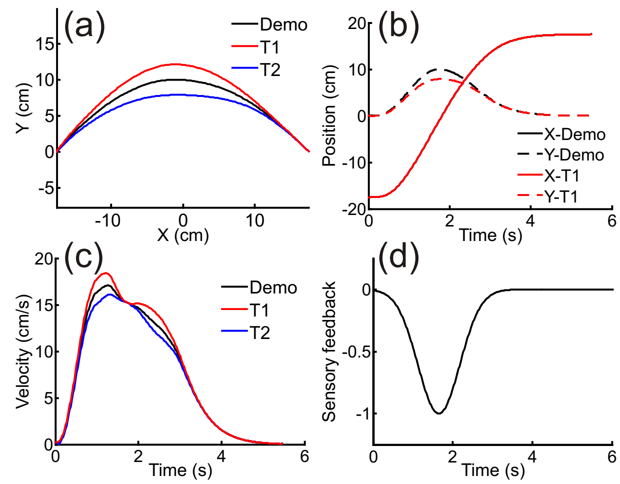


Fig. 6. Simulation results for altering position profile with a sensory feedback (e.g., force): (a) position profiles, (b) X and Y components for trajectories Demo and T1 (see panel [a]; X and Y components for T2 are not shown), (c) squared velocity for both X and Y components, and (d) sensory feedback for the T1 case. T2 was generated using sensory feedback of similar shape as in panel (d) but with a positive sign, i.e., varying from 0 to 1. Demo - learnt demonstrated trajectory, T1/T2 - generated new trajectories using sensory feedback.

We are using this method, so that when the system experiences increasing force exerted at the endpoints of e.g. the flexion extension exercise we can dynamically change the endpoints of the exercise and thereby adapt to the user intentions and/or increased range of motion.

IV. Conclusion

In this study we presented a novel approach for automated training of upper extremities by utilising industrial robot arm and dynamic movement primitives (DMPs) with force feedback. We demonstrated that our approach enables individualised and adaptive training for persons with different physical properties and impairments. Although some parts of this are mainly simulations and still needs to be extensively tested, we see the use of DMPs as a step in the right direction in order to allow for easy and flexible set-up of rehabilitation exercises allowing the therapists and patients much easier control over and interaction with such complex technology.

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