Learning Personalised Physical Patient-Therapist Interactions towards Varying Task Conditions in Neurorehabilitation

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Abstract

Task-specific training (TST) improves motor function and activities of daily living, yet robot-assisted TST has not consistently shown superior outcomes compared with conventional therapy, possibly due to limited task variation during robotic training. Introducing task variations typically require repeated manual adjustment of physical human–robot interaction (pHRI) parameters by a therapist, reducing practicality in clinical use. This work presents a therapist–patient–task-specific learning-from-demonstration (LfD) framework designed to learn interaction behaviours from a small number of demonstrations across selected task variations and to generalise the learned model to unseen variations, enabling automatic robot readjustment without continuous therapist involvement. The proposed protocol evaluates the similarity between reconstructed torque profiles generated by the learned model and the variability observed in therapist demonstrations, to verify that the generalised behaviour remains within the range of therapist-intended assistance.

1 Introduction

Task-specific training (TST) has strong evidence for improving motor function and activities of daily living (ADL) after neurological injury [1]. However, robot-assisted TST has not consistently shown superior outcomes compared with conventional therapist-led training [2], bringing into question the benefit of robotic assistance in rehabilitation.

A possible explanation is limited task variability [2], limited by the repetitive, fixed-condition nature of robotic training. Motor learning theory suggests that recovery improves when skills are practised under varied conditions, whereas repetitive and fixed movements may lead to overly movement-specific learning

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This project is funded by the Graeme Clark Institute as part of the Cross-Faculty Seed Funding Scheme. This work has been accepted as a publication for the 7th International Conference on NeuroRehabilitation (ICNR2026).

with poor generalisation [3]. Incorporating task variations, such as changes in target position, is therefore essential for effective TST.

Most rehabilitation robots employ predefined physical human–robot interaction (pHRI) schemes [4], and fix a scheme that imitates the intended therapist–patient interaction for each repetition. Introducing task variations or adapting to patient conditions requires manual selection and retuning of control parameters, limiting the practicality of robot-assisted TST. Automating robot controller selection and tuning in pHRI [5] or incorporating the understanding of the whole physical patient-therapist interaction into the robot over varying conditions of a task is therefore necessary for flexible and individualised therapy.

Here, we aim to achieve the latter by learning, from a few demonstrations during TST, the latent features of the physical interactions applied by the therapist along a patient's movement, and generalising the learned interaction to variations of the task. Learning-from-demonstration (LfD) provides a framework for modelling pHRI in varying environments under limited data [6], which could be suitable for modelling the patient-therapist physical interaction.

The proposed framework thus learns a therapist–patient–task-specific interaction model that maps motion to therapist-generated forces from few demonstrations. We extend existing works, [7, 8], into learning the therapist's interactions when facilitating therapy for variations (e.g. different task positions) of task-specific exercises, and evaluate the model's reconstructed interactions against the therapist's intended interaction in unseen task variations, with the aim of enabling robot-assisted TST that is consistent with therapist-intended interactions while enabling varied training.

2 Materials and Methods

2.1 Capturing Physical Patient–Therapist Interaction

The interaction measurements used for learning are defined as $\Gamma_t = [\boldsymbol{q}_t, \dot{\boldsymbol{q}}_t, \boldsymbol{\tau}_t]$, where $\boldsymbol{q}_t, \dot{\boldsymbol{q}}_t, \boldsymbol{\tau}_t \in \mathbb{R}^{10\times 1}$ denote the 10-DOF joint positions, joint velocities, and therapist-applied joint torques at time step t.

Joint kinematics $\boldsymbol{q}_t$ and $\dot{\boldsymbol{q}}_t$ are measured using the Xsens Awinda motion capture system (Xsens, Netherlands). The upper body (pelvis to wrist) is modelled as a four-link serial manipulator after XSENS's MVN Biomechanical Model [9].

Therapist interaction at the ith interaction point of the upper body (Fig. 1) is obtained from the wrench, $\boldsymbol{w}_{i,t}$, measured at the ith force sensor placed on the patient's upper-body, totalling up to three force sensors. The joint torque from this interaction point, $\boldsymbol{\tau}_{i,t}$ is computed using the corresponding Jacobian $\boldsymbol{J}_{i,t}$, and summed to obtain the total interaction torque, $\boldsymbol{\tau}_t$, given respectively as

$$\boldsymbol{\tau}_{i,t} = \boldsymbol{J}_{i,t}^T\ \boldsymbol{w}_{i,t}\ ,\ \boldsymbol{\tau}_t = \sum_{i=1}^{3} \boldsymbol{\tau}_{i,t}\ . \tag{1}$$

2.2 Study Design

Pairs of mock patients and therapists were recruited for this study. We defined three simulated ADL tasks shown in Fig. 1, each with a specified number of

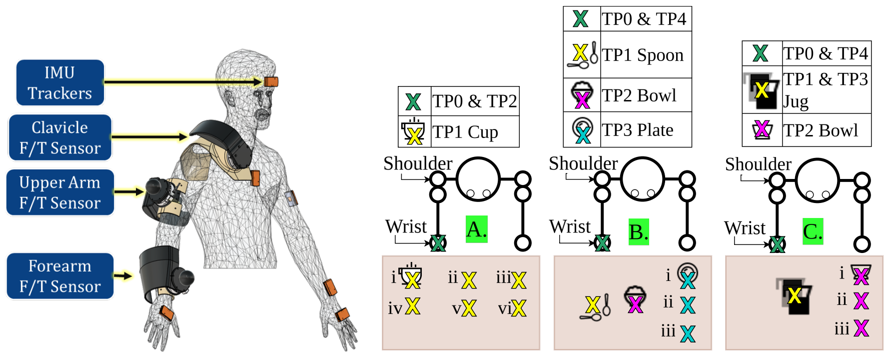

Figure 1: (Left): System for capturing physical patient-therapist interactions. (Right): ADL tasks performed in the study: A. Reach to six different positions respectively and return. B. Reach towards spoon at upright / sideways orientations, and transport rice from a fixed bowl to a plate at three different positions. C. Reach towards a jug at half / full weight, and pour rice into a bowl at three different positions. TP refers to task points where the joint kinematics are extracted from for the task frames

sub-movements to perform. For each therapist–patient pair $p \in \{1, \ldots, P\}$, each task $s \in \{1, 2, 3\}$, and each variation $v \in \{1, \ldots, 6\}$, the therapist performs four repetitions $r \in \{1, \ldots, 4\}$ of physical interactions. Each trial produces a dataset

$$\Gamma_\gamma = [\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{\tau}] \ , \tag{2}$$

where $\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{\tau} \in \mathbb{R}^{10\times T}$ are the joint positions, velocities, and interaction torques over T time steps, and $\gamma = \{p, s, v, r\}$ denotes the trial index. For each task s, two variations are reserved for testing generalisation to unseen variations, while the remaining four are used for training.

Γ_γ is segmented via each sub-movement onset and the movement offset at the specified task points (TP) in Fig. 1. Joint kinematics at the TPs are extracted to provide task frames required for the learning framework (Section 2.3). Γ_γ are aligned using dynamic time warping (DTW) on $\boldsymbol{q}, \dot{\boldsymbol{q}}$ per variation, and normalised to a $[0, 1]$ time scale to align variations across time.

2.3 Learning Physical Patient–Therapist Interaction

For each therapist–patient pair p performing task s, a therapist-patient-task-specific interaction model $g_{p,s}$ that maps joint kinematics to interaction torques, is optimised as

$$\boldsymbol{\tau} = g_{p,s}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \ . \tag{3}$$

Task-parameterised Gaussian mixture models (TP-GMM) was chosen to cluster the joint kinematics to interaction torques, as they encode known task frames (i.e. the joint kinematics when the patient reaches each TP) into the model optimisation. It generalises to new task variations via reconditioning the model with new task frames (readers can refer to [10, 11] on reconditioning TP-GMM using joint positions). Gaussian mixture regression is then applied on the reconditioned TP-GMM using the joint kinematics to reconstruct an 'equivalent' interaction torque.

3 Evaluation Metrics and Expected Outcome

Demonstrated torques from preliminary data and the reconstructed torque for unseen task frames in the cup-reaching task are shown in Fig. 2 to illustrate the results.

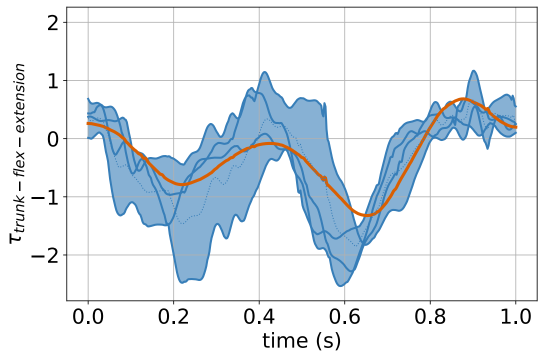

Figure 2: Therapist demonstrated torques (Blue lines and shaded region) and the reconstructed torque (brown) for trunk flexion / extension.

For the purpose of the analysis, the reconstructed profile, $\hat{\boldsymbol{\tau}} = g_{p,s}(\boldsymbol{q}_{test}, \dot{\boldsymbol{q}}_{test})$ is considered similar to the therapist's interaction, $\boldsymbol{\tau}$, if it is within the variability of the therapist's demonstrations (i.e. the shaded region). The therapist non-parametric variance in each unseen therapist-patient-task-variation $\zeta = \{p, s, v\}$, is represented by the therapist's mid-range interaction $\boldsymbol{m}_{\zeta,t}$ and peak torque $\boldsymbol{m}_{\zeta,\text{peak}}$, obtained from the $\gamma \in \{p, s, v, r\}$ set, given by

$$\boldsymbol{m}_{\zeta,t} = \frac{\max\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,t}\} + \min\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,t}\}}{2} \ , \tag{4}$$

$$\boldsymbol{m}_{\zeta,\text{peak}} = \frac{\max\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,\text{peak}}\} + \min\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,\text{peak}}\}}{2} \ . \tag{5}$$

Reconstructed torques $\hat{\boldsymbol{\tau}}_\gamma$, are evaluated against $\boldsymbol{m}_{\zeta,t}$ and $\boldsymbol{m}_{\zeta,\text{peak}}$ via the normalised average reconstruction error $\boldsymbol{\epsilon}_\gamma$, and peak torque difference $\Delta\boldsymbol{\tau}_{peak,\gamma}$:

$$\boldsymbol{\epsilon}_\gamma = \frac{1}{T} \sum_{t=0}^{T} \frac{|\hat{\boldsymbol{\tau}}_{\gamma,t} - \boldsymbol{m}_{\zeta,t}|}{\max\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,t}\} - \boldsymbol{m}_{\zeta,t}} \ , \tag{6}$$

$$\Delta\boldsymbol{\tau}_{\gamma,\text{peak}} = \frac{|\hat{\boldsymbol{\tau}}_{\gamma,\text{peak}} - \boldsymbol{m}_{\zeta,\text{peak}}|}{\max\limits_{r=1,2,3,4} \{\boldsymbol{\tau}_{\gamma,\text{peak}}\} - \boldsymbol{m}_{\zeta,\text{peak}}} \ . \tag{7}$$

The LfD framework is consistent to a therapist's interaction if $\boldsymbol{\epsilon}_\gamma$ and $\Delta\boldsymbol{\tau}_{peak,\gamma}$ are below 1. This would indicate that the generalised interaction stays within the variability of the therapist's interaction, producing physical inputs consistent with the intended therapist interaction under unseen variations, of which can be transformed into equivalent pHRI inputs.

The protocol is approved by the Melbourne Health Human Research Ethics Committee (#31992). Twenty-four physiotherapy students were recruited for the study and data collection completed in late April 2026.

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