Federated Joint Learning of Robot Networks in Stroke Rehabilitation

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Abstract— **Advanced by rich perception and precise execution, robots possess immense potential to provide professional and customized rehabilitation exercises for patients with mobility impairments caused by strokes. Autonomous robotic rehabilitation significantly reduces human workloads in the long and tedious rehabilitation process. However, training a rehabilitation robot is challenging due to the data scarcity issue. This challenge arises from privacy concerns (e.g., the risk of leaking private disease and identity information of patients) during clinical data access and usage. Data from various patients and hospitals cannot be shared for adequate robot training, further compromising rehabilitation safety and limiting implementation scopes. To address this challenge, this work developed a novel federated joint learning (FJL) method to jointly train robots across hospitals. FJL also adopted a long short-term memory network (LSTM)-Transformer learning mechanism to effectively explore the complex tempo-spatial relations among patient mobility conditions and robotic rehabilitation motions. To validate FJL's effectiveness in training a robot network, a clinic-simulation combined experiment was designed. Real rehabilitation exercise data from 200 patients with stroke diseases (upper limb hemiplegia, Parkinson's syndrome, and back pain syndrome) were adopted. Inversely driven by clinical data, 300,000 robotic rehabilitation guidances were simulated. FJL proved to be effective in joint rehabilitation learning, performing 20% - 30% better than baseline methods.**

I. INTRODUCTION

Stroke is a global healthcare problem contributing to individual disability and death [1]; rehabilitation typically aims to train patients in compensatory strategies with proximal (e.g., shoulder abduction, arm flexion) and distal (e.g., hand open, finger extension) movements to facilitate patient recovery on strength, speed, endurance, and precision of multijoint movements [1], [2]. While training a human expert for professional rehabilitation is expensive and lengthy, for example, an attending physician-level expert will need an average professional education and training time of 8-11 years and 0.2-0.5 million dollars [3].

Powered by sensor and control technologies, robots can precisely and durably provide patient training exercises to ensure quality rehabilitation exercise, significantly reducing human workload and economic/time costs; most importantly, powered by the latest learning algorithms, a robot with expert-level skills can be trained within several days [4].

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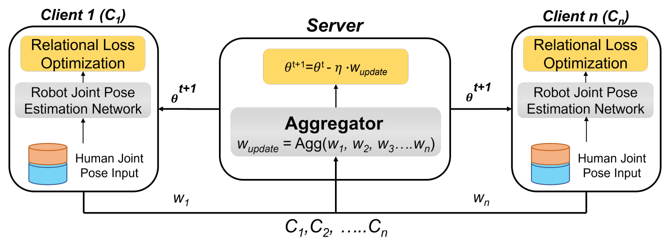

Fig. 1: Federated joint learning framework overview.

Therefore, it is promising to rely on robots for durable, reliable, and economical rehabilitation for movement disorder stroke diseases, such as hemorrhagic stroke and hemiplegic stroke [5].

However, training a professional and safe rehabilitation robot is challenging due to clinical data scarcity. Besides treatment-relevant information (e.g., stroke types and motor impairments), clinical rehabilitation data also includes irrelevant but private information (e.g., patients' identity, physiological characteristics, and other illnesses) [6]. Restrained by concerns of leaking patient information, clinical data cannot be accessed across hospitals; small-amount local data inadequately train a rehabilitation robot, further undermining its performance and safety and impeding widespread implementations of robotic rehabilitation [7]. Besides, patients vary in physical characteristics and motor impairments, adding challenges for robots to provide customized rehabilitation [8].

Therefore, to address the data scarcity issue, in this research, a novel joint training method – *Federated Joint Learning (FJL)* was developed to collaboratively train robots crossing hospitals. Particularly, our work in this paper mainly has three contributions:

- A federated joint learning network was developed to network robots crossing hospitals and enable them to mutually learn rehabilitation skills from each other without directly accessing original patient data.
- A LSTM-Transformer learning framework was developed to efficiently extract representative motion plans from complex spatiotemporal motions of patient joints with differences in body characteristics and motor impairment degree.
- A novel relational loss was designed to refine the robot pose estimation result and improve the accuracy of the pose estimation model.

II. OUR APPROACH: FJL NETWORK

The FJL framework shown in Figure 1, consists of three modules - 1) AFJL enables joint learning for robot rehabilitation while concealing sensitive patient data during shared learning. 2) The Robot Joint Pose Estimation module accurately infers robot poses from patient joint inputs, using the LSTM-Transformer. 3) A relational-based refinement module optimizes the robot pose estimation network parameters.

Robot Federated Joint Learning. The objective task is to define an objective training function F_i that maps the model parameters set $\theta_i \in \mathbb{R}^d$ to a training loss respect to private i-th robot data R_i.

$$\min_{\theta} \left\{ \mathcal{G}(\theta) := \sum_{i=1}^{m} F_i(\theta_i) + \lambda \sum_{i<j}^{m} A\left(\|\theta_i - \theta_j\|\right) \right\} \quad (1)$$

where $A\left(\|\theta_i - \theta_j\|^2\right)$ is an attention including function that described in [9] to measure the difference between θ_i and θ_j in a non-linear manner, and λ is a normalized parameter.

At last, the gradient that gets from clients is aggregated and updated by using the following formula:

$$\theta^{update} = \theta - \eta \cdot \frac{1}{n} \sum_{i=1}^{n} \delta_{C_i} \quad (2)$$

Robot Joint Pose Estimation. The proposed LSTM-Transformer-based robot joint pose estimation module consists of three parts. The model computation procedure $f\left(X_{t-P+1:t}\right)$ can be described as:

$$X_{concat} = \text{concat}\left(X_{t-p+1:t}\right) \quad (3)$$

$$X_{lstm}, h_{lstm} = \text{LSTM}\left(X_{concat}, h_{lstm}^{i-1}\right) \quad (4)$$

$$\hat{Y}_t = \text{TransformerBlock}\left(X_{lstm}\right) \quad (5)$$

At last, an MSE loss function is applied to train the robot joint estimation model:

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(f(X_{t-P+1:t}) - Y_t\right)^2 = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{Y}_t - Y_t\right)^2 \quad (6)$$

where Y_t is the t-th robot joint ground truth and N is the total$N$-timestamp. X is the robot Joint settings as the input including the joint's force, positions, velocity in space, and intrinsic positions.

Relational Loss. As defined in [10], to refine the pose estimation accuracy and improve metrics results through minimizing the correlation between MSE loss and PCK metrics, the only way is to improve the negative correlation between loss function and PCK metrics:

$$\mathcal{O}_s\left(\mathcal{L}\left(y, \hat{y}; \theta\right), \mathcal{M}\left(y, \hat{y}\right)\right) = \rho_S\left(\mathcal{L}\left(y, \hat{y}; \theta\right), \mathcal{M}\left(y, \hat{y}\right)\right) \quad (7)$$

where θ is the optimized parameters in the network.

III. Experiment Settings and Result Analysis

Clinical Data Driven Simulation. The experiment utilized the KiMoRe dataset [11], encompassing rehabilitation exercises for 200 stroke patients across three types. Using Coppeliasim [12], a simulation scenario mimicking robotic stroke rehabilitation was created. Human motions from the dataset were used to guide simulated robotic arm movements, generating robot data used for training the FJL model. This trained model's accuracy was validated to ensure its effectiveness in stroke rehabilitation (Figure 2).

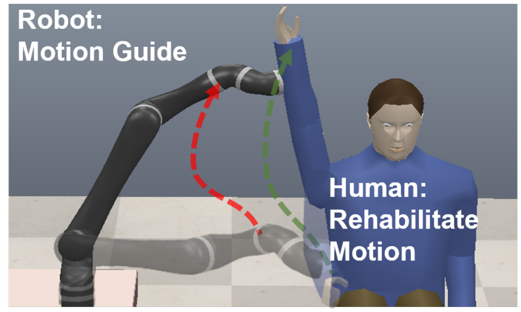

Fig. 2: Settings for robot-guided rehabilitation.

TABLE I: The comparison of PCK value of each model with relational loss and MSE loss

VIO Algorithms	MSE Loss	**Relational Loss (Ours)**
LSTM	0.674	**0.751**
Transformer	0.565	**0.630**
LSTM-Encoder-Decoder	0.541	**0.743**
LSTM-Transformer	0.706	**0.754**

Result Analysis. The final results are presented in Table I. This table highlights that the proposed LSTM-Transformer with relational loss exhibits the best performance, signifying that the LSTM-Transformer is adept at facilitating accurate patient rehabilitation. From the results presented in Table I, the superior accuracy and impressive generalization capabilities of the LSTM-Transformer network proved good performance in robot pose estimation. The experiment result indicates the performance of the LSTM-Transformer is 20%-30% higher than the baseline.

IV. Conclusion and Future Work

This study tackled challenges in federated joint learning for rehabilitating robots by introducing FJT, a tailored architecture enabling robot training without direct patient data access. FJT safeguards patient data, enhances robot training, and improves spatial-temporal rehabilitation learning for upper limb hemiplegia patients. Future work will focus on developing collaborative mechanisms for synchronized rehabilitation across patients' upper and lower limbs.

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