A Bicycle Cranking Model for Assist-as-needed Robotic Rehabilitation Therapy Using Learning from Demonstration

Mahdi Maaref[1], Alireza Rezazadeh[2], Kimia Shamaei[1], Renz Ocampo[1], Mahdi Tavakoli[1]

Abstract—**In recent years, demand for robot-assisted rehabilitation has increased due to the rising number of elderly and disabled people. Rehabilitation robots help patients to enhance muscle strength and recover motor functions, typically through practicing reaching movements. In this paper, we are interested in robot-assisted rehabilitation not only for simple trajectory following tasks but also for cooperative therapy tasks that elicit a force-based or an impedance-based behavior from the patient. When a patient is unable to complete the task, determining the minimum required assistance to be provided to the patient such that the task is accomplished is of interest. In this paper, we develop a Learning from Demonstration (LfD) framework in order to compare the performance of a therapist in multiple trials of the task (*demonstrations* in LfD terms) carried out previously with that of the patient in live performance of the task. Based on this *performance differential*, the LfD framework helps to determine the minimum required adjustment in the task's difficulty level on a patient-specific basis for the task to be completed. To encourage active and free participation of the patient, a dynamic bicycle cranking model is used such that provision of assistance (*reproduction* in LfD terms) is coupled to the variability observed in the therapist's behavior across various trials of the task. Experimental results show that the proposed framework effectively provides the patient with assistance as needed during a cooperative therapy task.**

Index Terms—**List of keywords (Rehabilitation Robotics, Learning and Adaptive Systems, Human detection tracking)**

I. Introduction

THE number of disabled people has been on the rise due to both an increase in the aging population and the number of people who suffer from stroke [1], [2]. For post-stroke disabilities, therapy exercises are prescribed to regain motor function [3]. However, physical therapy resources are limited, resulting in only limited outpatient therapy services being offered to a patient [4], [5]. This demand has motivated the incorporation of robotic systems into rehabilitation programs as robots are able to perform controlled and reproducible motions and are not subject to fatigue. Typically, rehabilitation robots are geared toward practicing reaching movements such that patients' muscle strength and motor functions are restored while freeing the therapist from repetitive actions required during hand-over-hand therapy [6].

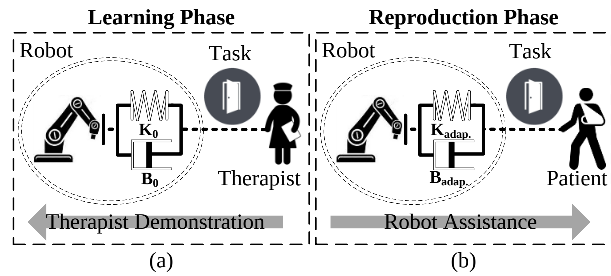

Figure 1: The proposed LfD scheme in a robotic rehabilitation system: (a) Learning (task demonstration by the therapist to the robot) and (b) reproduction (robot assistance to the patient).

In this paper, we are interested in robot-assisted rehabilitation not only for simple trajectory following tasks but also for cooperative therapy tasks that elicit a force-based or an impedance-based behavior from the patient. For instance, assume the rehabilitation robot is controlled to behave as a self-closing door. If pulling this simulated door open is the cooperative therapy task, the human user's hand should display a minimum required impedance. The challenge this imposes is the need for task-specific programming of the rehabilitation robot such that assistance in performing the task can be provided to the patient. Given the limited computer programming know-how available in clinical settings, we present a novel rehabilitation robot programming strategy using the Learning from Demonstration (LfD) framework [7], [8]. In the LfD paradigm developed in this paper, after qualitatively demonstrating [9] the task to the rehabilitation robot by a *perfect user*[1] (the therapist), the robot learns the desired behaviour and gains the ability to reproduce the task in cooperation with an *imperfect user* (a patient) who only affords a reduced contribution towards performing the task.

The proposed method is particularly useful for sophisticated impedance-based rehabilitation tasks in addition to the simpler position-following or force-following tasks. Fig. 1 illustrates the overall idea of presented method which encompasses two distinct phases. The following discussion is framed around a cooperative therapy task involving opening a self-closing door by the patient but not limited to it. The rehabilitation robot is

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controlled to behave similar to a self-closing door. During the first phase ("learning phase"), the therapist interacts with the robot to open the simulated door and complete the task Fig. 1 (a). Based on logged robot-therapist interaction data, the underlying specifications and constraints of this impedance-based task is statistically analyzed and learned by the computer-based robotic system. During the next step, the therapist is no longer in the rehabilitation loop (Fig. 1(b)) and the system adaptively determines the minimum adjustment in the task's difficulty level on a patient-specific basis that facilitates the task completion by the patient. To adjust the assistance based on the learned variability of therapist's behaviour across multiple trials, we propose a dynamic bicycle cranking model in the LfD framework. This is meant to encourage active and free participation of the patient in the cooperative performance of the task.

Previous research [10] has shown that key to an effective therapy is to modify the difficulty level of exercises adaptively, considering the state and progress of the patient. This has motivated recent work on Assist-as-Needed (AAN) therapeutic robotics. Squeri et al. [11] proposed the use of Bayesian mechanism to select the appropriate degree of assistance in human-robot interaction for motor skill learning and rehabilitation.

Pehlivan et al. [12], [13] used adaptive control as opposed to impedance control while using Gaussian radial basis functions (RBF) to model the ability and effort of the patient. Similarly, Wolbrecht et al. [14] proposed a control framework that is capable of compliantly assisting patients only as needed in completing reaching movements. Vergaro et al. [15] used a combination of impedance and adaptive control to adjust the amplitude of the force field according to the patient's performance. The force field generator provides an attractive component directed from the patient's hand to the target position. In [16] Y. Koniyoshi proposed a method to analyze the dynamic body motions by focusing on example of a roll-and-rise motion for a humanoid. In this paper, both variety and boundary conditions of a sample movement are evaluated and a new approach for analyzing of humanoid motion is presented considering the variance of the movement. In contrast to the work presented above, the approach in this paper provides adaptive assistance to a given patient in performance of tasks based on the *performance differential* the robotic system observes between the behavior of the therapist in the demonstrations phase and that of the patient in the reproduction phase. The proposed paradigm allows for teaching a rehabilitation robot the behavior expected from a perfect user (therapist) in performing the task by physically demonstrating it rather than explicitly programming the robot through machine commands. Since the robot learning is based on several demonstrations of the task performance by the therapist, the tolerable variance in the human behavior for completing the task is captured. This results in the ability to regulate the assistance provided to the patient in the reproduction phase based on the variability observed in the therapist's behavior in the demonstration phase.

The benefit of introducing LfD to the robotic rehabilitation therapy can be evaluated from two different perspectives. First, in rehabilitation robotics, conventional programming methods

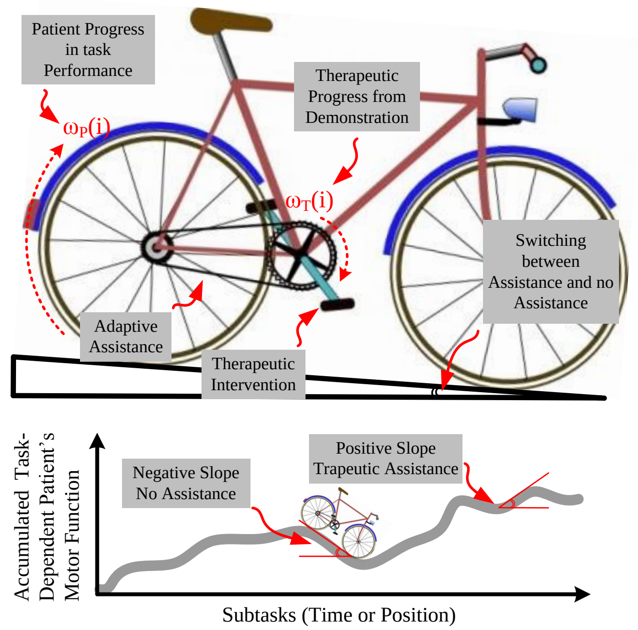

Figure 2: Dynamic cranking model of a bicycle in the i-th subtask (top) and the bicycle model of an entire rehabilitation task performance (bottom). In segments of the road where the slope is negative, the bicycle will be coasting on its own (no therapeutic assistance needs to be provided by the robot to the patient). In segments of the road where the slope is positive, the bicycle will slow down or halt, and the chain wheel needs to be cranked (therapeutic assistance needs to be provided by the robot to the patient).

encounter difficulties. The formulation of robot actions for the activities of daily living (one example of which is door opening) is demanding because it strongly depends on the environment, which is unstructured and may change significantly from one case to the other (in the self-closing door opening example, each door comes with s different spring stiffness). Since daily living activities can robustly be performed by a normal human being without any difficulty, the most promising way to alleviate the problem mentioned above is to take advantage of the human experience and skill in performing daily living activities and to transfer them to the robot via LfD [17].

Another benefit of using LfD for rehabilitation robotics can be evaluated when it comes to learning the variability of the movement. In [18], it is shown that providing variability in training enhances motor function recovery. It is also discussed that fixed trajectory training strategies drive the spinal cord into a state of learned helplessness. So, it is concluded that variable training paradigms appear to be more effective rehabilitative strategies. Since the nature of the LfD method is based on determining the variance of the demonstrated motion across different trials [7], it directly acts as powerful method for serving variable training to patients. In contrast to the similar work in the literature, we obtain this variability from the behavior of a therapist in daily living activities in an LfD context.

II. System Model

The proposed robotic assistance scheme that will be formulated in an LfD context is analogous in operation to the mechanics of a bicycle traveling on a road (see Fig. 2). Two important parameters of this model are transmission ratio and a hypothetical direction of power transmission. For a given therapy task composed of n steps or *subtasks*, the slope of the i-th segment of the road represents the difference between the task difficulty index (TDI) and the patient's motor index (PMI) for the i-th subtask:

$$\alpha(i) = TDI(i) - PMI(i) \tag{1}$$

For a given task and a given patient, $\alpha(i) > 0$ implies that the patient cannot complete the i-th subtask of the task if not provided with assistance. Conversely, the patient does not need assistance in the i-th subtask if $\alpha(i) < 0$.

In the bicycle in Fig. 2, the rear wheel rotates at a speed of $\omega_P(i) \geq 0$, which represents the rate of patient's progress in completing the i-th subtask. The chain wheel represents the therapeutic input and is rotated by the rehabilitation robot at a speed of $\omega_T(i) \geq 0$.

In segments of the road where the slope is negative ($\alpha(i) < 0$), the bicycle will be coasting on its own and, as long as the chain wheel is cranked at a speed lower than the rear wheel ($\omega_T(i) < \omega_p(i)$), it transmits no energy to the rear wheel. The following are the analogous requirements for the proposed robotic assistance scheme (see Fig. 2 (bottom)). In subtasks where the PMI is greater than the TDI, the patient does not require assistance in performing the subtasks, and if therapeutic input from the rehabilitation robot is provided at a rate lower than the patient's progress rate, no assistance should be transmitted to the patient.

Also, in a segment of the road where the slope is positive ($\alpha(i) > 0$), the bicycle (The model is quasi-kinematic and ignores the dynamical effects causing the bicycle's motion.) will slow down or halt (depending on the road segment length), and the chain wheel needs to be cranked at a speed higher than the rear wheel ($\omega_T(i) > \omega_p(i)$) such that sufficient energy is transmitted to the rear wheel in order to move the bicycle to the next road segment. The following are the analogous requirements for the proposed robotic assistance scheme. In a subtask where the PMI is smaller than the TDI, the patient cannot complete the subtask, and therapeutic input from the rehabilitation robot should be provided at a rate higher than the patient's progress rate in order to provide sufficient assistance to the patient to move to the next subtask. This model is used to simulate the progress rate of the patient and assistance rate of the therapist by means of physical variables such as cranking and moving speeds. Therefore, it is possible to merge these concepts to the LfD framework which will be presented in the following section.

III. Learning the Task

In the context of human-robot interaction, the goal of the learning phase is to analyze the sequences of the human behavior captured during the demonstration of a task and to retrieve underlying specifications and constraints of the interaction. For instance, in rehabilitation applications, the therapist demonstrates the ideal performance of the task to the robot such that the robot can analyze the behavior displayed by the therapist.

The use of statistical approaches such as Gaussian Mixture Model (GMM) for coming up with a generalized form of demonstrated behavior (which can involve motion, force or impedance) has been reported in [19]. A GMM is a probabilistic model obtained as a mixture of a finite number of Gaussian distributions with unknown parameters. Gaussian distribution is able to model the variability of the human's actions in performing the task across various trials.

In this paper, we present a learning model that is capable of characterizing different rehabilitation tasks including position-based (trajectory following), force-based, and impedance-based tasks. For developing the GMM algorithm, knowing the input and output vectors of the task model is of importance. For position-based tasks, the input and output vectors are time and position, respectively. Also, time and force are the input and output vectors of a force-based task model. Finally, position and force are assumed as the input and output vectors of an impedance-based rehabilitation task.

In general, demonstrating a rehabilitation task by a human to a robot involves a certain "trajectory" in the 3-dimensional space of position, force and time – note the meaning of trajectory is extended beyond the position versus time curve in this paper. The trajectory demonstrated by the therapist consists of force variables $\beta^f \in \mathbb{R}^p$ and position variables $\beta^p \in \mathbb{R}^p$, where p is the number of the degrees of freedom (DOF) of the task, and the time variable $\beta^t \in \mathbb{R}^1$. The task is modeled as $\beta = \left[\beta^I, \beta^O\right]$ where β^I is the input vector and β^O is the output vector. For instance, for an impedance-based task, $\beta^I = \beta^p$ and $\beta^O = \beta^f$. A GMM can be rewritten as

$$f\left(\beta\right) = \sum_{i=1}^{K} \pi_i \mathcal{N}(\beta|\mu_i, \Sigma_i) \tag{2}$$

where

$$\mu_i = \begin{bmatrix} \mu_i^I \\ \mu_i^O \end{bmatrix}, \Sigma_i = \begin{bmatrix} \Sigma_i^I & \Sigma_i^{IO} \\ \Sigma_i^{OI} & \Sigma_i^O \end{bmatrix} \tag{3}$$

In the above, $\mathcal{N}$ denotes the probability density function (pdf) of the multivariate $(2p+1)$-dimensional Gaussian. The model parameters include the number of mixture components (number of Gaussian distributions) K, prior weights π_i, means μ_i, and variances Σ_i.

In the presented approach, the output vectors are evaluated in both of the *Demonstration* and *Reproduction* phases. Therefore, we use β_D^O and β_R^O to denote the output vectors capturing the behaviour of the therapist and the patient, respectively.

For the purpose of reconstructing a unified model of the task, we apply Gaussian Mixture Regression (GMR) to the GMM. GMR allows to extract a single generalized model made up from the set of input/output pairs (dataset) that were used to train the GMM. The generalized model encapsulates all of the essential features of the dataset and can predict the outputs using new inputs that are not necessarily in the dataset. Position and time vectors are provided as query points and the

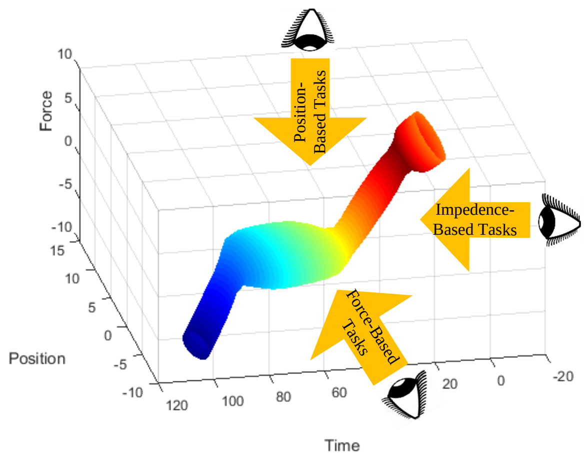

Figure 3: Probabilistic encoding of the demonstration in the force-position-time reference system for a trajectory following task. For trajectory following tasks, the projection of the mesh in the position-time coordinates characterizes the task. Similarly, the projection of the mesh in force-time and force-position planes represents the essential task data for force-based and impedance-based tasks respectively. We have used different colors in this figure to show a mesh in a 3D space.

corresponding output force vector is estimated by the GMR as [20], [21]:

$$f\left(\beta^O|\beta^I\right) = \sum_{i=1}^{K} \varpi_i . \mathcal{N}_{2p+1}\left(\hat{\mu}_i, \hat{\Sigma}_i\right) \tag{4}$$

In the above,

$$\begin{aligned} \hat{\Sigma}_i &= \Sigma_i^O - \Sigma_i^{OI}\left(\Sigma_i^I\right)^{-1}\Sigma_i^{IO} \\ \hat{\mu_i} &= \mu_i^O + \Sigma_i^{OI}\left(\Sigma_i^I\right)^{-1}\left(\beta_i^I - \mu_i^I\right) \\ \varpi_i &= \frac{\pi_i \mathcal{N}\left(\beta^I \mid \mu_i, \Sigma_i\right)}{\sum_{j=1}^{K}\pi_j \mathcal{N}\left(\beta^I \mid \mu_j, \Sigma_j\right)} \end{aligned} \tag{5}$$

So, the conditional expectation of output vectors is approximated by a single Gaussian distribution with the following parameters [20]:

$$\begin{gathered} f\left(\beta^O|\beta^I\right) = \mathcal{N}_{2p+1}\left(\hat{\mu}, \hat{\Sigma}\right) \\ \hat{\mu} = \sum_{i=1}^{K}\varpi_i . \hat{\mu_i} \quad , \quad \hat{\Sigma} = \sum_{i=1}^{K}{\varpi_i}^2\hat{\Sigma}_i \end{gathered} \tag{6}$$

Fig. 3 depicts the probabilistic encoding of the demonstration of a simple trajectory following task in the force-position-time coordinate system after applying Gaussian process (GMM and GMR) to the dataset.

Since the aforementioned 3D mesh contains essential data that characterize the performance of a task in terms of the required position, force and time, it can be useful for various types of rehabilitation tasks. Although daily living activities like door opening are a mix of impedance and trajectory controls, we can simplify and model them in separate domains (Impedance-based or Position-based) by choosing proper input and outputs. This has been done before in the literature where an input vector of force and output vector of impedance are chosen to model a cooperative robotic rehabilitation paradigm. [22] For trajectory following tasks, the projection of the mesh in the position-time coordinates characterizes the task (Fig. 3). Similarly, the projection of the mesh in force-time and force-position planes represents the essential task data for force-based and impedance-based tasks, respectively.

When a patient is unable to complete any subtask of a given task for which the performance expected from a perfect user was learned by the robot in the previous section, determining the assistance to be provided to the patient such that the patient can progress to the next subtask may be studied from a task reproduction perspective. Reproduction is based on comparing the performance of a therapist in demonstration of various subtasks with that of the patient. Based on this *performance differential*, the LfD framework helps to determine the required adjustment in the subtask difficulty level on a patient-specific basis for the subtask to be completed.

To calculate the performance differential, (6) interrogates the previously-demonstrated behavior of the therapist to provide the expected β^O for the present β^I. In the conventional LfD framework, where success in performing the task is the key, exact task reproduction is the focus of the robotic system. In robot-assisted rehabilitation, however, active participation of the patient in therapy exercises is more important. Therefore, in assist-as-needed therapy [2], external assistance is provided only in subtasks that the patient is unable to take to completion in order to promote active participation of the patient.

In order to develop the bicycle cranking model, which governs the provision of therapeutic assistance to the patient in the i-th subtask, we use a PID control law as follows:

$$\begin{aligned} \omega_T(i) &= K.e(i) + I.\int e(i)\mathrm{d}i + D.\frac{\mathrm{d}e(i)}{\mathrm{d}i} \\ \omega_P(i) &= \beta_R^O(i) \end{aligned} \tag{7}$$

where

$$e(i) = step(\beta_D^O(i) - \beta_R^O(i)) \tag{8}$$

Here, in each subtask i, $\beta_D^O(i)$ reflects the therapist's (demonstrated) behaviour using the model presented in (6) and $\beta_R^O(i)$ shows the patient's (reproduced) behaviour during the task performance. Also, in (8), the function $step$ is defined as

$$step\left(x\right) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Since the assistance should be stopped as soon as the patient's performance in any subtask exceeds that demonstrated by the therapist, we use the step function in (8) so that the error is calculated unilaterally. In this step function, x is any arbitrary variable. (Note that the therapist's performance can be greater than or equal to the patient's performance, but there is no need for assistance if the patient's performance is greater than or equal to the therapist's performance). The proportional term produces a therapeutic assistance in the i-th subtask that is proportional to the error between the patient's performance and the *average* demonstrated therapeutic performance in the i-th subtask. A high proportional gain results in a large assistance being provided for a given error. The integral term provides assistance that is proportional to not only the magnitude of the error but also the duration of the error (i.e., across how many recent subtasks has the error persisted). This term accelerates the convergence of the patient's performance towards the demonstrated therapeutic performance and theoretically (i.e., if a task is composed of an infinite number of subtasks) ensures zero error at the end of the task. Note that in the presented control law, the integral term suffers from accumulated errors, which make this term very large. A well-known technique known as integral anti-windup can be used to reset the integral value. The derivative term reacts in prediction to future errors and is meant to slow down the rate of change of the assistance provided to the patient. No term responds to the errors accumulated from the past, it can lead to so much therapeutic assiste that since the integraltance that causes an overshoot in the performance of the patient compared to the demonstrated therapeutic performance. However, given the unilateral error condition imposed by the use of the step function in (8), assistance will cease as soon as the patient's performance in a subtask exceeds that demonstrated by the therapist.

In the above PID law for provision of therapeutic assistance to the patient, it is possible to adaptively change the P, I and D gains such that the patient is actively engaged in the task, that assistance is provided to the patient only as needed and when needed, and that the variability in the therapist's demonstrated performance of the task in the learning phase is taken into account.

$$\begin{aligned} K(i) &= K_0 - K'(\Sigma^2(i) - |e(i)|) \\ I(i) &= I_0 - I'(\Sigma^2(i) - |e(i)|) \\ D(i) &= D_0 - D'(\Sigma^2(i) - |e(i)|) \end{aligned} \tag{9}$$

where $\Sigma^2(i)$ refers to the variability in the therapist's demonstrated performance of the task in the learning phase, which was calculated via GMR in (6). If in subtask i the patient is close to the therapist's average demonstrated performance, then $e(i)$ is close to zero and minimum assistance gains are employed (e.g., $K(i) < K_0$). If in subtask i the patient deviates from the above but is still within the range of the performances demonstrated by the therapist, then the assistance gains are increased (e.g., $K(i) = K_0$ when the patient is following the extreme performances demonstrated by the therapist). If in subtask i the patient deviates significantly from the performances demonstrated by the therapist, the assistance gains are further increased to bring the patient in line (e.g., $K(i) > K_0$).

The above is a therapy model in which the provision of assistance is coupled to the variability observed in the therapist's behaviour across various trials of the task. This will lead to encouraging free participation of the patient as therapeutic intervention (assistance) is more tightly enforced in those subtasks where there is low variability in the therapist's behaviour in different trials of the task.

IV. Results

The apparatus used is an HD2 Haptic Device (Quanser Inc., Markham, Ontario, Canada) that provides 6-DOF position sensing and 6-DOF force feedback. The device has a parallel mechanism that is highly back drivable and has negligible friction. Since the device uses capstan drives, the perceived endpoint inertia is low while the device has a rigid structure. For the purposes of the experiments in this paper, the HD2 device is controlled to only allow movements in the two DOFs that allow spanning the horizontal X-Y plane.

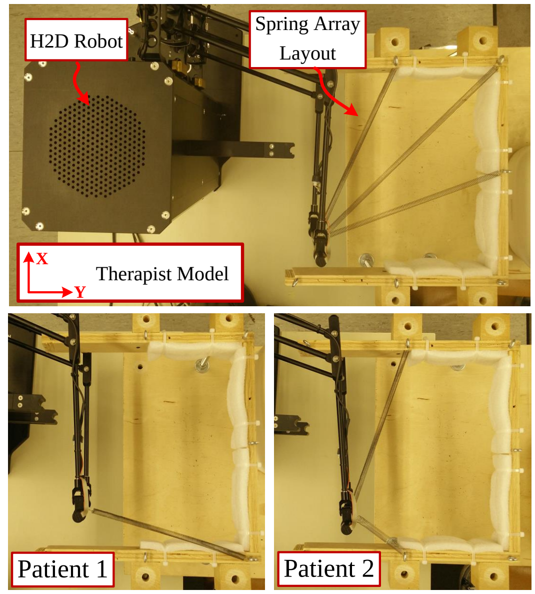

Figure 4: Spring arrays for simulating the behaviours of the patient and the therapist. (Top) First and during the demonstration phase, a symmetric arrangement of three springs is used to pull the self-closing door. These springs simulate the therapist's behaviour. (Bottom) Next and during the reproduction phase, by disconnecting two different springs, two different patients with different disabilities are simulated. In this phase, the robot generates the appropriate external assistance to help each patient with perform the task.

Each experiment consists of the two different phases shown in Fig. 1. For the trajectory following task , a 2-DOF mass-spring array is connected to the robot end-effector as shown in Fig. 4. This mass-spring array emulates both a therapist in the learning phase, and a patient affected by muscle impairment in the reproduction phase. In the first phase, where a therapist is to demonstrate the task performance to the robot, the array's springs are configured symmetrically around the line of motion to be taken by the robot end-effector as the task progresses. In the second phase, where a patient is to try to move the robot in order to perform the task, some of the array's springs are removed such that the remaining springs are no longer symmetric relative to the line of motion such that motor deficiency is simulated. We employ two asymmetric configurations of the springs in order to model two different patients with different motor capabilities. The symmetric (i.e., therapist) and asymmetric (i.e., patient) configurations of the mass-spring array are shown in Fig.4. Finally, in order to evaluate the effectiveness of the proposed method when a real human is involved, we report on the actual behavior of the human in the impedance-based task. Two humans played the roles of the therapist and the patient in this experiment for both the demonstration and the reproduction phases.

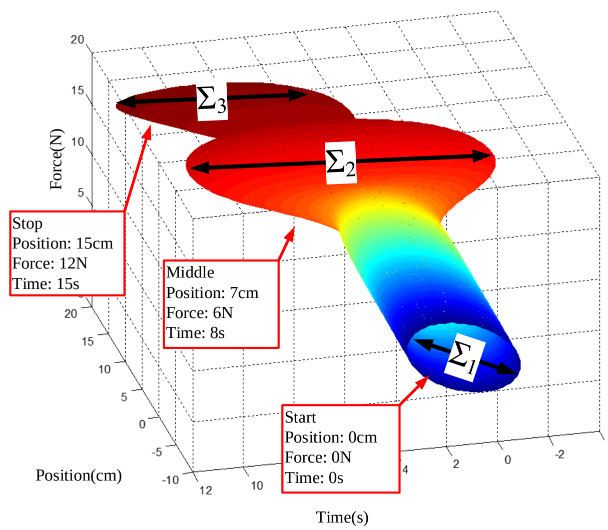

Figure 5: Encoding of the demonstrated behaviour by the therapist. The experiment portrays a scenario simulating a Door Opening Task.This figure illustrates the 3D representation of the trajectory required for successful performance of the task, which consists of time, force and position data. We have used different colors in this figure to show a mesh in a 3D space.

A. Position-based task

One of the highly accepted robot-assisted therapeutic approaches for patients with neurological lesions uses technologies that provide efficient, optimal and affordable means of movement therapy in order to improve motor function by leveraging the brain and spinal cord plasticity [12]. This will help patients regain their lost motor functions. In this context, rehabilitation robots with position-based tasks are seen as good candidates for accelerating neural recovery. Given that the task under consideration is position based, the input and output vectors of the assistance model are time and position, respectively. For evaluating the performance of the presented method for a trajectory-following task, the robot is passive (i.e., uncontrolled) in the learning phase. The number of demonstrations for an efficient reproduction of the task depends on the teaching efficiency of the user; an expert teacher produces demonstrations that explore as much of the variations allowed by the task as possible [7]. In the literature, the number of demonstrations is typically less than 10. For example, in [7], a very complex task of chess piece movement was learnt by a 21-DOF humanoid while the robot was shown the task 4 to 7 times by an expert user. In our experiment, a total of 5 demonstrations was found to be sufficient, each lasting around 10 seconds and therefore resulting in around 1,000 sample points (100 Hz is the data logging rate). For the demonstration, the aforementioned symmetric mass-spring array serving as the therapist is connected to the robot end-effector. The mass-spring array reaches equilibrium when the robot end-effector reaches the target position at the end of the motion. Since the human hand model is closer to a mass-spring-damper system than a mass-spring system, a virtual damper is implemented in the robot controller in order to complement the physical mass-spring model of the human. Some variability is introduced in the therapist's demonstrated performance by changing this virtual damping parameter randomly. The results of the learning phase are given in Fig. 5. This figure depicts the 3D representation of the trajectory required for successful performance of the task, which consists of time, force and position data. In order to illustrate the proposed method, we denote the variability of the therapist's behavior in the start, middle and stop of the motion by Σ_1, Σ_2 and Σ_3, respectively. As it can be seen, Σ_2 is greater than both Σ_1 and Σ_3. This is because the start and stop points for the door are the same across the trials while the trajectory to get from the start point to the stop point varies.

For extracting the essential data that characterizes the performance of the therapist in terms of the required position and time, the projection of the demonstrated mesh (Fig. 5) in the position-time coordinates is traced in Fig. 6(left(a)). In order to evaluate the generality of the method, two different patients have been simulated. As it can be seen in Fig. 6 (left(b)), the patient's performance deviate from the therapist's demonstrated performance, which means the patients cannot complete the task on their own. By using the previously presented assistance model, the robot provides assistance to the patients in the form of robot-generated forces so that the task can be done successfully; see Fig. 6 (left(c)). The magnitude of the assistance is also shown in the same figure. As it can be seen, the assistance is provided more strictly when the patient starts to deviate from the range of performances demonstrated by the therapist. When the patient moves inside the performance range allowed by the variability in the therapist's demonstrated performance, the assistance is provided in smaller extent. No assistance is provided when the patient's performance is equal to the average demonstrated performance of the therapist. Together, these show that the patient is only assisted as needed while promoting free and active participation of the patient.

B. Impedance-based task

The human sensorimotor system includes position and velocity sensory fibers and exhibits variant muscle impedance in accordance with the task at hand [23]. Impedance-based tasks can help the impaired limb to recover from neurological dysfunction and can improve both the motor control and the performance of a paretic arm in chronic stroke patients [24]. Also, impedance-based tasks have the ability of simulating daily living activities such as opening a door, holding and pushing a vacuum cleaner, controlling a dog on a leash, etc.

The impedance-based task we consider is one in which a human opens a self-closing door that displays an impedance due to its self-closing nature (please see the accompanying video file). Since this door has to be moved to a final position, it can be assumed as a position-based task rather than an impedance-based task. Also if a certain speed of movement has to be realized, this task only needs a matching impedance. For defining the door opening task as an impedance-based task, we implement a virtual damper-spring based on model presented in [25] and extend impedance behaviors of the robot requiring to pass through the position trajectory while the

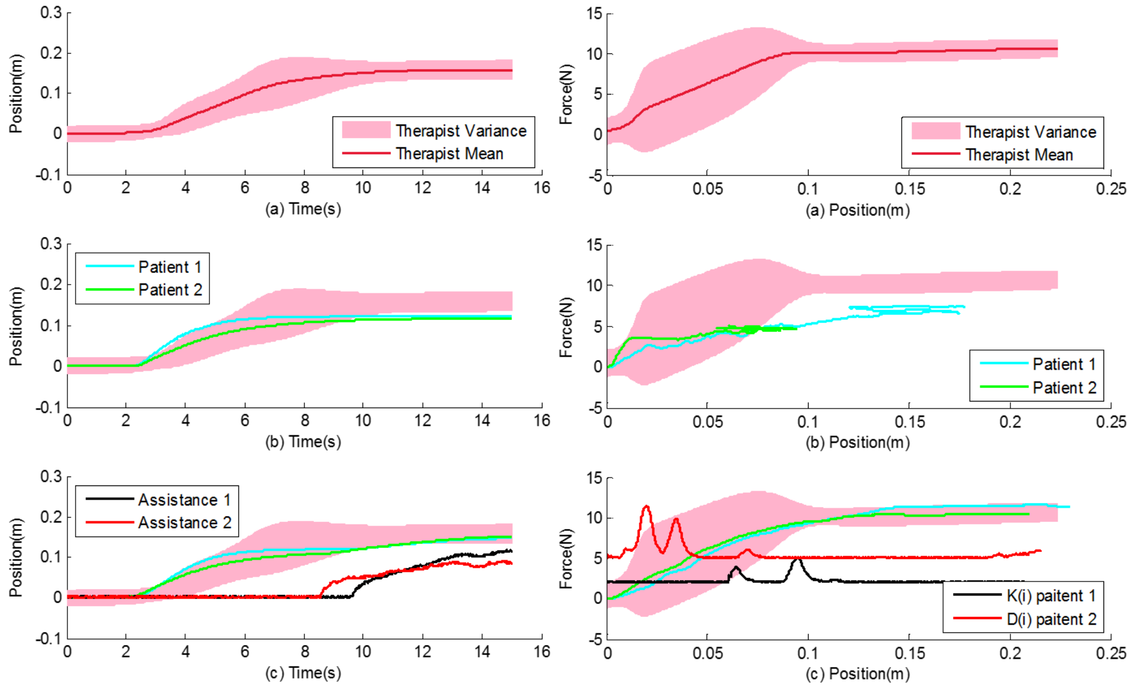

Figure 6: The proposed method as applied to a trajectory following task (left) and an impedance-based task (right). (a) The projection of the demonstrated mesh of the therapist's behaviour in the position-time coordinates (left) and force-position coordinates (right). As it can be seen, the essential characteristics and constraints of the therapist's performance can be extracted based on the mean and the variance in this figure. (b) The task performance of two different patients. As it can be seen, both patients deviate from the therapist's demonstrated performance. In this case, the patients cannot complete the task on their own. (c) Robot provides external assistance as needed to the patients using the presented model so that the task can be completed successfully. The magnitude of the assistance for both of the patients has also been traced in this figure.

position parameters are constraint. To illustrate the above, assume the entire position trajectory is divided to subtasks in which, required impedance has to be shown to move from subtask i to subtask $i+1$. In this case, moving through the position trajectory is not of importance any more and exerting required force in each step of position is necessary. In such a model, we assume every single step of the trajectory as a final position in which a specific force has to be present to keep a constant position. So, In an impedance-based task, the input and output vectors of the assistance model are position and force, respectively.

We will have the HD2 device controlled to behave as the self-closing door. For pulling this simulated door open, the human user's hand should display a minimum required impedance. A total of 5 demonstrations are carried out, each lasting around 6 seconds and therefore resulting in around 600 sample points (100 Hz is the data logging rate).Two humans played the role of the therapist and the patient by grabbing the robot end-effector in the demonstration and reproduction phases, respectively. In the first phase, the person playing the therapist's role demonstrated the task performance to the robot, which consisted of moving the end-effector on an arc in the x-y plane (simulating the door opening task). In the second phase, the person playing the patient's role began to move the robot in order to perform the task but did not exert the required forces for opening the door.

Since the door has a specific impedance, the patient arm should show a minimum required impedance to open the door. In Fig. 6(right(a)), the red line represents the the therapist's demonstrated performance. In contrast to this, in Fig. 6(right(b)), the blue and green line show a large deviation when a patient performs the task without receiving assistance from the robot. By using the previously presented assistance model, the robot provides assistance to the patient in the form of robot-generated forces so that the task can be done successfully; see Fig. 6(right(c)). In order to show that the proposed method provides the assistance adaptively, we show the evolution of the PID gain $K(i)$ for the first patient and $D(i)$ for the second patient in Fig. 6(right(c)). As it can be seen, the gains are changed more rigorously when the patient starts to deviate from the range of performances demonstrated by the therapist while the changes are minimal otherwise. This shows that the patient is only assisted as needed to promote free and active participation of the patient.

V. Conclusion

In this paper, a new framework has been proposed for assist-as-needed rehabilitation therapy in both position-based and impedance-based tasks (as well as force-based tasks). Assist-as-needed therapy is desirable as it encourages active participation of the patient. The main contribution of the work is to develop a Learning from Demonstration based technique for the provision of assistance to the patient. In the learning from demonstration framework, first the robot learns how a healthy person (a therapist) perform the given task and then adaptively interacts with the patient to provide enough assistance so that the patient can perform the task successfully. We describe a bicycle cranking model to mimic the supportive role of the therapist in such a way that the provision of assistance to the patient is coupled to the variability observed in the therapist's behavior. The validity of the proposed approach has been shown using experiments involving symmetric (representing a therapist) and non-symmetric (representing a patient) spring arrays. In future, we will expand our LfD approach to tele-rehabilitation robotics. Finally, we will attempt to bring the proposed paradigm to a clinical setting for patient studies.

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