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Ways to Learn a Therapist's Patient-specific Intervention: Robotics- vs Telerobotics-mediated Hands-on Teaching

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Abstract— **Due to the limitations of therapists time and healthcare resources to cover the increasing demand for rehabilitation services, robot-assisted rehabilitation is becoming an appealing, powerful and economical solution. In our previous research, a solution that combines Learning from Demonstration (LfD) and robotic rehabilitation to save the therapists time and reduce the therapy costs was proposed. In this paper we compare two modalities, Robot- and Telerobotic-Mediated Kinesthetic Teaching (RMKT and TMKT), for implementing LfD in robotic rehabilitation. Our results show that behaviors demonstrated in both modalities are able to be imitated accurately, but demonstrations in TMKT have less repeatability.**

I. Introduction

Recent increases in demand for rehabilitation therapy combined with limited therapist time have created a significant burden on healthcare systems worldwide. In order for patients with a disability to regain neuromuscular coordination, they must engage in repetitive exercises, typically under the supervision of experienced therapists. Traditionally, therapies can be divided into three categories: assistive therapy (therapist assists the patient to complete the task), resistive therapy (therapist opposes the patient's actions), and functional therapy (emulating Activities of Daily Living (ADLs)) [1]. This means there is a wide variety of interactions or behaviours that therapists can present to patients.

Rehabilitation robotics is an attractive solution to address the growing demand for rehabilitation services. The behaviours of existing robotic systems during rehabilitative therapies are typically pre-programmed, which is highly restrictive in the presence of unstructured task environments and given the variation in patients abilities and therapists' approaches. This is in contrast to the flexibility with which a skilled therapist can adjust the parameters of conventional non-robotic therapy based on years of experience. To directly incorporate the therapist's skills in robotic therapy for the purpose of providing patient-specific intervention, we propose the combination of Learning from Demonstration (LfD) algorithms and the therapist's experience. LfD is a paradigm focused on allowing a human user to program a robot through demonstration of desired behaviours, as opposed to explicit computer programming [2]. In general, the behaviours are actions or movements to be later imitated by the robot. The paradigm involves a machine learning algorithm that statistically encodes the demonstrations, and performs regression on the learned model at a later time to imitate the behaviours. Physically moving the robot in order to teach it is referred to as kinesthetic teaching.

One important question is, in what manner should the therapist and patient interact with each other to best take advantage of the incorporated LfD paradigm? We explore two modalities here; robotics-mediated kinesthetic teaching (RMKT) where the therapist and the patient interact by using a single robot that learns their movements; and telerobotics-mediated kinesthetic teaching (TMKT), where the therapist and the patient interact using two robots, generally a master-slave system with force feedback. We hypothesize two outcomes:

Hypothesis 1: RMKT will allow a therapist to provide more consistent demonstrations of therapy tasks than TMKT.
Hypothesis 2: RMKT and TMKT can be applied in similar scenarios, allowing for adequate learning and robotic imitation of the demonstrated therapeutic behaviors.

Although we hypothesize that RMKT will provide better demonstrations for LfD algorithms, we would like to show that TMKT, an unexplored concept, is a feasible alternative to RMKT, which has been previously researched and published. Therefore, the main contribution of this paper is to study and develop the basis to support the feasibility of TMKT for rehabilitation with similar results as in RMKT. This paper is organized as follows. Section II discusses previous works and Section III outlines the two robotic interaction modalities. Section IV describes the impedance control scheme used and Section V provides a brief introduction to the LfD algorithms incorporated into the robot control system. Section VI describes the experiments performed and their corresponding results are provided and discussed in Section VII. Lastly, Section VIII leaves off with closing remarks and possible future directions.

II. Related work

A selection of our group's previous works follow. In [3], the authors proposed a paradigm called *learn and replay* to build a bilateral telerehabilitation system that encompasses two distinct phases to save the time of a therapist. In the first phase, the system learns the therapists arm impedance in performing a task. Later, in the second phase, the system uses the learned impedance to imitate the therapist behaviour

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in his/her absence. Note that this system does not use LfD because it does not generalize the learned impedance for different scenarios using statistical encoding methods. In another work [4], the authors developed a robot-assisted rehabilitation system for co-operative therapy combining LfD and Assistance-as-Needed strategies. In the demonstration phase, the system learns the therapists impedance using a statistical encoding algorithm and builds a model of the therapists behaviour. Later, based on the difference between the patients performance and the learned therapists behaviour, the method determines whether to assist the patient in completing the task or not. In [5], the proposed system learned and imitated the therapist's force and motion behaviour using a different encoding algorithm designed to ensure global stability. In [6], an alternative method of learning a therapist's assistive impedance-based behaviour was investigated with the purpose of better parameterizing ADLs. Lastly, in [7] the authors implemented a neural-network-based system for upper-limb post-stroke motor disabilities. Aside of these articles, some authors such as [8], have proposed a similar system where a user interacts with a robot to complete a cooperative task, while [9] [10] proposed a similar cooperative task interaction using Machine Learning algorithms. The biggest difference lies in the fact that these works do not explore implementation in the medical field.

RMKT has thus seen extensive implementation in our works. On the other hand, teleoperation systems have not been implemented in the rehabilitation field using LfD, i.e., TMKT. [3] showed the potential of teleoperation-based systems; now we aim to expand on our works and create the first TMKT systems. In this work, we will design a fair comparison between the two modalities, with the same therapy task used to record experimental data for. Ideally, we will be able to show that TMKT is as feasible and effective as RMKT.

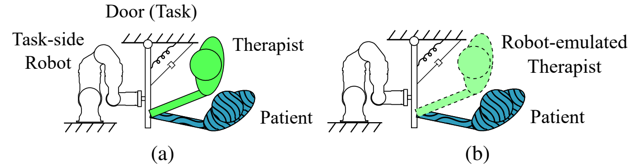


Fig. 1. A generalized diagram for the LfD procedure combined with RMKT applied to a self-closing door task. Note that in this work we are using these concepts to a different task than depicted here. (a) depicts the patient interacting with the therapist and the robot. This demonstration can be taken as the ideal task performance, or used to establish a performance differential between the patient's capabilities and the therapist-patient combined capabilities. Whichever is chosen can be used later in (b), which depicts the patient interacting with the task-side robot at a later time. The robot emulates the therapist's behaviour learned in (a).

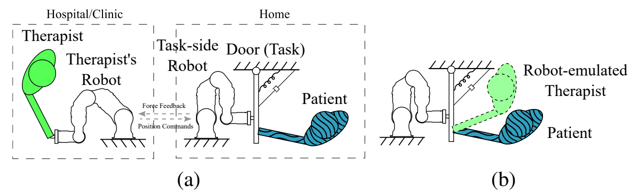


Fig. 2. A generalized diagram of the LfD procedure combined with TMKT. (a) depicts the patient interacting with the therapist through telerobots. Similarly to the RMKT case, a performance differential could be established with these demonstrations, and is, in fact, easier to measure with two separate robots. (b) depicts the patient interacting with the task-side robot at a later time, where the robot emulates the therapist's behaviour.

III. Therapist-Patient Interaction Modalities in Robotic Rehabilitation

The first approach we consider is enabling demonstrations through RMKT. RMKT provides an intuitive method for users to teach the robot movements. This entails making the robot manipulator as compliant as possible to an operators physical input, allowing a user to grasp and move the robot along the desired trajectory. Force or impedance controllers, which use readings from force and torque sensors, facilitate this. Fig. 1 depicts this concept.

The second proposed approach involves a TMKT system. In this approach, our focus is on telerehabilitation through a bilateral (haptics-enabled) TMKT system. Haptic feedback provides a human who operates a tele-robot with a sense of touching a virtual/physical environment. This system can simulate the so-called hand-over-hand therapy [11] over a distance, as shown in Fig. 2. Haptic tele-robots are also the ideal vehicles for moving the rehabilitation process to the home, as the therapist can train different patient-side robots in different houses without changing his/her location. Thus, tele-robots can increase access to and reduce costs of health care for patients living in remote areas [12]. One aspect of teleoperation to keep in mind is the possibility of delay. Given that TMKT incorporates LfD, the training process occurs offline. Therefore, during the imitation phase, there is no interaction between the two robots. As a result, the system does not present any delay.

Note that both approaches are performed with the therapist and patient interacting concurrently with the robot to perform demonstrations. It is possible to have the therapist and patient provide demonstrations of their guidance and capabilities in a sequential manner, where two sets of demonstrations would be recorded (one with the therapist performing the task alone, and one with the patient alone). While the sequential method makes establishing a performance differential easier, concurrent demonstration more closely resembles conventional, non-robotic rehabilitation in which the therapist and patient frequently interact to practice therapy tasks together. Also, for this work, we only require the robot to imitate the ideal task performance, without the need for establishing a performance differential. Lastly, variation in the therapist's performance is akin to patient variation in concurrent demonstration as the robot sees a fusion of the therapist and patient, thereby making each demonstration patient-specific.

IV. Impedance Control for Therapist-Patient-Robot Interaction

An impedance control scheme is selected to allow the therapist and patient to interact with one robot in the RMKT case safely, and for the therapist's robot to move the task-side robot in the TMKT case. Impedance controllers produce the desired force based on a predefined relationship with the robot's motion. We use a heavier industrial robot in this work, with internal gearing in the joints. These kinds of robots are typically impossible to move passively. Implementing impedance control allows for a user to move geared robots easily. Impedance controllers also remain stable when in contact with environments with high impedance, such as a human gripping and holding a robot in place [13]. Impedance controllers require the dynamics of the robot to be well modelled [14]. In our scenario, the robot dynamics can be written as

$$M_r\left(\theta_s\right)\ddot{\theta}_r + C_r\left(\theta_r, \dot{\theta}_r\right)\dot{\theta}_r + g_r\left(\theta\right) + f_f\left(\theta_r, \dot{\theta}_r\right) - J_r F_e = \tau_r \quad (1)$$

where θ_r represents the robot joint angles, M_r the moment of inertia matrix, C_r the Coriolis and centrifugal matrix, g_r the gravity vector, J_r the robot's Jacobian, f_f the robot's joint friction vector, F_e the force exerted by the patient on the robot end-effector, and τ_r the controller's output motor torque. The dependence on θ_r will be dropped for brevity. The non-linear terms M_r, C_r, g_r and f_f can be roughly modelled, but will likely be inaccurate, potentially leading to undesired dynamics.

The Time Delay Estimation (TDE) method (as in [3], [15]) is used here to reduce the inaccuracy when estimating these non-linear terms. We encourage reading these works for further details. We then take the desired impedance dynamics to be given by a mass-spring-damper model

$$M_d\left(\ddot{x}_r - \ddot{x}_{r,d}\right) + B_d\left(\dot{x}_r - \dot{x}_{r,d}\right) + K_d\left(x_r - x_{r,d}\right) = \tau_r \quad (2)$$

where M_d, B_d, and K_d represent the desired mass, damping, and stiffness impedance parameters and x_r represents the robot's Cartesian end-effector position. Using the relationship between Cartesian and joint space acceleration

$$\ddot{x}_r = J_r\ddot{\theta}_r + \dot{J}_r\dot{\theta}_r$$

we can combine (1), the dynamics estimation provided by TDE (not shown), and (2) in order to express the desired robot joint torque controller in Cartesian space:

$$\begin{aligned}\tau_r = \bar{M}_r J_r^{-1}\{\ddot{x}_{r,d} - M_d^{-1}\left[B_d\left(\dot{x}_r - \dot{x}_{r,d}\right)\right. \\ \left. + K_d\left(x_r - x_{r,d}\right) - F_e\right] - \dot{J}_r\dot{\theta}_r\} \\ + \bar{M}_r\ddot{\theta}_r + \bar{C}_r\dot{\theta}_r + \bar{g}_r + \bar{f}_f + \tilde{N} - J_r F_e \quad (3)\end{aligned}$$

We use this final representation of the controller in two different ways. For RMKT, the input comes from the therapist, patient, and environment acting on the force sensor. Therefore, F_e is used as the input signal for RMKT. For TMKT, the input comes from the desired motion of the master robot, given as velocities in this case. $\dot{x}_{r,d}$ is therefore used as the input signal instead. Note that the task performed with the robot will be solely in 1 DOF, greatly simplifying the dynamics model estimation.

V. Learning from Demonstration

LfD is a paradigm focused on allowing a human user to program a robot through demonstration of desired behaviours [2], [16], [17]. In general, the behaviours are actions or movements to be later imitated by the robot.

A cornerstone and driver of our LfD-based approach is the assumption that programming know-how is limited in clinical settings. This requires that reprogramming the robotic system between different tasks must be made as simple and user-friendly as possible. State-of-the-art LfD techniques allow for this and facilitate robot learning based on only a few real demonstrations of the task by a human without any additional computer programming overhead.

LfD is divided into two phases, known as the demonstration and imitation phases. In the demonstration phase, a trainer interacts with the robot and performs an action that is to be learned by the robot. Multiple demonstrations of the task can be completed to provide a wider knowledge base for the robot. The imitation phase then imitates the learned behaviour based on the inputs the robot receives in real time.

In this paper, Gaussian Mixture Models (GMM) and Gaussian Mixture Regression (GMR) are used as the underlying learning and imitation algorithms for the LfD paradigm. The GMM algorithm takes multiple demonstrations and extracts the necessary parameters to describe the data with Gaussian functions. This process avoids redundancy of data in memory. The GMR algorithm uses the stored data and, based on the regression input, retrieves the general form of the output.

A. Gaussian Mixture Models (GMM)

GMM is a probability density function widely used for generatively modelling data [18], [19]. The model parameterizes a set of datapoints and its underlying function as weighted sums of Gaussian component densities, with each Gaussian having its own mean and covariance. Because of the simplistic, adaptable nature of Gaussian functions and the advantages that come with generative modelling, GMM is widely used for LfD.

GMM is a weighted sum of K component Gaussian densities given by the equation,

$$p(\xi_j) = \sum_{k=1}^{K} p(k)p(\xi_j|k) \quad (4)$$

where $p(k)$ are the prior probabilities, $p(\xi_j|k)$ is the conditional density function, and ξ_j represents the D-dimensional continuous-valued data vector. The Expectation-Maximization algorithm is widely used to train the GMM parameters (the prior probabilities and others associated with the density function). It takes the GMM parameters and iterates them until convergence of an optimization factor. It has a simple local search technique that guarantees the increase of the likelihood; details can be found in [19]. The GMM implementation in concert with the rest of the robotic control system is shown in Fig. 3.

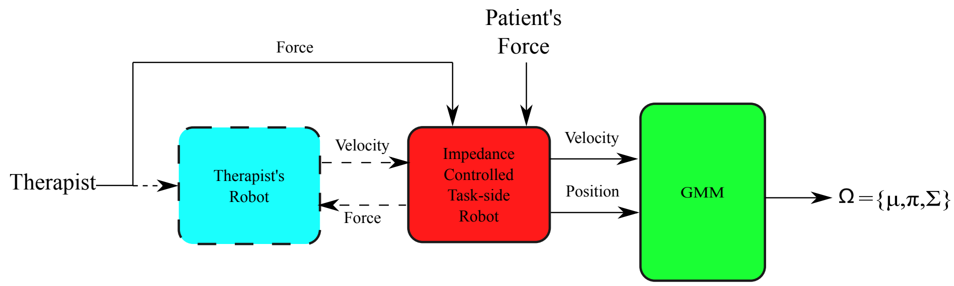


Fig. 3. Block diagram of the system when used to provide demonstrations, which are used to train the GMM.

B. Gaussian Mixture Regression (GMR)

The GMR model uses the Gaussian conditioning theorem and linear combination properties of Gaussian distributions to retrieve the desired output values from a GMM [19]. GMR traditionally uses temporal values (ξ_t) as query points to estimate the corresponding spatial values ($\hat{\xi}_s$) through regression. Given a set of temporal and spatial values for a kth component of a GMM, the representations of the mean and covariance matrices are given as

$$\mu_k = \{\mu_{t,k}, \mu_{s,k}\}, \Sigma_k = \begin{pmatrix} \Sigma_{t,k} & \Sigma_{ts,k} \\ \Sigma_{st,k} & \Sigma_{s,k} \end{pmatrix} \quad (5)$$

Conditional expectation ($\hat{\xi}_s$) and conditional covariance ($\hat{\Sigma}_s$) of the output ξ_s given ξ_t are then calculated for a mixture of all GMM k components.

For additional details, readers are encouraged to see [19]. Note that while the query points are described as temporal points, these inputs to the GMM and GMR can be any type of data; in our work, these are spatial coordinates. A diagram of the GMR output being used in the task imitation phase is shown in Fig. 4.

VI. Experiments

We implement each teaching modality using the same task. Comparing these two different ways of reprogramming a rehabilitation system using LfD shows us the strengths and weaknesses of each implementation, and where they perform similarly. In both experiments, we evaluate the system on a simple cooperative task where the participants open a drawer fully, similar to [6], as shown in Fig. 5a. The drawer contains objects with a small mass which creates friction between the drawer and the shelf's rails. Therefore, it resists the opening movement and tends to keep the drawer to its position. In the experiments, the patient is emulated by a weak (low stiffness) spring attached to the front of the drawer, which tends to open the drawer but cannot do so completely. This means the emulated patient cannot complete the task alone due to the simulated disability. The therapist (the role of which is played by our able-bodied human participants[1]) provides assistance to the simulated patient by helping to pull the drawer open while trying to follow a specific reference motion trajectory (Fig. 6a). In all trials, the robot's end-effector position and velocity are recorded and later used to train the system as outlined in Fig. 3. Later, during the imitation phase, the GMR takes the robot's current end-effector position as query points to compute the desired velocity used by the controller to imitate the therapist's behaviour (Fig. 4). The position and velocity data of the robot end-effector are again collected, as well as the output variance of the GMR. The robot end-effector is attached to the front of the drawer. An impedance controller is used to provide robot compliance to participant input in 1 Degree of Freedom (DOF).

[1]Ethics approval was granted by the University of Alberta Research Ethics Office under study ID MS10_Pro00033955.

A. Robotics-mediated Kinesthetic Teaching

In this experiment, the participant (i.e., therapist) trains the robot by holding its end-effector and assisting the simulated patient to complete the task. Each participant was asked to follow one given reference trajectory, which varied between each participant. The participants complete the task five different times following their given trajectory. Reference trajectories are randomized for the purpose of showing that the imitation results of the LfD algorithms are generalizable, and second to vary the difficulty of the task. A Motoman SIA5F 7 DOF industrial manipulator (Yaskawa America, Inc., Miamisburg, Ohio, USA) is used as the task-side robot for rehabilitation of the patient.

B. Telerobotics-mediated Kinesthetic Teaching

The second experiment requires the therapist and the patient to collaborate to complete the task while using a telerobotic system. As shown in Fig. 5b, the therapist interacts with the patient using a master-slave system, where the master robot is controlled by the therapist and the slave robot is the task-side robot with which the patient interacts. Once again, each participant helps the simulated patient to complete the task in a similar way as before for a total of five demonstrations. To improve the transparency between the therapist and the patient, force feedback is used on the therapist's side. The same Motoman SIA5F robot as in the RMKT case is used as the task-side (slave) robot here, while an HD^2 6 DOF robot (Quanser Inc., Markham, Ontario, Canada) is used as the therapist's user interface (master).

VII. Results & Discussion

We present our results and analysis of the obtained data in three ways. First, we compare the participant-demonstrated

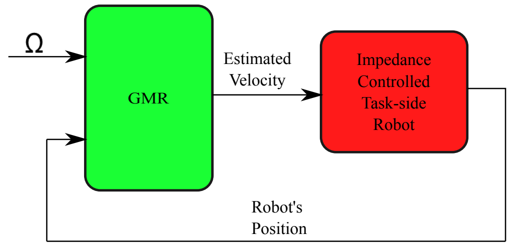


Fig. 4. Block diagram of the system when imitating the therapist's demonstrated behavior, using the output of the GMR.

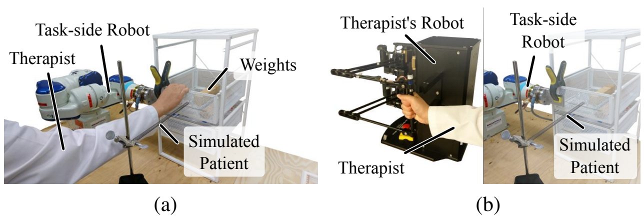


Fig. 5. Experimental setups. (a) shows the RMKT setup. The therapist, patient, and robot force sensor hold and open the drawer together. (b) shows the master robot that is added in TMKT. The therapist holds the master robot and moves the task-side robot through a direct force reflection control loop.

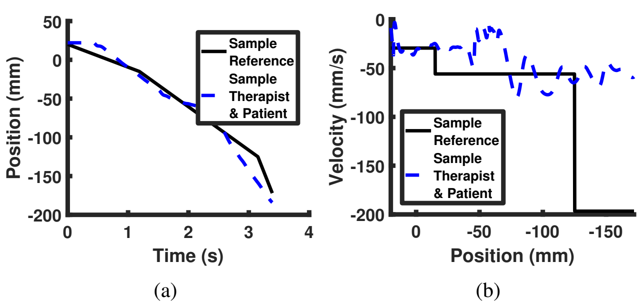


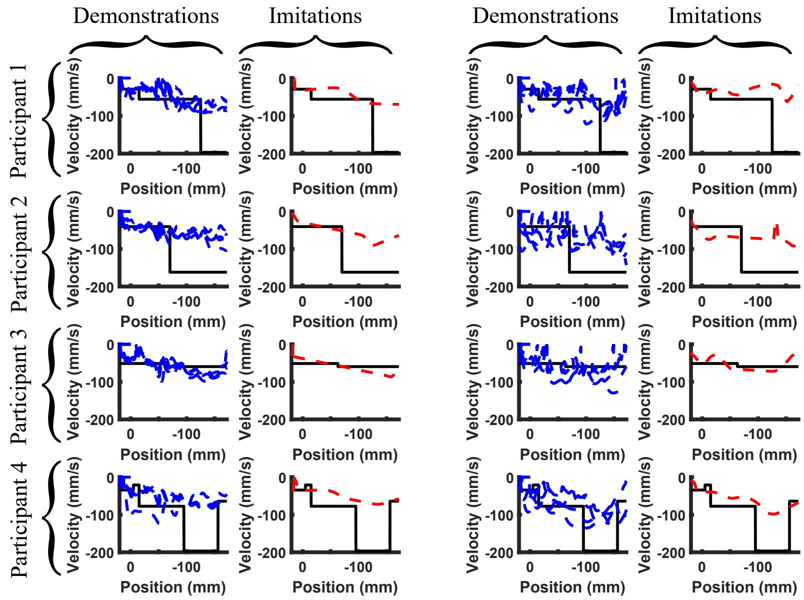
Fig. 6. (a) shows an example of the trajectory data displayed to a participant during an experiment. The position and time data of the participant and patient's collaborative motion are plotted in real time as they attempt to follow a reference trajectory. (b) shows the extracted velocity-position trajectory performed by the participant, which is used to train the GMM.

velocity vs. position and the GMR-generated velocity vs. position for each experiment. Using the robot end-effector's recorded velocity and position data, we plot the results in Fig. 7a and 7b. The figures provide a qualitative overview of how accurate the participants and the system trained by them were in following the reference trajectory. Second, we provide the variances of the GMR outputs for each imitation in order to quantitatively evaluate how repeatable and, by extension, how easy demonstrating the reference trajectories are for each modality. Lastly, we perform a Student's T-Test is performed to compare the GMR output variances so as to provide a numerical evaluation of the modalities' similarity or difference. A box plot (Fig. 8) is used for visualization.

The results in Fig. 7c show a wide spread of GMR output variances, differing across each participant. It can be noted that Participants 2, 3, and 4 exhibited larger variance results than Participant 1, meaning that their demonstrations were less consistent during the training phase. We can infer that the level of consistency in demonstrations, therefore, varies greatly on a user by user basis. A clear example of this is that Participant 1 shows smaller average and maximum variances when using TMKT while the rest of the participants show larger variances while using the TMKT modality. This observation may indicate that in general, it is more difficult to provide consistent demonstrations with the teleoperation setup, detracting from the feasibility of TMKT and corroborating Hypothesis 1. From a different perspective, minimum variances are in general consistently low, so for some participants, there are at least some portions of the trajectory that are repeatable for both modalities. Fig. 8 visualizes the T-Test results comparing the average velocity variance values obtained from the imitation GMR velocities. The results are not statistically similar ($p = 0.0348$), confirming the conclusions drawn from the data in Fig 7c.

As seen in Fig. 7a and 7b, the participants sometimes experienced difficulties following the reference velocity depending on their reference trajectory's level of difficulty. Therefore, the GMR results do not match the reference velocity accurately. However, the GMR output does closely resemble its training data, specifically in that portions of the trajectories that require changes in speed are properly conveyed and appear similar. These similarities can be interpreted as a good statistical reconstruction of the therapist's behaviour for both modalities. We can conclude that incorporating LfD techniques with both modalities is indeed possible, as in Hypothesis 2. This can be seen as an important step towards the introduction of TMKT as a research focus. We can summarize the conclusions in that TMKT may lead to less consistent demonstration data resulting in a less user-friendly interface, but does indeed allow for LfD algorithms to properly learn user demonstrations as in RMKT.

Several possible factors contributing to TMKT's lower performance, as well as general improvements to the experimental procedure, come to mind. The most likely factor would be a lack of co-location between the user and the task. In RMKT, it is highly intuitive for the therapist to match their input to the resulting change in the task performance. However, with TMKT the spacial disconnect could have a negative effect on the user's perception. This in part leads to a possible second factor, in that the TMKT system was designed with ideal transparency as the target in mind, but without replicating the task-side robot's dynamics (e.g., inertia) on the therapist's robot's side. In this work, this meant



(a) RMKT

(b) TMKT

		Mean (mm/s)	Max (mm/s)	Min (mm/s)
Participant 1	RMKT	273.4	781.1	56.3
	TMKT	223.1	530.5	62.2
Participant 2	RMKT	151.5	714.6	75.2
	TMKT	686.8	1468.8	215.1
Participant 3	RMKT	170.5	760.3	44.0
	TMKT	596.8	1444.2	63.8
Participant 4	RMKT	258.9	660.3	72.8
	TMKT	489.1	1281.6	166.2

(c) GMR-generated Variance

Fig. 7. (a) and (b) show velocity-position data from demonstrations (dashed blue, under demonstrations) and GMR imitations (dashed red, under imitations), plotted against their respective reference trajectories (black). (a) shows the trajectories recorded from the RMKT experiments while (b) shows the trajectories recorded from the TMKT experiments. (c) shows the average, minimum, and maximum variances for the GMR output corresponding to each participant's demonstration sets for both modalities.

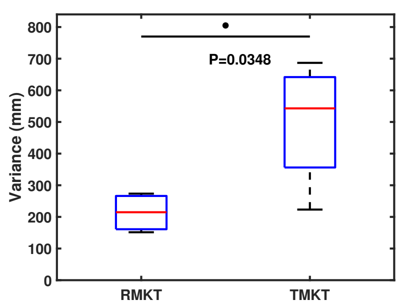


Fig. 8. Box plot of average GMR trajectory variances for RMKT and TMKT.

the therapist's robot was much easier to move and could have resulted in difficulty in perceiving the degree of motion the task-side robot was undergoing. This work also focused on making TMKT as close to RMKT in performance, but one unused advantage of teleoperation is that workspace or force scaling is possible, which can be used to lower effort requirements for the master robot operator. More general factors could be that the task may have been too difficult for some participants and that the sample size was small. Further investigation into these factors could potentially produce more favourable results for TMKT, although the modality was still able to properly incorporate LfD regardless.

VIII. Conclusion and Future Directions

In this work, two different modalities for incorporating LfD techniques into robotic rehabilitation, RMKT and TMKT, were compared for feasibility and ease of use. A simple cooperative task of opening a drawer was used to represent a therapy task upon which to perform the comparison. The results indicated that both modalities were capable of providing demonstration data to the LfD algorithms to a satisfactory degree (validating Hypothesis 2), although TMKT demonstrations had a larger variance on average and were not statistically similar to their RMKT counterparts ($p = 0.0348$) (validating Hypothesis 1). Future works will focus on improving the user immersion in TMKT (e.g., mimicking task-side robot dynamics on the master robot), taking advantage of teleoperation-based techniques to make interaction easier, tuning experimental procedures, and using larger sample sizes. We would also like to test both approaches with and collect feedback from patients and therapists in an effort to properly validate the patient-specific aspect of the proposed system, for which we expect favorable results based on our previous works.

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