Kinesthetic Teaching of a Therapist's Behavior to a Rehabilitation Robot

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***Abstract*—The use of robots for rehabilitation has become increasingly attractive in recent years. Robots are capable of providing highly repetitive hands-on therapy for patients. In this paper, we present a robotic system for learning a therapist's behavior when interacting with a patient to complete a therapy task. Learning from Demonstration (LfD) techniques are utilized to statistically encode the therapist's behaviors during interaction with a patient. Demonstrations are provided by having the therapist move the patient (and the robot) during the therapy task, which is known as kinesthetic teaching. Later, reproduction of the therapist's interaction is performed by a robot in the absence of the therapist, allowing a patient to continue practicing the therapy task. The results show the system is able to provide interactions similar to the therapist's demonstrated behavior for a given task.**

***Index Terms*—Robotic rehabilitation, kinesthetic teaching, activities of daily living**

I. Introduction

With an increase in the age of the population, integration of robotic assistance in rehabilitation medicine has grown more attractive in recent years. Robots enable the provision of repetitive, high-intensity hands-on therapy [1]. These benefits are applicable to post-stroke rehabilitation as an example, where repeated activation of muscle motor groups is necessary to reassociate damaged neural structures [2]. Stroke is the fifth leading cause of death globally, causing approximately 6.5 million deaths each year [3]. In Canada alone, stroke costs the healthcare system $22.2B annually [4], leaving more effective and efficient treatments to be desired. Conventional hand-over-hand therapy for stroke patients, in which the therapist would monitor the patient and directly apply assistive/resistive forces when necessary, is too burdensome on the therapist. This limits the amount of time a therapist can effectively spend with a patient which in turn limits the opportunity for the patient to practice.

Rehabilitation medicine has also recently come to focus on practicing functional tasks, also referred to as Activities of Daily Living (ADLs). ADLs take the form of day-to-day tasks such as opening doors, cooking, and dressing to name a few, and are practiced in order to provide gains in neuromuscular coordination that are directly translatable to daily life. Current practice is for therapists to either perform assessments of rehabilitation gains using ADLs in tests, or to perform in-home training for practicing ADLs. Use of ADLs as a focus for stroke rehabilitation has been shown to provide improved independence and quality of life outcomes [5]. This is opposed to the more traditional movement therapy, in which a patient simply moves and exercises their affected limbs. Robots have traditionally been preprogrammed to provide interactions appropriate to predefined tasks, which is sufficient in the simple case of movement therapy. However, ADLs are inherently more complex; the tasks are performed in unstructured environments where task parameters may vary greatly (e.g., the shape of a door handle, the location of the handle, etc.) and full knowledge of the task is unobtainable. As a result, ADL-based therapy has only recently begun to see computer implementation as in [6], and has seen little to no integration with robotics in particular. Despite these limitations, healthy humans can perform ADLs robustly. In order to take advantage of this robustness, rehabilitation robots should be programmed to enable quick redefinition of therapy tasks and the therapeutic behavior by therapists that have minimal programming knowledge. This redefinition happens not by manipulating computer codes but by physically moving the rehabilitation robot as will be explained later.

Learning from Demonstration (LfD) techniques [7] can be implemented to allow for hands-on kinesthetic demonstration-based reprogramming of robots for this purpose. Demonstration refers to the performance of a task which a robotic system observes either indirectly (e.g., through motion capture) or directly (i.e., the robot is moved by the demonstrator through the task trajectory). By statistically encoding behaviors learned through demonstrations, the robot can be programmed intuitively to imitate desired actions such as providing therapeutic forces to patients interacting with the robot. Learning methods making use of Gaussian Mixture Models (GMMs) [8] have become especially prevalent in the field of robotic automation in recent years. These models require relatively few demonstrations for recreation of the demonstrated behavior as opposed to other machine learning methods such as reinforcement learning, and so are ideal for the described scenario [7]. Research in the area of robotic rehabilitation

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has seen a rise in the incorporation of LfD techniques. LfD techniques have been used to succesfully teach a robot to guide a patient through specified trajectories for ADL training [9], [10]. Authors in [11] present an LfD approach that allows an assistive robot to cooperatively dress a user while being able to adapt to the highly unstructured nature of the task. LfD has also been employed to teach robots to assist a patient in completing a trajectory based specifically on the variance of the therapist's demonstrations [12], [13]. However, there is a lack of literature aiming to learn a therapist's impedance, and using the learned impedance to provide assistance to a patient practicing ADLs.

Providing demonstrations to the learning system itself should also be as intuitive as possible. Kinesthetic demonstration provides such an intuitive method. As a first step, this entails making the robot manipulator as compliant as possible to an operator's physical input. For smaller lightweight robots, this can often be achieved simply through the operator's input overcoming the inertia and other dynamics of the robot's mechanical components, i.e., motors. For larger robots, however, this is typically impossible as internal gearing and friction make the structure non-backdrivable. Admittance control is a common technique for introducing compliance in such cases [14]. A force sensor is attached to the robot end-effector. Interaction forces sensed at the end-effector cause movements such that a pre-set dynamic relationship between the applied force and the ensued motion holds. This second method will be employed with the setup presented in this work.

We present a proof of concept system for kinesthetic teaching of rehabilitation robots based upon LfD principles. The system is intended to be kinesthetically programmed by users with little to no programming experience, e.g., physiotherapists. Provided with motion and force data from various demonstrations, the system aims to extract a data-driven model of the therapist's behavior (e.g., the levels of assistive/resistive forces) throughout the performance of an ADL task. This will require a set demonstrations involving both the therapist and the patient completing the task (successfully), and another set involving only the patient attempting to complete the task (unsuccessfully). Through this, a so-called "performance differential" [12] may be defined, inherently describing the therapist's behavior. Fig. 1 depicts a generalization of the system.

The paper is organized as follows. Section II outlines the proposed components involved in the design of the system, and Section III describes the experimental evaluation and presents the results. Section IV provides discussion of results and finally Section V offers concluding remarks and comments on future directions for the work.

II. Proposed Approach

We aim to produce a system that learns and replicates the impedance-based behavior of a therapist in 3-dimensional space, where a robot and two humans (i.e., a therapist and a patient) will perform a collaborative task. The robot manipulator acts as a separate agent interacting with the task, much like how the therapist and the patient will contact the task environment. We fix the robot end-effector having an attached wrist force sensor to the task. We need three components: an admittance controller for making the robot compliant, an algorithm for learning the task trajectory, and an algorithm for learning and reproducing the therapist's impedance-based behaviors. Fig. 2 provides an overview of the system.

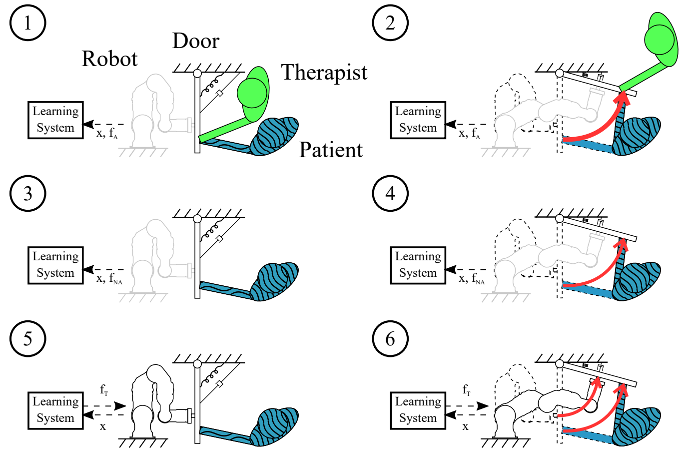

Fig. 1. A generalized diagram for the LfD procedure employed in this work, where in this example the participants open a (self-closing) door. In diagram 1, the therapist and patient cooperatively interact while completing the task, moving the door to the position shown in diagram 2. In diagrams 3 and 4, the patient attempts to complete the task on their own. In phases 1-4, the robot is compliant and only passively observes and records the demonstrations. The learning system then learns the therapist's behavior from the provided demonstrations in phases 1-4. Then, in diagrams 5 and 6, the robot replicates the learnt behavior, allowing the patient to practice the therapy task in the therapist's absence while experiencing the therapist's interactions.

A. Admittance Control Scheme

A simple admittance control scheme is used to introduce compliance to the robot. Admittance controllers produce a desired displacement based on a predefined relationship with sensed forces. In implementation, this takes the form of the transfer function

$$G(s) = \frac{x_{S_{des}}(s)}{f_S(s)} = \frac{1}{\Lambda s^2 + \Psi s + \Gamma}$$

where f_S is the force exerted on the sensor, $x_{S_{des}}$ is the desired displacement of the robot, and Λ, Ψ, and Γ represent the inertia, damping, and stiffness constants, respectively. The control law is given by

$$f_S = \Lambda \ddot{x}_{S_{des}} + \Psi \dot{x}_{S_{des}} + \Gamma x_{S_{des}} \tag{1}$$

Fig. 3 provides a schematic of the admittance control loop. The admittance control adds the displacement $x_{S_{des}}$ calculated from (1) to the robot's current position. As the patient and therapist exert forces on the robot end-effector, the forces measured by the sensor can be expressed as

$$f_S = f_E + f_P + f_T \tag{2}$$

where f_E is the force presented by the task environment, f_P is the force exerted by the patient, and f_T is the therapeutic force exerted by the therapist on the robot end-effector.

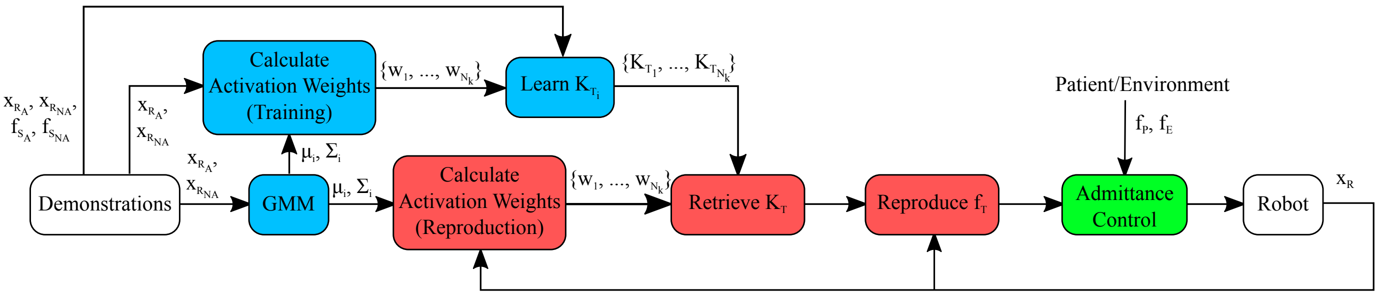

Fig. 2. Process for reproducing the therapist's behavior learned through demonstrations. Demonstrations are provided to train the learning system (in blue). Then, in reproductions, the patient and task environment exert forces on the robot's force sensor. The admittance controller (in green) causes changes in the robot's end-effector position according to the measured forces. Reproduction of the therapist's behavior (in red), which in this scenario is an applied force, is determined using position feedback from the robot and the learned model.

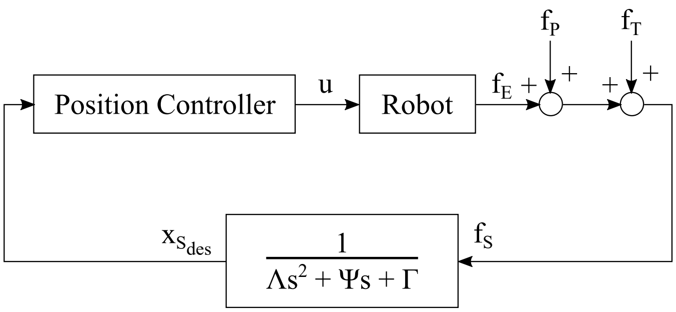

Fig. 3. Admittance control block diagram. The force measured by the force sensor f_S produces the desired displacement $x_{S_{des}}$ through the control law in (1). A position controller produces the robot control torques u using the displacement.

B. Algorithm for Task Trajectory Encoding

LfD is employed in the system to generalize and learn the spatial movements necessary to complete the task. LfD typically involves two separate phases: a demonstration phase where trajectories are learned and statistically encoded, and a reproduction phase where the system performs regression using the generated model to provide a rendition of the earlier demonstrated behavior. A GMM is trained using all demonstrations, providing a probabilistic representation of the motion required to complete the task. GMMs are probability density functions used to cluster data, constructed as weighted sums of Gaussian component densities [8]. This is expressed as

$$p\left(\xi\right) = \sum_{k=1}^{N_k} p\left(k\right) p\left(\xi|k\right)$$

with a total of N_k Gaussian components in the model, $p\left(k\right)$ being the priors, $p\left(\xi|k\right)$ being the conditional density functions, and ξ being a D-dimensional data vector. In this work, $\xi = x_R = \left[x, y, z\right]^T$, is the position of the robot end-effector expressed in the robot's base frame. The parameters $p\left(k\right)$ and $p\left(\xi|k\right)$ are computed through the use of each Gaussian's parameters $\{\pi_k, \mu_k, \Sigma_k\}$, representing the prior probabilities, mean vectors, and covariance matrices, respectively. For details, see [8].

The Gaussian parameters are trained using the Expectation-Maximization algorithm, iterating the parameters until the convergence of an optimization measure (typically the log-likelihood) is achieved. The E-step is of particular interest, where the likelihood or activation weight of each i^{th} Gaussian is computed for each data point ξ as follows:

$$w_i = \frac{\pi_i \mathcal{N}\left(\xi|\mu_i, \Sigma_i\right)}{\sum_k^{N_k} \pi_k \mathcal{N}\left(\xi|\mu_k, \Sigma_k\right)} \tag{3}$$

C. Algorithm for Encoding Therapist's Impedance-based Behavior

We propose that during performance of a task, the interaction forces exerted on the robot end-effector by each of the agents (task environment, patient, therapist) can be simplified as a set of spring forces, linearized about points of the demonstration. We then rewrite (2) as

$$\begin{aligned} f_S &= f_E + f_P + f_T \\ &= \left(K_E + K_P + K_T\right)\left(x_f - x_R\right) \\ &= \left(K_E' + K_T\right)\left(x_f - x_R\right) \end{aligned} \tag{4}$$

where x_f is the approximate position of the task goal point (taken as the average of the demonstration endpoints), and K_E, K_P, and K_T represent the stiffnesses of the linearized task environment, patient, and therapist, respectively. As the system aims to learn specifically the therapist's force, we combine the spring constants for the patient and the task environment forces into K_E', i.e., $K_E' = K_E + K_P$.

Demonstrations will be recorded for two cases: when the task is performed by the therapist and the patient together (assisted), and when the patient attempts to perform the task by themselves (not assisted). We define the spring constants linearized from the data associated with these cases as $K_A = K_E' + K_T$ and $K_{NA} = K_E'$, respectively. The spring constant for the therapist's force can then be estimated from the difference between the assisted and unassisted spring constants as follows

$$K_T = K_A - K_{NA} \tag{5}$$

Estimation of the linearized spring constants will be performed in a manner similar to [15] and [16]. Weighted Least Squares (WLS) estimation is used to compute the

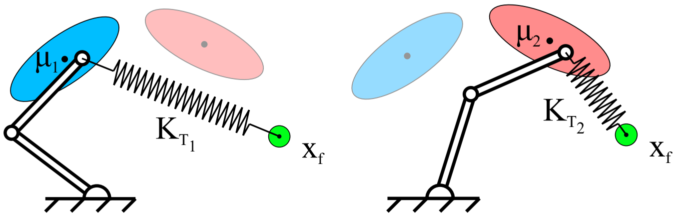

Fig. 4. Simplified diagram of position-based impedance retrieval for reproduction of the therapist's behavior. In (a), activation weights for the first Gaussian component (colored blue) are highest when the robot is in close proximity to the component. A stiffness constant is retrieved for the corresponding Gaussian and used to generate the forces learned from the therapist. In (b), a different stiffness constant is used when the patient progresses into the spatial coordinates associated with a different Gaussian component (colored red). In actual reproduction, the retrieved stiffness constant may be a mixture of the learned stiffness constants influenced by multiple components, instead of a single constant from the influence of a single component as shown here.

stiffness constant associated with each Gaussian component $K_i = \left[\left(X^T W_i X\right)^{-1} X^T W_i F_S\right]$, where by concatenating all N datapoints from every demonstration together, we have $X = \left[(x_f - x_{R_1}), \ldots, (x_f - x_{R_N})\right]^T$, $W_i = \mathrm{diag}\left([w_{i_1}, w_{i_2}, \ldots, w_{i_N}]\right)$ as calculated in (3), and $F_S = \left[f_{S_1}, f_{S_2}, \ldots, f_{S_N}\right]^T$. In this work, we assume no correlation exists between forces and positions across different Cartesian axes. As a result, the WLS estimation is performed for each axis and all spring constant matrices simplify to $K_i = \left[K_{i_x}, K_{i_y}, K_{i_z}\right]^T$. K_A and K_{NA} are estimated for each Gaussian component in this way, where position and force data from the assisted demonstrations are used in X and F_S to calculate K_A, and from the unassisted demonstrations to calculate K_{NA}. Then, the estimated K_T for each Gaussian component is taken as the difference between K_A and K_{NA} as in (5).

In the reproduction phase, the estimated therapist force applied by the robot is given as

$$f_T = \sum_{i=1}^{N_k} w_i \left[K_{T_i} \left(x_f - x_R\right)\right] \tag{6}$$

where K_{T_i} is the therapist's stiffness associated with each i^{th} Gaussian component, calculated as described previously. The robot's position x_R is used to calculate the weights w_i of each component. The applied force f_T is then given by the mixture of the spring forces from all of the components according to the robot's distance from the target point. Fig. 4 depicts this concept.

III. Evaluation

A. Experimental Setup

We evaluate the system on a simple cooperative task where the participants open a drawer fully. The drawer has a spring attached to its back, which resists the opening movement and tends to return the drawer to its closed position. In the experiments, the patient is emulated by a spring attached to the front of the drawer, which tends to open the drawer. The

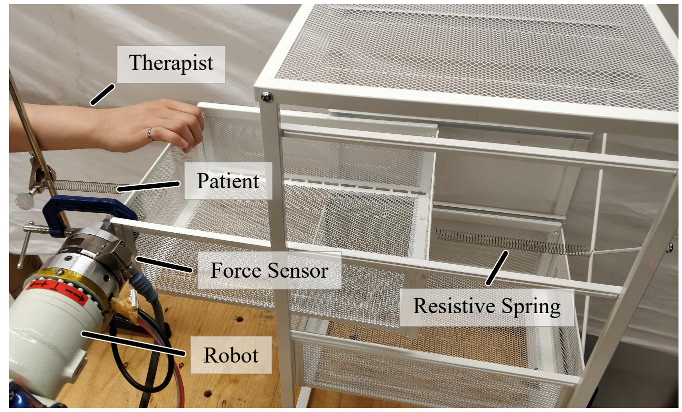

Fig. 5. Experiment setup.

constants of the resistive and patient springs are equal, but the springs come to relaxation at a point before the drawer is fully opened. This means the emulated patient cannot complete the task alone. A Motoman SIA-5F (Yaskawa America, Inc., Miamisburg, Ohio, USA) seven Degrees-of-Freedom (DoF) serial manipulator is used as the rehab robot, with a 6-DoF ATI Gamma Net force and torque sensor (ATI Industrial Automation, Inc., Apex, North Carolina, USA) attached at the wrist joint before the end-effector. The therapist is represented by an able-bodied participant. Fig. 5 shows the experimental setup.

The admittance parameters in (1) were chosen experimentally, where Λ and Γ were given values permissive to free movement, while the damping parameter Ψ was given a higher value and decreased until instability was observed. Final values for admittance parameters are given as $\Lambda = 0$, $\Psi = 5$ N·s/mm, and $\Gamma = 0.1$ N/mm.

Three demonstrations are performed for each of the assisted and unassisted scenarios, providing six demonstrations in total. In the assisted scenario, the user representing the therapist provides assistance when the motion of the patient alone begins to slow. In the unassisted scenario, the spring representing the patient is allowed to pull the drawer to equilibrium. To acquire more data, the drawer is moved to its fully extended position and released, moving against the patient back to equilibrium. Complete force profiles for the full motion trajectory are generated for the unassisted case in this manner.

B. Results

A model of 12 components $(N_k = 12)$ was generated from the provided demonstrations. This selection is partially motivated by the biomechanics of human reaching movements; a person first accelerates their hand, travels towards the goal at velocity, and finally decelerates to accurately end their movement. As such, we choose the number of components to be a multiple of three. Fig. 6 shows the generated model against the training data. The learned model is then used to estimate the spring constant values K_{T_i} as described in Section II-C.

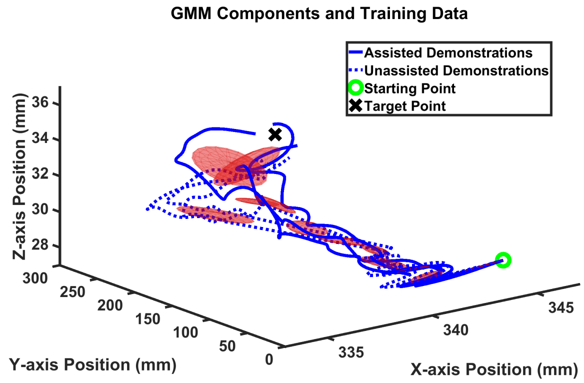

Fig. 6. Decomposition of motion trajectory into $N_k = 12$ components using a GMM.

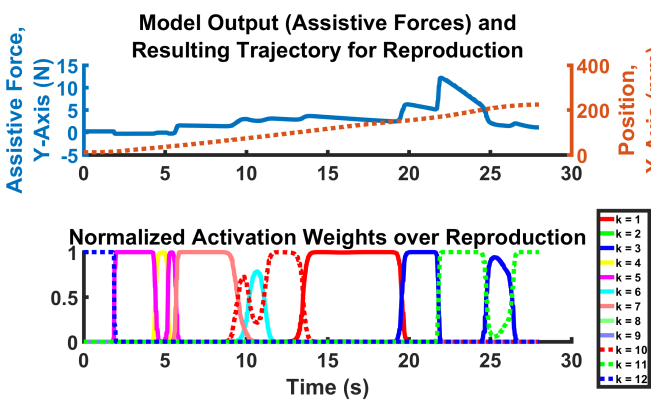

Fig. 7. Reproduced assistive force output and component weights for a patient-only reenactment of the task. The model outputs a noticeably large force for the $k = 11$ Gaussian component.

The system is then evaluated in the real-world experimental setup. The drawer is released from its initial closed state with only the patient-emulating spring and the rehab robot acting against the resistive spring to open the drawer. Since the motions and forces associated with the task are almost completely in the y-axis, only those results are shown hereon. Resulting trajectory and force data is captured in Fig. 7.

We compare the resulting net forces from the reproduction to the mean of those obtained during demonstrations. The force profiles are arranged against their respective position profiles, shown in Fig. 8. Note that for plotting purposes, the net reproduction force data is calculated by summing the model's assistive force f_T, obtained from (6), with the sensor's perceived force f_S. Mean absolute error (MAE) for the reproduction is found to be $MAE = 1.8763$ N with the maximum instantaneous absolute error found as $AE_{max} = 8.012$ N. Lastly, the datasets have a correlation coefficient of $\rho = 0.4034$.

IV. Discussion

Reproduction of the therapist's assistance is performed successfully. When releasing the drawer from its initial closed position, the system is able to command the robot to assist

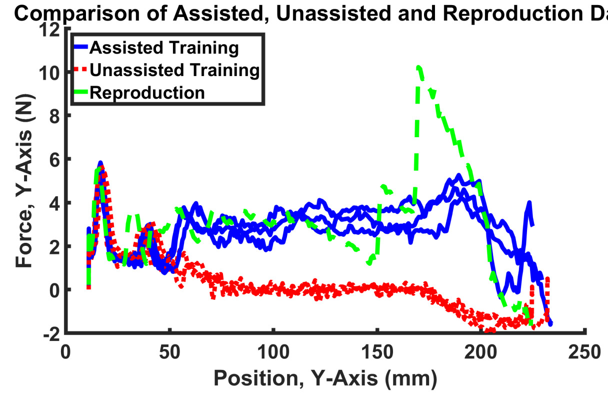

Fig. 8. Net force profile comparisons across reproduction and training datasets. The unassisted case force data is in dotted red, the therapist-assisted case force data is in solid blue, and the robot-assisted data is in dashed green. The model force output closely matches that of the therapist demonstrations until nearer to the target point; the forces afterwards provide sufficient assistance to complete the task, but are noticeably higher.

the patient in opening the drawer fully. No sudden, unsafe movements or moments of instability were observed. However, the MAE and correlation appear to indicate that the system produces only a moderately accurate reproduction of the therapist's assistive force. The results presented in Fig. 8 provide some insight on a possible source of the error. The system reproduces appropriate force output with minimal discrepancy for the majority of the period in which there is therapist intervention, roughly between $y = 50$ mm and $y = 170$ mm. However, forces after this point quickly diverge from the real therapist's and are responsible for the high AE_{max}. Relating this to Fig. 7 identifies the Gaussian component $k = 11$ as potentially problematic. This is likely because the demonstration data have greater variance near the end of their trajectories, as seen in Fig. 6. Gaussian $k = 11$, which is nearest to the target point, must cover a larger spatial volume than most of the other Gaussians. However, the linearization of the assistive stiffness constants may be too general as a result. A finer resolution is needed for the model, but simply adding more Gaussian components may be an impractical solution as it increases model complexity and computation time, making the system less user-friendly. The EM algorithm may also place the additional Gaussian components away from that portion of the trajectory anyways. A possible solution would be to restructure the task in order to take advantage of more sophisticated Gaussian modeling methods such as the Stable Estimator of Dynamical Systems (SEDS), which provides a global-asymptotically stable task model [17].

With regards to the compliant nature of the system, the results are satisfactory. The system is kinesthetically movable, but not transparent to an ideal degree since the damping coefficient is high. Implementing an adaptive admittance controller, such as in [18] or [19] is a possible solution where the controllers adapt the admittance parameters online in response to parameters like the force tracking error or signal energy. Alternatively, an impedance controller can be used with torque control. The robot dynamics would be required however, which are not readily available in this case.

V. Conclusion

In this paper, kinesthetic teaching of a robot was used for learning a therapist's behavior from recorded demonstrations. GMMs were used as the basis for learning the movements necessary for completing an activity of daily living task, and an assistive force was reproduced by the robot based on estimations of the therapist's impedance-based behavior in the therapist's absence. We show that the system is able to properly reproduce the therapist's behaviors to assist a patient in completing the task. Future work will aim to incorporate improved learning algorithms that better generalize across demonstrations. We will also incorporate assistance-as-needed (AAN) features, in which the robot delivers assistance depending on the patient's performance.

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