

# Learning a Shape-adaptive Assist-as-needed Rehabilitation Policy from Therapist-informed Input

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**Abstract**—Therapist-in-the-loop robotic rehabilitation has shown great promise in enhancing rehabilitation outcomes by integrating the strengths of therapists and robotic systems. However, its broader adoption remains limited due to insufficient safe interaction and limited adaptation capability. This article proposes a novel telerobotics-mediated framework that enables therapists to intuitively and safely deliver assist-as-needed (AAN) therapy based on two primary contributions. First, our framework encodes the therapist-informed corrective force into via-points in a latent space, allowing the therapist to provide only minimal assistance while encouraging patient maintaining own motion preferences. Second, a shape-adaptive ANN rehabilitation policy is learned to partially and progressively deform the reference trajectory for movement therapy based on encoded patient motion preferences and therapist-informed via-points. The effectiveness of the proposed shape-adaptive AAN strategy was validated on a telerobotic rehabilitation system using two representative tasks. The results demonstrate its practicality for remote AAN therapy and its superiority over two state-of-the-art methods in reducing corrective force and improving movement smoothness.

## I. INTRODUCTION

Rehabilitation robots can provide precise and intensive therapies for patients with neurological injuries, offering a promising solution to the shortage of healthcare resources [1]. Numerous robotic systems [2], [3] and control methodologies [4], [5] have been developed to promote robot-assisted rehabilitation. Particularly, adaptive control and machine learning techniques have shown promising results in programming flexible therapy strategies tailored to patients' individual needs, known as *assist-as-needed* (AAN) strategies [6], [7]. Nevertheless, the flexibility of existing AAN strategies cannot match the capability of a skilled therapist due to the difficulty of acquiring sufficient knowledge and programming experience-based adjustments [8], [9], [10]. To address this limitation, *therapist-in-the-loop* robotic rehabilitation has emerged as a paradigm that integrates therapists' expertise into robot controllers [11], [12], [13]. However, most existing robotic systems still struggle to complete effective therapist-in-the-loop rehabilitation training because of their limited interaction and adaptation capabilities.

Firstly, current robotic rehabilitation systems lack effective mutual interaction to safely integrate therapists' expertise into robot execution [14], [15]. Robot controllers are typically designed to follow the predefined reference based on the measured interaction forces and motion tracking for desired rehabilitation targets [8]. Therapists, in turn, contribute by setting rehabilitation goals and modulating the therapy strategies tailored to individual patients for robot execution based on previous expertise in evaluating individual patient status [10]. In practice, therapists typically demonstrate therapeutic movements/forces for robot-mediated rehabilitation using the same robot in a teach-and-play mode [16]. By contrast, telerobotics-mediated systems enable therapist and patient to operate separate devices, enabling real-time mutual interaction [17], [12]. For instance, therapists utilize a haptic device to perceive the interaction force between the patient and the robot. Existing robotic telerehabilitation systems employ additional sensors and estimation methods to achieve concurrent demonstration and therapy [18]. However, no current telerobotic-mediated systems can intuitively incorporate therapist's input into robot control without relying on reprogramming.

Secondly, current robotic rehabilitation strategies struggle to deliver effective AAN therapy due to their limited adaptability. The key challenge in developing AAN training strategies is to encourage active participation while only providing the necessary level of assistance [5], [8], [19]. Patient's voluntary output forces and motion tracking errors are commonly used as metrics to assess patient engagement and guide the design of robot controllers for various rehabilitation goals [6], [20], [21]. While therapists' expertise allows for comprehensive evaluation of the patients' status through multi-modal feedback, therapist's corrective actions are essential to promote therapist-level adaptive assistance [22]. Numerous studies have leveraged probabilistic models to reproduce therapist expertise for reference trajectory shaping and force generation in AAN therapy [4]. In these methods, rehabilitation outcomes are defined by the therapist and the corresponding references are generated for robot controllers [5], [23]. However, the effectiveness of therapy remains constrained by the difficulty of balancing robotic assistance with patients' active participation. Therefore, a promising therapist-in-the-loop AAN training strategy that maximizes patient engagement while seamlessly integrating therapist-informed corrections remains necessary.

This article proposes a novel therapist-in-the-loop rehabilitation framework that leverages two isomorphic collaborative robots to deliver the AAN movement therapy. The contri-

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contributions of this study are twofold. First, therapist-informed corrective forces are encoded as via-points in a latent space, ensuring that the therapist only provides the minimal necessary assistance instead of re-planning the entire reference trajectory or force profile. Second, a shape-adaptive AAN rehabilitation policy is learned to partially and progressively deform the reference trajectory based on the encoded patient motion preferences and therapist-informed via-points.

## II. RELATED WORKS

### A. AAN Training Strategies

AAN training strategies have been investigated at multiple levels for patients with various rehabilitation goals by modulating the amount of assistance based on the biomechanical status of the patient or task completion performance [20], [24]. At the force level, adaptive controllers have been developed to successfully modify the level of assistance in real time [6], [25]. Furthermore, multi-modal adaptive controllers have been proposed to provide flexible assistive force across multiple training modes [26], [27]. Beyond the adaptation of assistive force, impedance control, a popular compliant control approach, was utilized to regulate the patient-robot interaction dynamics during movement therapy [23]. Variable impedance controllers (VICs) have been commonly developed to enable impedance-level AAN therapy, where individual reference stiffness parameters are predefined according to patient's task completion performance [28], [23], [29]. These training strategies typically achieved the force-level and impedance-level AAN therapy given a fixed reference trajectory [28]. By contrast, the individualized reference trajectory deformation for motion-level AAN therapy has demonstrated the improved stability [30]. The reference trajectory was modified based on optimization deformation for patients with different mobility disabilities and different recovery stages [31]. Additionally, probabilistic model learning methods, Gaussian Mixture Model (GMM)/Gaussian Mixture Regression (GMR) [11], were applied to reproduce the therapist-demonstrated reference trajectories [8]. More recently, moving beyond single rehabilitation tasks, task-level AAN strategies have been explored. These approaches employ linear Gaussian policies or neural network-based policies to encode mappings from task contexts to a latent space of lower-level policies for robot execution [32], [33].

Most of existing AAN rehabilitation strategies rely on predefined metrics and corresponding robot controllers for execution. However, these approaches cannot match the flexibility of skilled therapists. An ideal AAN training strategy should combine the strengths of therapists' expertise with the precise execution of robots. Crucially, the therapist should provide only the minimal necessary guidance, thereby maximizing patients' active participation.

### B. Therapist-in-the-loop Rehabilitation Training

Therapist-in-the-loop training strategies rely on the therapist to demonstrate therapeutic movements or force profiles for robot execution [8], [12]. The ability to modify therapy movements or intensity has been validated in the teach-and-play mode [4]. In the demonstration phase, the

therapeutic movement or force delivered by therapists is recorded and fitted by probabilistic models [11], [12]. In the reproduction phase, the learned probabilistic model can reproduce the reference trajectory or force profiles without the therapist in the loop [16]. The therapeutic intensity was modulated by modifying controller parameters of the patient-side robot to provide AAN therapy [5]. Additionally, leader-follower robotic systems have been developed for telerobotic-mediated rehabilitation to provide concurrent demonstration and therapy. Therapists use a haptic device to demonstrate the reference trajectory and perceive patient-side interaction force [10], which allows for adjusting the therapeutic movement and force in real-time to ensure effective therapy [10], [34]. External sensors, such as EMG sensors, are amounted to infer control parameters for modulating the therapy intensity.

In summary, compared with methods using a single robot, a telerobotics-mediated rehabilitation system enables the decoupling of evaluation and therapeutic treatment. Unfortunately, in existing strategies, therapists are required to modulate entire therapeutic movements or force profiles [12]. By contrast, an ideal AAN therapy strategy would encode therapist-informed corrective force into a latent space to smoothly guide patient movement therapy.

## III. PROBLEM FORMULATION

The objective of the proposed controller is to enable the therapist to provide necessary guidance for completing the AAN therapy with patients. As illustrated in Fig. 1, the telerobotic system consists of two identical collaborative robots to complete the therapist-in-the-loop training. One robot, located at the patient side (patient-side robot), is driven using an impedance controller to guide the patient to compliantly complete the movement therapy. Another robot, located on the therapist side (therapist-side robot), is driven using another impedance controller to allow him/her to perceive the actual trajectories of the patient-side robot. Two GUIs are developed for the mutual visual interaction between therapists and patients. For effective AAN therapy, the reference trajectory is adapted to encourage the active participation of patients where the patient motion preferences are considered and maintained. Furthermore, the therapist-side robot isolates the therapist-informed corrective force from the patient-side interaction force, which enables it to provide accurate guidance.

This article focuses on movement therapy given a set of predefined desired motions (see Fig. 1), following the implementation in Algorithm 1. Once a rehabilitation task is selected by the therapist, the desired motion  $x_e$  is displayed on GUIs to provide task instructions for both therapists and patients. The robot-assisted rehabilitation relies on repetitive implementations based on two lower-level interactive controllers depicted in Section IV-A. During each therapy iteration, the patient's actual trajectories  $x_t$  are measured from the patient-side robot. The patient motion preferences are encoded from recent actual trajectories by learning a probabilistic model (see Section IV-B). To minimize therapist as-

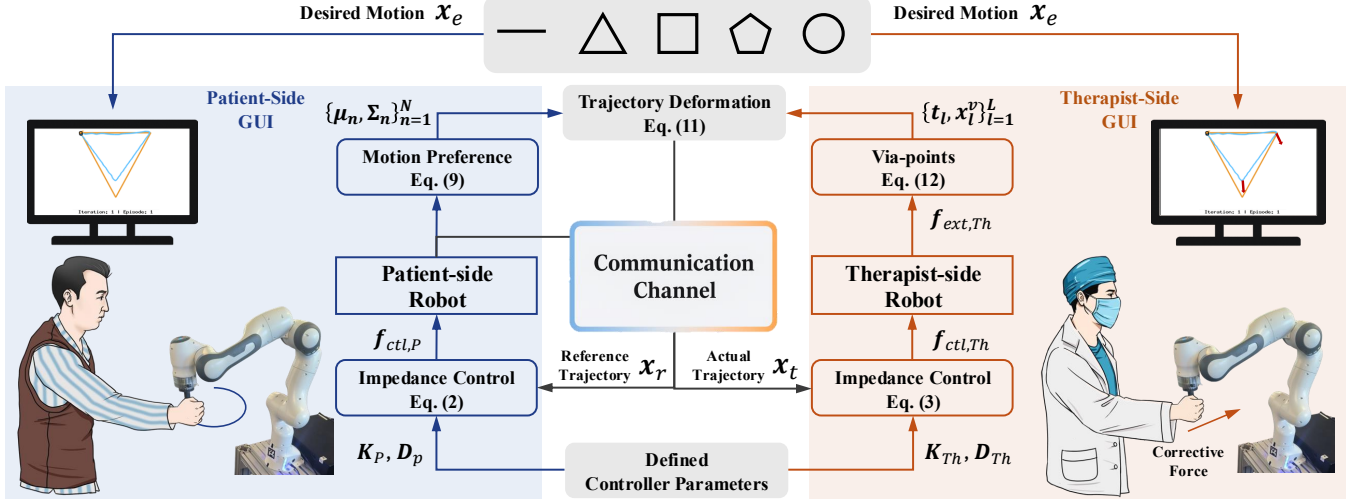


Fig. 1: Overview of learning our shape-adaptive AAN rehabilitation policy based on two isomorphic robots interacting with patient and therapist through the end-effector, separately. The therapist first selects a specific rehabilitation goal, whose desired motion is displayed on both patient-side and therapist-side GUIs. Two impedance controllers with pretested control parameters are implemented for patient-side and therapist-side robots to repetitively complete the therapy. On the patient side, the reference trajectory is iteratively deformed during movement therapy. The patient motion preferences are encoded from previously collected actual trajectories. On the therapist side, another impedance controller is implemented to reproduce the actual motion of patient in real time, allowing the therapist to apply the corrective forces. The via-points are extracted for reference trajectory deformation, which are the transmitted to patient-side robot for the implementation of next therapy iteration.

sistance and encourage patient active participation, therapist-informed via-points are extracted from the measured corrective force instead of transmitting the whole force profile or reference trajectory for patient-side robot control. The corresponding reference trajectory  $x_r$  for subsequent therapy iteration is then partially deformed according to the therapist-informed via-points, while preserving the patient's motion preferences in the remaining segments (see Section IV-C). Most importantly, the therapist's input therapeutic skills are encoded by using via-points a latent space according to the feature of patient motion preferences. Finally, a partial least squares regression function is fitted to reproduce the therapist's input therapeutic skills (see Section IV-D).

#### IV. METHOD

##### A. Lower-level Interactive Control

The robot dynamics in  $n$  Degree of Freedom (DoF) Cartesian space is written as,

$$\begin{aligned} M_{C,i}(x_i)\ddot{x}_i + c_{C,i}(x_i, \dot{x}_i) + g_{C,i}(x_i) \\ = f_{cmp,i} + f_{ctrl,i} + f_{ext,i} \end{aligned} \quad (1)$$

where  $M_{C,i} \in \mathbb{R}^{n \times n}$  denotes the inertia matrix of the robot, and  $c_{C,i} \in \mathbb{R}^n$  and  $g_{C,i} \in \mathbb{R}^n$  represent the Coriolis/centrifugal and the gravity vector, respectively.  $f_{cmp,i} \in \mathbb{R}^n$  is the control force which compensates the Coriolis/centrifugal and the gravity vectors.  $f_{ctrl,i} \in \mathbb{R}^n$  is the control command. Moreover,  $f_{ext,i} \in \mathbb{R}^n$  is the force human user applies on the robot. The subscript  $-i$  is indexed by  $i \in \{P, Th\}$ , where  $-P$  indicates the robot at the patient side, and  $-Th$  for the therapist-side robot.

1) *Patient-side Robot Control*: On the patient side, the robot is following the reference trajectory generated by the therapist input, thus the controller at the patient side can be written as

$$f_{ctrl,P} = K_P(x_r - x_P) + D_P(\dot{x}_r - \dot{x}_P), \quad (2)$$

where the  $K_P, D_P \in \mathbb{R}^{n \times n}$  are positive definite stiffness matrices and damping matrix, respectively. And the  $x_r$  is the generated reference trajectory.

2) *Therapist-side Robot Control*: The robot on the therapist side is following the patient-side robot such that the therapist understand the situation of the patient. Thus the controller on the therapist-side robot is designed as,

$$f_{ctrl,Th} = K_{Th}(x_P - x_{Th}) + D_{Th}(\dot{x}_P - \dot{x}_{Th}), \quad (3)$$

where the  $K_{Th}, D_{Th} \in \mathbb{R}^{n \times n}$  are the positive definite stiffness and damping matrices for the therapist-side robot, respectively. and the force interaction force between the therapist  $f_{ext,Th}$  will be the input of the trajectory generation.

##### B. Patient Motion Preferences Encoding

For each therapy iteration, the impedance control in (3) is utilized to complete the movement therapy following a reference trajectory  $x_r$  for  $J$  times. Most recent actual trajectories of patient (e.g. gray lines in the Fig. 2(a)) are collected and down-sampled into a set of waypoints with length  $N$  for learning a probabilistic model to encode the motion preferences. The dataset  $\mathcal{D}_P$  is constructed as  $\mathcal{D}_P = \{\{\xi_{n,j}^i, \xi_{n,j}^o\}_{n=1}^N\}_{j=1}^J$ .  $\xi_{n,j}^i \in \mathbb{R}^{d_i}$  and  $\xi_{n,j}^o \in \mathbb{R}^{d_o}$  represent the input and output vectors with dimensions of  $d_i$  and  $d_o$ . This study focuses on time-driven trajectories for movement therapy, where the input  $\xi_{n,j}^i$  corresponds to time  $t$ , and the output  $\xi_{n,j}^o$  corresponds to the end-effector position  $x$  of patient-side robot. GMMs are used to encode the mean and variance of motion preferences using collected waypoints in  $\mathcal{D}_P$ . The covariance encodes the variability of the actual trajectories. The resulting joint probability distribution of time  $t$  and position  $x$  is given as

$$\mathcal{P}(t, x) = \sum_{c=1}^C \varpi_c \mathcal{N}(t, x | \mu_c, \Sigma_c) \quad (4)$$

where  $C$  is the number of Gaussian components, which controls the smoothness of the fitted mean trajectory. The

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**Algorithm 1** Shape-adaptive AAN Rehabilitation Policy
 

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- 1: Select task and desired motion  $\mathbf{x}_e$
  - 2: Set hyperparameters  $N, L, C$
  - 3: Initialize controller parameters in Section IV-A
  - 4: Initialize datasets  $\mathcal{D}_P^0 \leftarrow \emptyset, \mathcal{D}_T \leftarrow \emptyset$
  - 5: Initialize parameter of linear regression function  $\psi_T^0$
  - 6: **for** each therapy iteration  $i = 0$  **to**  $I$  **do**
  - 7:   Estimate motion preference using  $\mathcal{D}_P^i$  (Section IV-B)
  - 8:   Collect therapist state  $\mathbf{s}_i$  according to (13)
  - 9:   Collect therapist applied force  $\mathbf{f}_{ext,Th}(\mathbf{t})$
  - 10:   Infer via-points  $\mathbf{x}_v^i$  using (12)
  - 11:   Generate reference trajectory  $\mathbf{x}_r^i$  in Section IV-C
  - 12:   **for** each therapy episode  $j = 0$  **to**  $J$  **do**
  - 13:     Execute therapy following Section IV-A
  - 14:     Collect  $\mathbf{x}_t$  and save to  $\mathcal{D}_P^i \leftarrow \mathcal{D}_P^i + \{\mathbf{x}_t\}_{t=0}^T$
  - 15:   **end for**
  - 16:    $\mathcal{D}_T \leftarrow \mathcal{D}_T + \{(\mathbf{s}_i, \mathbf{x}_v^i)\}, \mathcal{D}_P^i \leftarrow \emptyset$
  - 17: **end for**
  - 18: Output optimized parameters:  $\psi_T^*$
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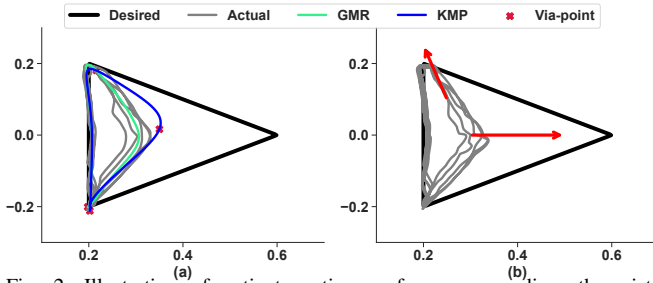


Fig. 2: Illustration of patient motion preferences encoding, therapist-informed via-point extraction, and reference trajectory deformation in the proposed framework. (a) Gray lines are patient's actual motion trajectories. The green line indicates the estimated mean motion trajectory according to Section IV-B. Red scatter points indicate therapist-informed via-points inferred from the therapist-informed corrective force and the desired motion. The blue line indicates the generated reference trajectory according to Section IV-C. (b) Gray lines represent actual motion trajectories reproduced by therapist-side robot, while therapist applies the effective corrective force as the red arrows to inform the via-points.

Gaussian component parameters  $\{\mu_c, \Sigma_c, \varpi_c\}_{c=1}^C$  are characterized by its mean  $\mu_c$ , covariance  $\Sigma_c$ , and weight  $\varpi_c$ , which can be estimated from  $\mathcal{D}_P$  using the *Expectation-Maximization* algorithm [35] (see green line and ellipses in Fig. 2(a)). The conditional probabilistic trajectory, denoted by  $\{\hat{\mathbf{x}}_n\}_{n=1}^N$ , is then retrieved via GMR as

$$\mathcal{P}(\hat{\mathbf{x}}_n | \mathbf{t}_n) \sim \mathcal{N}(\hat{\mu}_n, \hat{\Sigma}_n) \quad (5)$$

where  $\hat{\mu}_n$  and  $\hat{\Sigma}_n$  are the conditional mean and covariance that can be calculated using the estimated GMMs parameters.

The parameterized potential trajectories of patient can be modeled as

$$\mathbf{x}(\mathbf{t}) = \Theta(\mathbf{t})^T \mathbf{w} \quad (6)$$

where  $\Theta \in \mathbb{R}^{d_B d_o \times d_o}$  is the basis feature matrix,  $d_B$  is the dimensionality of the basis feature, and  $\mathbf{w} \in \mathbb{R}^{d_B d_o}$  is the weight vector, assumed to follow a normal distribution  $\mathbf{w} \sim \mathcal{N}(\mu_w, \Sigma_w)$  with unknown mean  $\mu_w$  and covariance  $\Sigma_w$ . The parameterized probability of trajectory distribution is then represented as

$$\mathcal{P}_w(\mathbf{x} | \mathbf{t}) = \mathcal{N}(\Theta(\mathbf{t})^T \mu_w, \Theta(\mathbf{t})^T \Sigma_w \Theta(\mathbf{t})) \quad (7)$$

where  $\{\mu_w, \Sigma_w\}$  are the unknown mean and covariance to be estimated by minimizing the Kullback-Leibler (KL) divergence objective as

$$\mathcal{J}(\mu_w, \Sigma_w | \mathcal{D}_P) = \sum_{n=1}^N D_{KL}(\mathcal{P}_w(\mathbf{x} | \mathbf{t}_n) || \mathcal{P}_p(\mathbf{x} | \mathbf{t}_n)) \quad (8)$$

where  $\mathcal{P}_p(\mathbf{x} | \mathbf{t}_n)$  denotes the prior probability distribution of reference trajectory estimated from the dataset  $\mathcal{D}_P$  as shown in distribution (5). Leveraging the properties of KL-divergence for Gaussian distributions, the mean and variance can be obtained by solving two sub-problems [35]. Thanks to the kernel treatment, both mean and variance for a new input  $\mathbf{t}^*$  are obtained as

$$\begin{aligned} \mathbb{E}[\mathbf{x}(\mathbf{t}^*)] &= \mathbf{h}^*(\mathbf{H} + \lambda_\mu \Sigma)^{-1} \mu \\ \mathbb{D}[\mathbf{x}(\mathbf{t}^*)] &= N / \lambda_\Sigma (\mathbf{h}^{**} - \mathbf{h}^*(\mathbf{H} + \lambda_\Sigma \Sigma)^{-1} \mathbf{h}^{*T}) \end{aligned} \quad (9)$$

where  $\mu$  and  $\Sigma$  are the derived reference mean and covariance, respectively.  $\mathbf{h}^*$ ,  $\mathbf{h}^{**}$ , and  $\mathbf{H}$  denote the kernel matrices derived from the kernel function  $\mathbf{h}(\cdot, \cdot; \varrho)$ .  $\varrho$  is the kernel parameter.  $\lambda_\mu$  and  $\lambda_\Sigma$  are regularization factors.

### C. Therapist-informed Trajectory Deformation

The therapist-side robot can reproduce the actual trajectory of patient for  $J$  times during each therapy iteration. The patient motion preferences can be estimated from the previous dataset  $\mathcal{D}_P^i$  as in Section IV-B. For AAN therapy, the therapist applies corrective forces to partially deform the reference trajectory instead of updating the weight vector  $\mathbf{w}$  to re-plan the entire reference trajectory as in (6). The therapist-applied corrective force  $\mathbf{f}_{ext,Th}(\mathbf{t})$  is measured from the therapist-side robot during the reproduction of the patient's actual trajectory. When  $\mathbf{f}_{ext,Th}(\mathbf{t})$  exceeds a pretested threshold  $|\mathbf{f}|$ , it indicates that the therapist intends to correct the therapeutic movement for the patient-side robot. As shown in Fig. 2(b), when a corrective force is activated at time  $\mathbf{t}_v$ , a therapist-informed via-point is inserted at  $\mathbf{t}'_v = \mathbf{t}_v + \delta \mathbf{t}$  to enable the partial deformation of reference trajectory. An additional dataset  $\mathcal{D}_T$  that contains all therapist-informed via-points is introduced for one episode therapy to deform the reference trajectory for next therapy iteration.  $\mathcal{D}_T$  shares the same structure as dataset  $\mathcal{D}_P$  but consists of far fewer therapist-informed via-points ( $L \ll N$ ) to encourage the active participant of patients at other time.

When the therapist-informed via-points  $\{\mathbf{t}_l, \mathbf{x}_l^v\}_{l=1}^L$  are assumed to follow a Gaussian distribution  $\mathcal{P}_v(\mathbf{x}_l^v | \mathbf{t}_l) \sim \mathcal{N}(\hat{\mu}_l^v, \hat{\Sigma}_l^v)$ , the objective in (8) for estimating  $\{\mu_w, \Sigma_w\}$  can be reformulated, following the idea of KMP [35], as

$$\begin{aligned} \mathcal{J}(\mu_w, \Sigma_w | \mathcal{D}_P, \mathcal{D}_T) &= \sum_{n=1}^N D_{KL}(\mathcal{P}_w(\mathbf{x} | \mathbf{t}_n) || \mathcal{P}_p(\mathbf{x} | \mathbf{t}_n)) \\ &\quad + \sum_{l=1}^L D_{KL}(\mathcal{P}_w(\mathbf{x} | \mathbf{t}_l) || \mathcal{P}_v(\mathbf{x} | \mathbf{t}_l)) \end{aligned} \quad (10)$$

where  $\mathcal{P}_p(\mathbf{x} | \mathbf{t}_n)$  and  $\mathcal{P}_v(\mathbf{x} | \mathbf{t}_l)$  denote the prior probability distribution estimated from datasets  $\mathcal{D}_P$  and  $\mathcal{D}_T$ , respectively. To achieve a closed-form solution as in (9), an extended dataset  $\mathcal{D}_U = \mathcal{D}_P \cup \mathcal{D}_T$  is constructed, and the objective function is reformulated as

$$\mathcal{J}(\mu_w, \Sigma_w | \mathcal{D}_U) = \sum_{j=1}^{N+L} D_{KL}(\mathcal{P}_w(\mathbf{x} | \mathbf{t}_j) || \mathcal{P}_u(\mathbf{x} | \mathbf{t}_j)) \quad (11)$$



where the prior probability  $\mathcal{P}_u(\mathbf{x}|\mathbf{t}_j) \sim \mathcal{N}(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$  is estimated from the extended dataset  $\mathcal{D}_U$ . Intuitively, the therapist-informed via-points are extracted from the corrective force and the desired motion  $\mathbf{x}_e$  of the selected rehabilitation task. The mean and covariance of each therapist-informed via-point at  $\mathbf{t}'_v$  are designed as

$$\begin{aligned}\boldsymbol{\mu}(\mathbf{t}'_v) &= \beta_\mu \cdot (\mathbf{x}_e(\mathbf{t}'_v) - \boldsymbol{\mu}_w(\mathbf{t}'_v)) \cdot \frac{\mathbf{f}_{ext,Th}(\mathbf{t}_v)}{|\mathbf{f}_{ext,Th}(\mathbf{t}_v)|} + \mathbf{x}_r(\mathbf{t}'_v) \\ \boldsymbol{\Sigma}(\mathbf{t}'_v) &= \boldsymbol{\Sigma}_w(\mathbf{t}'_v)\end{aligned}\quad (12)$$

where  $\beta_\mu$  is the scale factor determining the amplitude of the reference trajectory deformation. Furthermore, to enable smooth complete trajectory deformation, another two via-points at  $\mathbf{t}_s = 0$  and  $\mathbf{t}_e = \Delta T$  are inserted at the start and end points.  $\Delta T$  is the duration of each therapy episode. The mean values of these via-points are defined as  $\{\mathbf{x}_e(\mathbf{t}_s), \mathbf{x}_e(\mathbf{t}_e)\}$  and the corresponding covariance matrices  $\{\boldsymbol{\Sigma}(\mathbf{t}_s), \boldsymbol{\Sigma}(\mathbf{t}_e)\}$  are defined to encourage high-precision tracking. The blue line in Fig. 2(b) represents the generated reference trajectory for the next therapy iteration, which preserves the patient's previous motion preferences while adapting to the therapist-informed via-points.

#### D. Reproducing Therapist Input Skills

In contrast to directly re-demonstrating the reference trajectory, we constructed a latent space to represent the therapist's input  $\chi_v$  with the dimension of  $M$ . As depicted in Algorithm 1, at each  $i$ -th therapy iteration, the therapist state is denoted as  $\mathbf{s}_i$  with a dimension of  $N$ , defined as:

$$\mathbf{s}_i = \boldsymbol{\mu}_w^i - \chi_e, \in \mathbb{R}^N \quad (13)$$

where  $\boldsymbol{\mu}_w^i$  is the mean waypoints encoded from patient's actual trajectories and  $\chi_e$  is the extracted waypoints from desired motion  $\mathbf{x}_e$ .

A dataset was constructed as  $\mathcal{D}_T = \{(\mathbf{s}_i, \mathbf{x}_{l,i}^v)\}_{i=1}^I$ . A partial least squares regression function is utilized to reproduce the therapist input  $\mathbf{Y} \in \mathbb{R}^{I \times M}$  from the collected feature  $\mathbf{X} \in \mathbb{R}^{I \times N}$ , as,

$$\mathbf{Y} = \mathbf{X}\mathbf{B} \quad (14)$$

where  $\mathbf{B} \in \mathbb{R}^{N \times M}$  is the weight matrix.  $\mathbf{X}$  and  $\mathbf{Y}$  can be decomposed as,

$$\mathbf{X} = \mathbf{T}\mathbf{P}^T + \mathbf{E}, \mathbf{Y} = \mathbf{U}\mathbf{Q}^T + \mathbf{F} \quad (15)$$

where  $\mathbf{P}$  and  $\mathbf{Q}$  are the loading matrices. When only using several latent dimension, the weight matrix is derived as

$$\mathbf{B} = \mathbf{W}(\mathbf{P}^T\mathbf{W})^{-1}\mathbf{Q}^T \quad (16)$$

where  $\mathbf{W}$  is the weight matrix of the input matrix.

## V. EXPERIMENTAL RESULTS

### A. Experimental Testbed

A telerehabilitation robotic system is setup, which is taken as an example to validate the effectiveness of proposed framework for upper-limb rehabilitation. The system consists of two identical 7-DoF Franka Emika Panda robots, which are controlled by two PCs running a real-time Linux kernel at

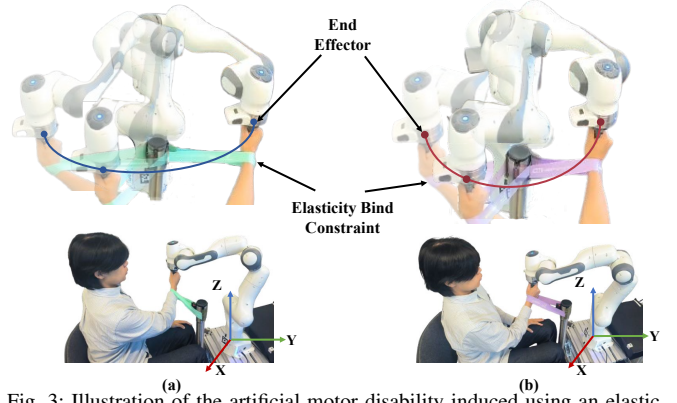


Fig. 3: Illustration of the artificial motor disability induced using an elastic band to provide resistance. (a) Patient at Stage #1 using a band with lower elasticity. (b) Patient at Stage #2 using a band with higher elasticity.

TABLE I: Controller Parameters

$\mathbf{K}_P = \text{diag}(200, 200, 1000, 50, 50, 50)$	$C_1 = 10, C_2 = 10$
$\mathbf{D}_P = \text{diag}(10, 10, 57, 13, 13, 13)$	$ \mathbf{f} =10\text{N}, N=200$
$\mathbf{K}_{Th} = \text{diag}(800, 800, 800, 50, 50, 50)$	$L_1 = 4, L_2 = 5$
$\mathbf{D}_{Th} = \text{diag}(51, 51, 51, 13, 13, 13)$	$\lambda_\mu = 1, \lambda_\Sigma = 60, \varrho = 2$
$I = 10, J = 5$	$\delta t = 0.05s, \beta_\mu = 1.0$

the control frequency of 1000 Hz. Both the patient-side GUI and therapist-side GUIs were developed using PyQt5 to visualize the desired and actual motions as illustrated in Fig. 1. Data transmission between the therapist-side PC and the patient-side PC was achieved using ZeroMQ within the same network, resulting in negligible communication delay. The parameters used for the lower-level interactive controllers in the subsequent rehabilitation tasks are predefined and summarized in Table I. Without loss of generality, the robot in this work is constrained to planar motion; specifically, all rehabilitation tasks are executed within the  $X$ - $Y$  plane relative to the robot's base frame (see Fig. 3).

### B. Experimental Protocol

The objective of the subsequent human study is to validate the effectiveness of the proposed controller in incorporating the therapist inputs for AAN therapy, instead of evaluating the biomechanical responses of the patient. Two able-bodied participants from the authors' laboratory were recruited to play the role of therapist and patient. As illustrated in Fig. 3, participants acting as patients were unable to follow the desired motions due to the impediment introduced by the elastic band. Moreover, different levels of band elasticity were applied to simulate the patient's various stages of recovery. Two rehabilitation tasks, each involving distinct motion patterns, are designed to demonstrate the effectiveness of the proposed controller in enabling personalized AAN therapy. For each task, one participant acts as the therapist who is assumed to be able to successfully follow the desired motion, while another participant acts as the patient to accept the AAN therapy. Therefore, given the desired motion and predefined parameters, the therapist-informed repetitive therapy will be implemented following the procedure in Algorithm 1. Two commonly used baseline methods are also implemented to demonstrate the strength of our method. First, Baseline #1 was implemented similar to [30], [5], the

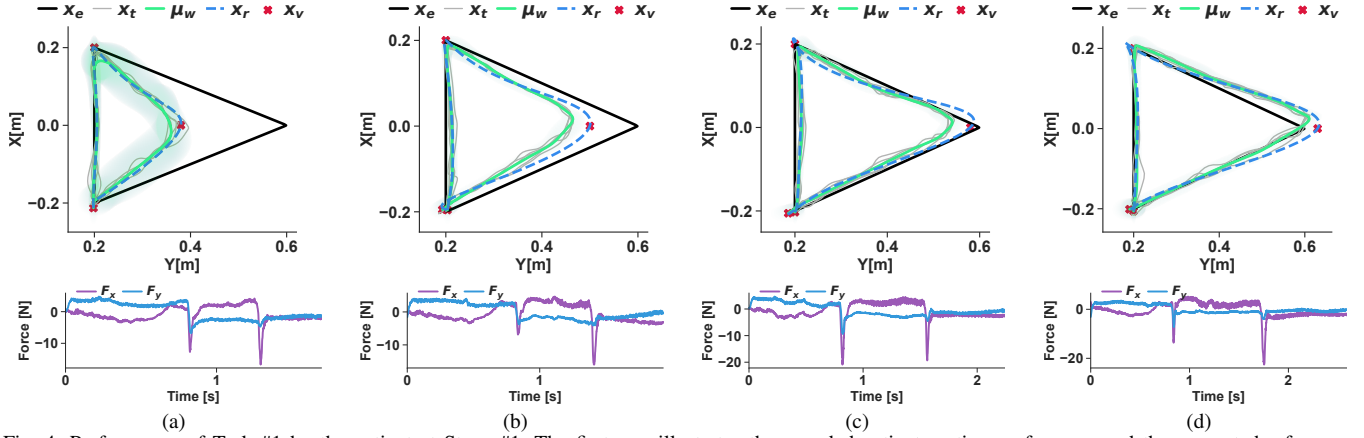


Fig. 4: Performance of Task #1 by the patient at Stage #1. The first row illustrates the encoded patient motion preferences and the generated reference trajectories, while the second row shows the corrective forces applied by the therapist. (a) Iteration 1; (b) Iteration 3; (c) Iteration 6; (d) Iteration 9.

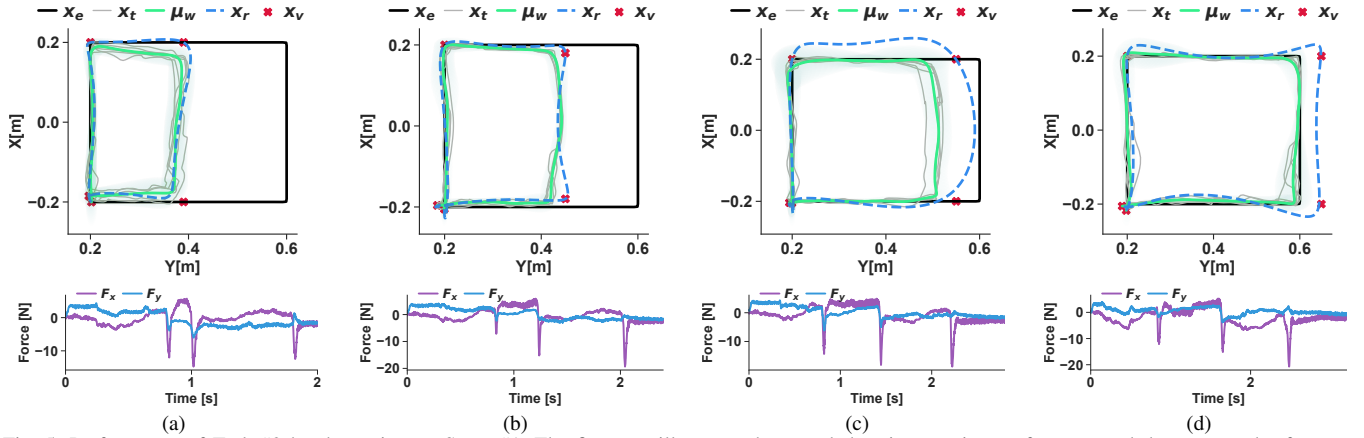


Fig. 5: Performance of Task #2 by the patient at Stage #1. The first row illustrates the encoded patient motion preferences and the generated reference trajectories, while the second row shows the corrective forces applied by the therapist. (a) Iteration 1; (b) Iteration 3; (c) Iteration 6; (d) Iteration 9.

desired motion was selected as the reference trajectory and a variable impedance control was applied to complete the movement therapy. Second, Baseline #2 was implemented similar to [12], the therapist's input force was directly transmitted to the patient-side robot whenever the therapist deemed assistance necessary. Furthermore, two metrics were calculated for a fair comparison. First, the corrective force measured from patient-side robot was utilized to evaluate the robot's input and patient's active participation, denoted as  $M_1$ . Second, movement smoothness, a commonly used indicator of kinematic control, was calculated by spectral arc length [30] to assess the quality of movement therapy, denoted as  $M_2$ .

### C. Experiment Results of Human Study

The participant using the elastic band with small elasticity acts as the patient to complete two representative tasks (see Fig. 3(a)). Each task was repeated for  $I = 10$  therapy iterations without relying on other termination. The learned patient motion preferences and generated reference trajectories during four therapy iterations are visualized in Fig. 4 and Fig. 5.

1) *Therapist-informed AAN Therapy*: The desired motion of Task #1 (a triangle trajectory) was visualized by black lines as shown in Fig. 4. At  $i$ -th therapy iteration,  $J = 5$  therapy actual trajectories, visualized by gray lines, are collected to encode the motion preferences using GMMs with

$C_1 = 10$  components. The green line and the green region represent the learned mean and variance. For fair comparison, the therapist's skill is assumed to enable the patient to complete the key points of the desired motion. Therefore,  $L_1 = 4$  via-points (see Section IV-C) were extracted from the therapist-informed corrective force and visualized by red scatters. We can see that the therapist-informed corrective force plotted in the second row demonstrates that the therapist did not actively intervene in the current therapy session. Instead, the therapist only informed two via-points to guide the trajectory deformation for AAN therapy. The reference trajectory for next therapy iteration was then generated and shown as the dotted blue line.

The desired motion of Task #2 (a rectangle trajectory) was visualized by black lines as shown in Fig. 5. At  $i$ -th therapy iteration,  $J = 5$  actual trajectories, visualized by gray lines, are collected to encode the motion preferences (green lines) using GMMs with  $C_2 = 10$  components. Following the same assumption of therapist's skills in Task #1,  $L_2 = 5$  via-points were extracted from the therapist-informed corrective force visualized by red scatters. The therapist-informed corrective force plotted in the second row indicates that the therapist only informed three via-points for patient therapy to reach three corners of the rectangle trajectory. The reference trajectory for the next therapy iteration was then generated and is illustrated by the blue line. For a fair comparison, rather than defining a specific rehabilitation termination condition,

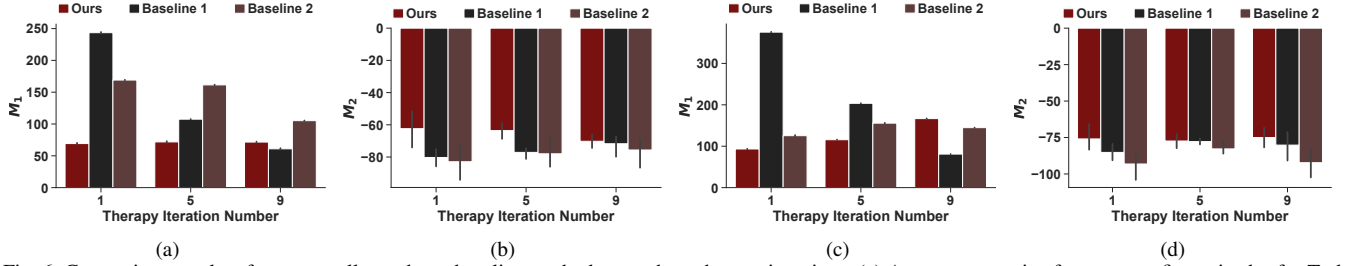


Fig. 6: Comparison results of our controller and two baseline methods over three therapy iterations. (a) Average corrective force across five episodes for Task #1; (b) Average movement smoothness index across five episodes for Task #1; (c) Average corrective force across five episodes for Task #2; (d) Average movement smoothness across five episodes for Task #2.

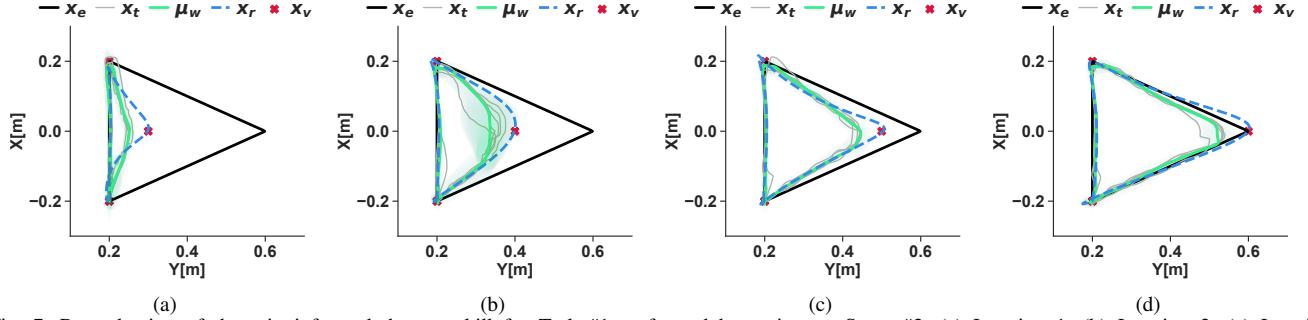


Fig. 7: Reproduction of therapist-informed therapy skill for Task #1 performed by patient at Stage #2. (a) Iteration 1; (b) Iteration 3; (c) Iteration 6; (d) Iteration 9.

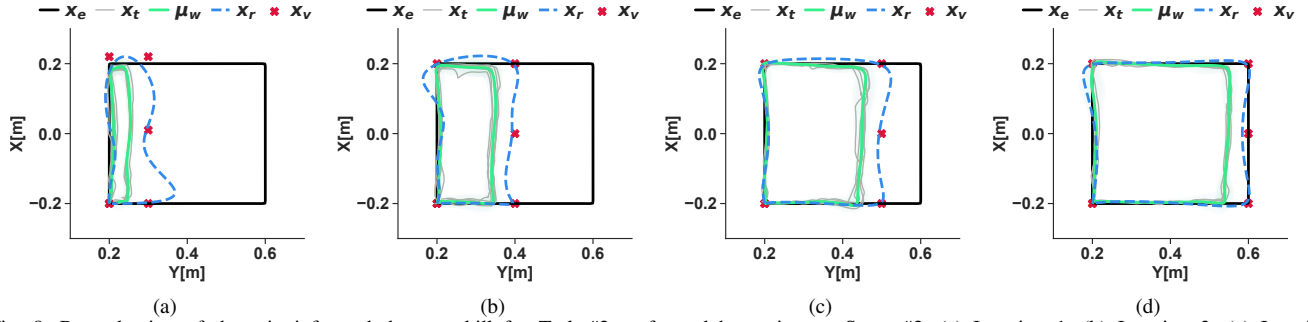


Fig. 8: Reproduction of therapist-informed therapy skill for Task #2 performed by patient at Stage #2. (a) Iteration 1; (b) Iteration 3; (c) Iteration 6; (d) Iteration 9.

$I = 10$  therapy iterations were conducted to evaluate the effectiveness of Baseline #1 and Baseline #2 on both Task #1 and Task #2 performed by the patient using the same elastic band. Baseline #1 was implemented using the variable impedance controller given the desired motion (black lines in Fig. 4 and Fig. 5) as the reference trajectory. The stiffness is modulated according to the tracking error and the damping matrix was derived from the stiffness using a fixed relation. Baseline #2 was implemented using a zero-impedance control for the patient-side robot to allow patient maximum participant, while directly adding the therapist-informed corrective force from therapist-side robot. The average values of two metrics are calculated for three therapy iterations. As shown in Fig. 6(a) and 6(c), Baseline #1 results in the large corrective force when the patient's actual motion is far from the desired motion (see therapy iteration 1). Although the Baseline #2 can reduce the corrective force from the robot and encourage patient's active engagement, as illustrated in Fig. 6(b) and 6(d), movement smoothness is affected by the therapist-informed therapeutic force. In summary, the proposed controller can not only maximally encourages the patient's active participant without introducing excessive corrective force, but also ensures that the smoothness of the

movement therapy remains unaffected.

2) *Reproducing Therapist's Therapy Skill*: The collected therapist-informed via-points in dataset  $\mathcal{D}_T$  are employed to learn regression parameters  $\psi_T^*$  for Task #1 and Task #2. Afterwards, the via-points are generated from the regression function for patient at another recovery Stage #2, which is acted by the able-bodied participant using another elastic band with greater elasticity (see Fig. 3(b)). Results in Fig. 7 and Fig. 8 indicate that the patient can achieve the set desired motion for both Task #1 and Task #2 after  $I = 10$  therapy iterations without additional instruction from the therapist. The performance of reference trajectory deformation depends on the hyperparameters as shown in Table I. In this study, we assumed that the therapist primarily focused on providing corrective force to help the patient capture the key motion features enabling  $L_1 = 4$  and  $L_2 = 5$ .

## VI. DISCUSSION AND CONCLUSION

This article proposed a novel framework for therapist-in-the-loop AAN therapy. Its effectiveness and advantages in utilizing therapist's expertise over state-of-the-art methods were validated using a telerobotics-mediated upper-limb rehabilitation system. For instance, in [18], the therapist needs to re-plan the entire reference trajectory for

each therapy iteration or adapt the impedance parameters for varied therapy intensity [23]. Our framework aims to maintain patient motion preferences and partially deform the reference trajectory, which maximally encourage the active participation of patients and utilize therapist-informed corrective force. Moreover, [12], [3] rely on a low-impedance robotic system or additional sensors to detect the corrective force and add to patient-side therapy. By contrast, we build a latent space to infer the via-points for trajectory partial deformation from therapist-informed corrective force. The results demonstrate that our framework can ensure the safety by avoiding the large corrective force and mitigating the effect of communication delay for movement therapy. Most importantly, therapist-informed therapy skills can be encoded using the collected via-points in latent space and reproduced through a regression function.

This study presents a feasibility evaluation of the proposed controller with able-bodied participants under simulated motion disabilities. In future work, our framework can be extended for telerehabilitation applications by integrating the telerobotics-mediated system with advanced communication protocols (e.g., 5G). Most importantly, our framework enables that therapists only need to provide corrective force through the robot without programming the reference trajectory or manually tuning the control parameters. To further assess its therapeutic benefits, clinical studies will be conducted based on analyzing the biomechanical feedback. Currently, a partial least squares regression function for therapist's skill reproducing is task-dependent depending on collecting labeled data from each task. Future works will focus on the in-context regression function capable of reproducing the therapeutic skill of therapist across different tasks.

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