2023 IEEE International Conference on Robotics and Automation (ICRA 2023)
May 29 - June 2, 2023. London, UK

A Dual-Arm Participated Human-Robot Collaboration Method for Upper Limb Rehabilitation of Hemiplegic Patients*

Lufeng Chen[1], Jing Qiu[2], Xuan Zou[1] and Hong Cheng[1]

Abstract— **Upper limb rehabilitation robots are mainly used as a physical therapy method to passively or actively train the affected side. However, they are rarely implemented in accordance with the occupational therapy theory, which is dedicated to improving the sensorimotor coordination of hemiplegic patients by considering both healthy and affected limbs. To realize the occupational therapy concept in robot-assisted upper limb rehabilitation, we propose a new human-robot collaboration framework for hemiplegic patients that integrates healthy/affected limbs and robot. The strategy aims at achieving patient-specific movement capabilities and improving the participation of the affected limb during rehabilitation. To accomplish this task, we have addressed two essential issues: accurate motion estimation of the healthy limb and the rehabilitation trajectory learning technique. The posture estimation is achieved by introducing the calibration model to reduce static and time dependent errors during the measurement. We also introduce a force term to the conventional imitation learning method to improve the adaptability in integrating the affected side in cooperation with the robot. Various experiments have been conducted to validate the feasibility and effectiveness of our proposed dual-arm collaboration strategy.**

I. INTRODUCTION

Hemiplegia is one of the most common symptoms of stroke patients. The rehabilitation of hemiplegic stroke patients is of great concern to society and the medical profession. The essence of hemiplegia rehabilitation is to repair the damaged nervous system of patients and help them regain the ability to take care of themselves in daily life, so that they can return to their families and society as soon as possible. Restoration of upper limb motor function is of great importance for patients with hemiplegia [1].

In clinical rehabilitation, occupational therapy (OT) is often used to improve the activity of daily living (ADL) of hemiplegic patients, mainly based on manual rehabilitation. In recent years, various types of upper limb rehabilitation training systems have been developed to assist therapists in stroke recovery. Recently, rehabilitation robots have become a research trend in medical robotics due to their high precision, reliability and repeatability in motor recovery and improvement.

*This work was supported in part by the National Key Research and Development Program of China (No. 2018AAA0102505), the Natural Science Foundation of China (No. 52005082) and Sichuan Science and Technology Program (No. 2022ZDZX0032).

[1]Lufeng Chen, Xuan Zou, and Hong Cheng are with the Department of Automation Engineering, University of Electronic Science and Technology of China, Chengdu, China

[2]Jing Qiu (*Corresponding author*) is with the Department of Mechanical and Electric Engineering, University of Electronic Science and Technology of China, Chengdu, China. She is also with the Buffalo Robot Technology (Chengdu) Co., Ltd. qiujing@uestc.edu.cn

There is evidence that bilateral arm training has a beneficial effect on upper limb paresis after stroke. Other studies have also shown that recovery of motor function in the affected limb is partly related to activity in the healthy side of the brain, and that the healthy side of the movement in turn promotes recovery of motor function in the affected brain [2]. However, both manual and robotic rehabilitation have limitations. On the one hand, manual rehabilitation is often carried out on a one-to-one basis with tailored treatments, which has good rehabilitation effects but low rehabilitation efficiency, high labour costs and is highly dependent on the experience of the therapist. On the other hand, rehabilitation robots often provide different training modes, such as passive or active, which is highly appreciated after stroke recovery. To the best of our knowledge, the rehabilitation training strategy for OT that integrates healthy and affected upper limbs is rarely seen in academia and clinical practice.

To alleviate the conundrum that the state-of-the-art robotic rehabilitation strategy lacks the ability to actively train both limbs in accordance with the occupational therapy concept, we focus on the integration of both healthy and affected limbs in a robotic rehabilitation paradigm.

II. RELATE WORKS

A. Upper Limb Rehabilitation System

The upper limb rehabilitation system can be categorized as a medical robot that assists patients in exercising the upper limbs, such as the shoulder, elbow and hand. Active and passive training improves the strength of the patient's muscle movements and the flexibility of the upper limb joints [3]. In recent years, many rehabilitation robots have been invented to perform upper limb rehabilitation. Considering the mechanical structure, the robotic devices can be divided into two categories: the end-effector type (such as MIT Manus, ACRE, NeReBot, CRAMER, MACARM, etc.) and the exoskeleton-based (ARMin, CADEN-7, Pneu-WREX, etc.) robots [4]. The end-effector type robot uses its end-effectors (usually a handle) to guide the movement of one or more upper limb joints of the patient. The simple structure of the configuration makes it easy to control, but it cannot fully resemble the versatility of the human arm to its maximum extent, with single or very limited rotational movements [5]. As the name suggests, the exoskeleton type allows the patient to wear it. The alignment of the robot axes with the anatomical axes of the wearer controls the patient's joint locomotion in a passive pattern that has been successfully applied to the upper extremity [6]. Due to the complexity of the human musculoskeletal system, the design of the exoskeleton-type robot to resemble human joints is a challenging task. The issue of human-robot misalignment is still an open problem [7]. In addition, the interaction between the arm and the exoskeleton and the human-robot collaboration should also be considered [8].

B. Human-Robot Collaboration

Human-Robot Collaboration (HRC) is one of the core technologies for rehabilitation robots. Its main goal is to enable the robot to interact with the patient and then autonomously perceive, understand, learn and provide feedback on environmental information during the interaction process, providing the possibility of machine transparency and human-robot intelligence [9]. In robotic rehabilitation, the critical issue is to achieve mutual understanding of the intentions of the rehabilitation robot and the patient under uncertain conditions, and to provide feedback on each other's intentions. The main physiological feedback signals commonly used in rehabilitation robots are electromyography (EMG) and electroencephalography (EEG) [10], while the physical feedback often includes contact force and inertial difference [11]. Currently, the movement assistance provided by the upper limb rehabilitation robots can be divided into passive and active modes. The passive mode mainly focuses on the repetitive movement of the patient's joints, with relatively little involvement of the hemiplegic patient in the process. The active mode mainly uses EMG, EEG or interactive force to obtain the active intention of humans to realise a more active rehabilitation movement of the upper limbs with the assistance of a robot, which improves the active participation of patients to a certain extent.

In order to ensure better imitation of the experienced therapist, the generation of the rehabilitation trajectory is required to learn the patterns behind these demonstrations, known as imitation learning. It can be categorized into Dynamic Movement Primitives (DMP) [12], Stable Estimator of Dynamical Systems (SEDS) [13], Probabilistic Movement Primitives (ProMP) [14] and Kernelized Movement Primitives (KMP) [15], etc. In upper limb rehabilitation, the motion trajectory of the rehabilitation robot in HRC is one of the key factors to help hemiplegic patients recover. An effective motion trajectory can improve the rehabilitation training effect of patients.

All the above endeavours inspire us to develop the HRC strategy for upper limb rehabilitation. In this study, we propose a new dual-arm participated human-robot collaboration framework for hemiplegic patients by improving participation during upper limb rehabilitation, focusing on two key issues: accurate acquisition of movement on the healthy limb and dominant motion trajectory modulation of the affected limb in the dual-arm participated treatment.

III. METHODS

A. Human-robot collaboration strategy for upper limb rehabilitation

In upper extremity rehabilitation, bilateral arm training is inspired by our common daily activities that involve both arms [16]. For example, when we consider limb function deficits after stroke, we find that upper extremity paresis affects the ability to use the affected limb in daily activities, leaving many patients unable to perform bimanual tasks such as pouring water into another cup. The emergence of rehabilitation robots can address the shortage of therapists, reduce the intensity of work, improve the consistency of therapeutic effects, etc. To further address the shortcomings of current rehabilitation robots, most of which only perform passive training and lack bimanual occupational therapy for upper limb hemiplegia patients, in this paper we propose a human-robot collaborative framework for upper limb rehabilitation with healthy/affected limb and robot cooperation, where the movement of the healthy side is used as movement guidance, and the affected side (which may include the healthy side) cooperates with the robot to perform task-oriented movements. Fig. 1 illustrates the three types of upper extremity rehabilitation paradigms: the conventional manual rehabilitation, the passive/active robot-assisted rehabilitation on the affected limb, and our proposed dual-arm participated collaboration (DPC) rehabilitation strategy.

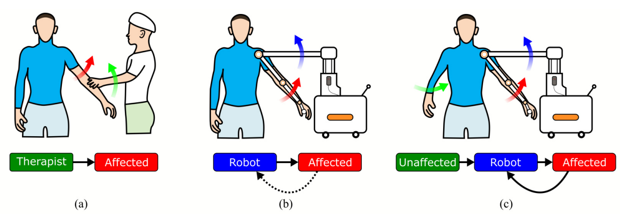


Fig. 1. Comparison of three different types of upper extremity rehabilitation paradigm. (a) Manual rehabilitation; (b) Passive/active robot-assisted rehabilitation on the affected limb; (c) DPC-based rehabilitation strategy.

To realize our proposed DPC, in this paper we focus on two significant aspects: the upper limb movement parameterization method and the human-robot collaboration control method, which will be elaborated.

B. Parameterization of upper limb movements

Our proposed DPC starts with the acquisition of motion data from the healthy limb. We use the inertial measurement unit (IMU) to record the motion accurately. However, due to the irregularity and flexible surface of the human arm, the wearable sensors cannot precisely coincide with the coordinate system of the arm, and the acquired motion data may require better accuracy, more repeatability, and more robust adaptability. Our first task is to propose a parametric method for upper limb movements based on posture estimation, which improves the accuracy of motion trajectory estimation.

1) Upper extremity biometric modeling and posture calibration: From the biomechanical analysis, the human limb can be represented as a joint and linkage structure, and the skeletal joints of the human body can be established as a coordinate system, as shown in Fig. 2. $\{G\}$ denotes the world coordinate system as a reference; $\{S_i\}$ is the wearable sensor coordinate system, where i denotes the number of each sensor; $\{J_i\}$ and $\{B_i\}$ represent the joint and skeletal coordinate system of the human limb, respectively. Note that there is a slight difference between $\{B_i\}$ and $\{J_i\}$ due to the misalignment of the rotation axes. The modelling analysis will also take into account the measurement error caused by the small movement between them.

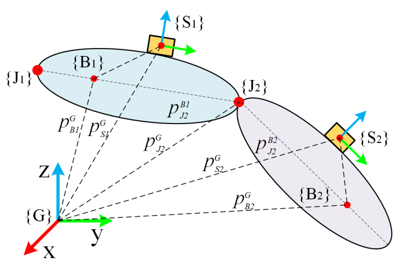


Fig. 2. Coordinate systems on the upper limb.

Due to the small contractions and deformation of soft tissues during the limb movement and the misalignment of the IMU installation, the posture information of B_i can not be directly measured by the corresponding S_i. To estimate the actual postures of the upper limb, we introduce a time-dependent parameter e to describe this difference. The relationship between the wearable sensor and the upper limb can be represented as:

$$p^G_{S_i,t} = p^G_{B_i,t} + R^G_{B_i,t}(p^{B_i}_{S_i} + e^{S_i}_{p,t}) \tag{1}$$
$$q^G_{S_i,t} = q^G_{B_i,t} q^{B_i}_{S_i,t} \exp{(e^{S_i}_{q,t}/2)} \tag{2}$$

where: $p^G_{S_i,t}$ and $q^G_{S_i,t}$ denote the position and orientation of the sensor w.r.t the ground, $R^G_{B_i,t}$ is rotational matrix, $e^{S_i}_{p,t}$ and $e^{S_i}_{q,t}$ represents the position and orientation error of the sensor coordinate system over time following the Gaussian distribution, i.e., $e^{B_i}_{p,t} \sim \mathcal{N}(0, \sum_p)$ and $e^{S_i}_{q,t} \sim \mathcal{N}(0, \sum_q)$.

To achieve an accurate estimation of human upper limb posture by two IMU sensors (S_1 and S_2), in this paper, we propose a linear calibration model based on upper limb kinematics by introducing linear calibration coefficients for each joint value. The determination of the coefficients turns into an optimization problem as follows.

$$\begin{aligned} &\min\nolimits_{\lambda_i} ||\kappa(\theta_i\lambda_i) - T^s_w||(i = 1, \cdots, k) \\ &\text{s.t.} p^G_{B_1,t} + R^G_{B_1,t} p^{B_1}_k - p^G_{B_2,t} - R^G_{B_2,t} p^{B_2}_k = 0 \end{aligned} \tag{3}$$

where: κ denotes the upper limb kinematic model with k joints. θ_i and λ are the joint value and the corresponding calibration coefficient, respectively. T^s_w denotes the transformation matrix from wrist to shoulder. Referring to Fig. 2, the constraint reveals the kinematic relationship between the posterior arm and the forearm, where $p^{B_i}_k$ is the distances from J_k to B_i. The estimation of the calibration coefficients can be easily solved by the least square optimization method once given a series of demonstrations with known positions and orientations.

2) Upper limb joint angle and position estimation: Once the calibration is set, the angular information of the shoulder and elbow joints can be retrieved by constructing a 5 degree of freedom (DoF) upper limb kinematic model consisting of the shoulder and elbow joints.

The shoulder joint is modeled as a spherical joint with 3 DoF. Given the kinematic model, the calibration coefficient λ and the static error e in the Euler frame, the shoulder joint angle θ can be calculated as follows:

$$\theta_i = \lambda_i \alpha^1_i + e_i, i = 1, 2, 3 \tag{4}$$

where: $\alpha^1_i (i = 1, 2, 3)$ corresponds to the yaw, pitch, and roll angle of the IMU sensor S_1 mounted on the posterior arm.

Similarly, the elbow is modeled as a 2 DoF joint. Because of the kinematic relationship between the posterior arm and the forearm, the calculation of the elbow joint angles can be expressed as:

$$\theta_i = \lambda_i(\alpha^2_{i-2} - \alpha^1_{i-2}) + e_i, i = 4, 5 \tag{5}$$

Once joint values are obtained, the position and orientation of wrist can be calculated by substituting the joint angles θ_i of the shoulder and elbow joints into the forward kinematic model $\kappa(\theta_i\lambda_i)$.

C. Human-robot collaboration based on force-coupled dynamic motion primitives

1) Coupling dynamic motion primitive: In order to perform task-oriented occupational therapy by integrating the healthy/affected limb with the robot, we adopt an improved imitation learning method applied to upper limb rehabilitation by introducing a force-coupled term into the classical DMP method [12], named Coupling Dynamic Movement Primitives (CP-DMP). CP-DMP improves the adaptation of generalized movements to the environment through the introduced coupled term while learning the movements demonstrated by the healthy limb.

The principle of the algorithm is to establish a dynamic model using a spring-mass-damper model and modulate the system by introducing a nonlinear forcing term based on a stable dynamic system, so that the system can eventually reach the expected attractor state. The original DMP method only learns the trajectory of the demonstration without considering the influence of environmental factors. In this paper, inspired by the idea of adding a repulsive force as a constraint to the system [17], we introduce the interaction force between the patient and the robot as a force-coupled environmental factor to the DMP, the trajectory learning and imitation ability of the revised method can be improved under the change of the factor, so that the original DMP system not only has the ability to encode motion trajectories and trajectory planning, but also has dynamic characteristics. The force-coupled DMP becomes:

$$\tau \dot{z} = \alpha_z(\beta_z(g-y)-z)+f(x)+c_1\dot{C} \tag{6}$$

$$\tau \dot{y} = z + C \tag{7}$$

$$C = c_2 F(t) \tag{8}$$

where: y, $\dot{y}$ and $\ddot{y}$ denote position, velocity, and acceleration, respectively, g denotes the desired target of the system, α_y and β_y are gain coefficients, and τ is a time constant. C denotes the force coupling term, and c_1 and c_2 are scaling coefficients that can rapidly reduce the contact force between the robot and the arm. A more compliant control effect can be achieved by choosing appropriate coefficients. $F(t)$ is the human-robot contact force, equal to the difference between the desired contact force $F_d(t)$ and the measured one $F_i(t)$, i.e. $F(t) = F_d(t) - F_i(t)$. Note that the desired human-robot contact force $F_d(t)$ can be set to a constant or measured during the demonstration in practice. $F(t)$ also serves as a safety factor to limit the patient-robot interaction.

The term $f(x)$ is a normalized linear superposition of several nonlinear radial basis functions $\phi_i(x)$ as follows:

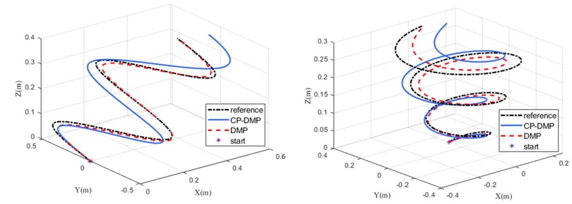
$$f(x) = \frac{\sum_{i=1}^{N}\phi_i(x)\omega_i}{\sum_{i=1}^{N}\phi_i(x)} x(g-y_0) \tag{9}$$

where: y_0 is the initial position, ω_i denotes the weight of the basis function, N is the number of basis functions, which will affect the trajectory fitting.

Given a demonstration y, the forcing term $f(x)$ can be obtained using Equation 9. The weights ω_i that best approximate the desired forcing term are computed using Locally Weighted Regression (LWR). During the execution phase, given the start and end points of the trajectory, the obtained weights ω are superimposed on the nonlinear function f, and the motion information (position, velocity, and acceleration) of the target trajectory can be computed by the transformation system. The shape of the target trajectory is desired to behave like the demonstrated one, but with different endpoints.

Fig. 3 compares the motion Fig. 3 compares the trajectory learning of the DMP and the CP-DMP for two common occupational therapy actions, the abrasive board and dowel training. The former moves the arm left and right in an upward motion, and the latter holds a wooden nail in an upward spiral motion. The figure compares the learned trajectories between DMP and CP-DMP for a given demonstration. In the experiment, we add a predefined time-dependent forcing term to our CP-DMP. The results show that the learned trajectories (red dashed and blue solid lines) remain almost the same as in the demonstration, but the CP-DMP method induces the geometric variation due to the perturbation of the force term.

2) Dual-arm participated collaboration method: As demonstrated in Fig. 4, we propose a human-robot collaboration strategy for upper limb rehabilitation containing three parts: a healthy limb motion teaching module, an affected limb motion trajectory generation module, and an upper limb rehabilitation robot platform.



(a) (b)

Fig. 3. Comparison of imitation learning methods for two classic occupational therapy actions: (a) abrasive board training; (b) dowel training.

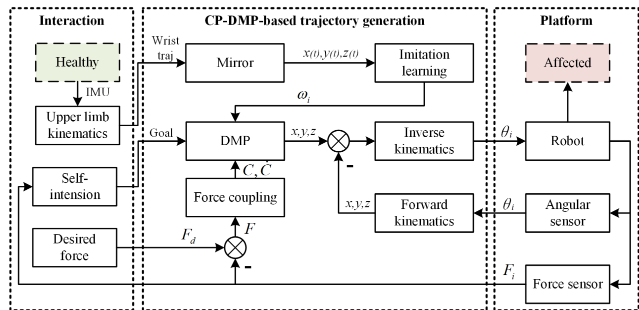


Fig. 4. Framework of the human-robot collaboration strategy integrating the healthy/affected limbs and the robot.

Motion demonstration in the healthy limb. The module serves as a model training for human-robot rehabilitation training movements. Since the hemiplegic patient has one limb with normal motor function and one with motor dysfunction, the personalized motor ability of the healthy limb can be used to generate the teaching trajectory, and the teaching trajectory $y(t)$ can be obtained by the motion parameterization method proposed in Section III-B. The teaching trajectory is first converted into the mirrored trajectory $\mathcal{M}(y(t))$ and fed into our proposed CP-DMP, which provides the affected limb with the generalization ability to simulate the motion of the healthy side. Moreover, the spatial position of the healthy limb can be used as the target point of the generalized trajectory to adjust the motion of the affected side as a control quantity to realize the synchronized motion.

Motion trajectory generation for the affected side. This module is mainly responsible for imitation learning and modulation of the training trajectory. Given the mirror trajectory $\mathcal{M}(y(t))$, the weight coefficient ω is calculated using LWR. When the module receives the start and end points of the task, a learned trajectory is generated on the affected side under the force-coupled factor. The inverse kinematics calculates the corresponding robot joint coordinates and passes them to the rehabilitation robot platform for execution.

Upper limb rehabilitation robot platform. The rehabilitation robot receives motion commands from the trajectory generation module and then interacts with the affected limb to perform collaborative rehabilitation movements. The angular and contact force information is sent back to the control system to control the rehabilitation movements.

IV. EVALUATION

A. Experiment setup

To validate the proposed DPC, we built an exoskeleton-type upper extremity rehabilitation system shown in Fig. 5, which consists of a serial linkage mechanism, the main control board (BeagleBone Black), and a client PC. The six-degrees-of-freedom mechanism (Fig. 5(a)) can fully resemble the upper limb motions.

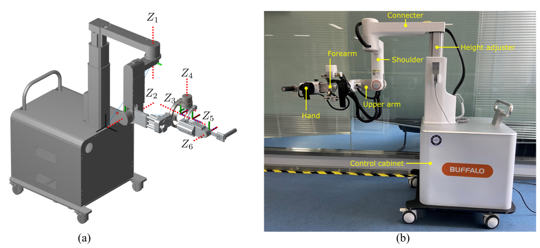


Fig. 5. Upper extremity rehabilitation system overview. (a) Kinematic modeling of the system; (b) System layout.

Other auxiliary devices containing two IMU sensors (MPU9250), two six-axis force sensors (Sunrise Instrument M37xx), a motion capture system (Vicon), and a myoelectric acquisition system (Noraxon-DTS) are also utilized in the experiment.

B. Validation of upper limb motion movement parameterization

In order to validate the upper limb movement parameterization method proposed in Section III-B, we designed four sets of typical rehabilitation movements and compared the trajectory computed by our proposed method and the data acquired by Vicon, which serves as a benchmark. Each action was performed three times, and the results of the spatial trajectory comparison are shown in Fig. 6. In addition, a statistical analysis of the errors of different motions is also performed. The results show that the method proposed in this paper has a relatively small error (average spatial error of $29mm$) when performing simple motions (such as single joint motion) and can track the upper limb motion well. However, the tracking error increases (the average spatial error reaches $78.4mm$ for an arbitrary spatial motion) when more complex spatial motions are performed, but within an acceptable range.

C. Validation of the human-robot collaboration strategy

To verify the feasibility and practical effect of the collaborative method in everyday activities, we designed a human-robot collaboration task consisting of two subtasks: cup catching by the affected limb and cup moving with dual-arm collaboration.

To ensure the balance between the trajectory fitting effect and real time, we choose the model parameters: the number of trajectory learning Gaussian kernel functions $N = 30$, the gain coefficients $\alpha_z = 25$ and $\beta_z = \alpha_z/4$, and the force coupling scale coefficients $c_1 = 0.02$ and $c_2 = 5$.

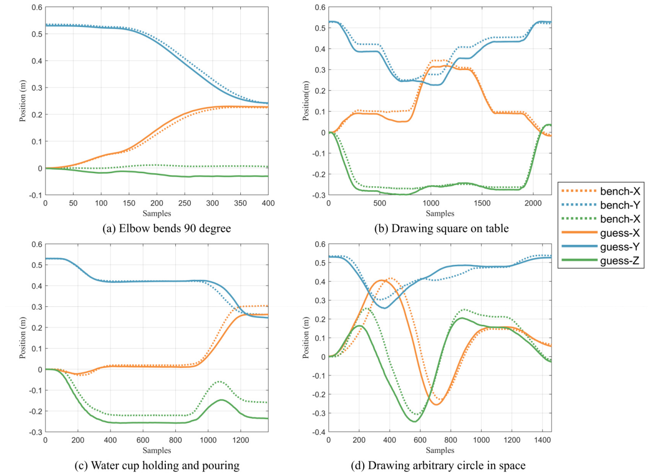


Fig. 6. Comparison results of wrist trajectories in space recorded and estimated from Vicon and IMU data.

These parameters ensure that the generalized trajectory can converge to the target point.

An illustration of the task is given in Fig. 7. Prior to the experiment, the unaffected limb demonstrates the movement of grasping and moving a water cup. Then the experiment begins with the healthy limb picking up the cup from the table and moving it to another location. The affected limb tries to passively reproduce the cup grasping action with the help of the robot by planning a trajectory from the current position to the cup position. Once the cup is reached, both the healthy and the affected limb participate in a collaborative manner to move the cup with the robot to another location.

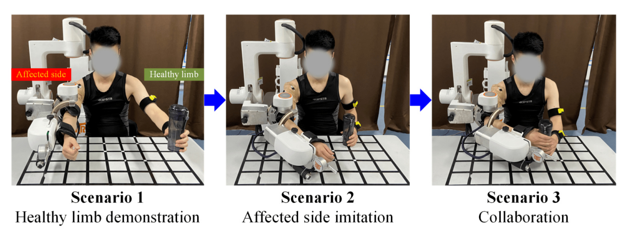
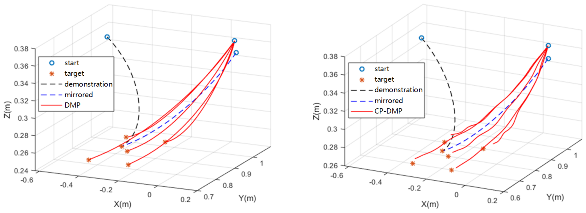


Fig. 7. Illustration of the task for the DPC validation.

First stage. The CP-DMP model is updated after the demonstration of catching a water cup with the healthy limb. By bringing the cup to five different locations, the computed weights are used to generate trajectories from the current position of the affected side to the targets. The comparison between the DMP and our proposed CP-DMP is shown in Fig. 8. It can be clearly seen that both methods show a good imitation of the previous demonstration and reach the desired positions. It is worth noting that even though the passive mode is triggered, the relatively small interaction force between the affected side and the robot still changes the trajectory during the catch. Therefore, the final position may not coincide with the target, resulting in an average error of $40.16mm$. Since there is movement flexibility in the human wrist area, all five experiments successfully grasp the water cup.



(a) (b)

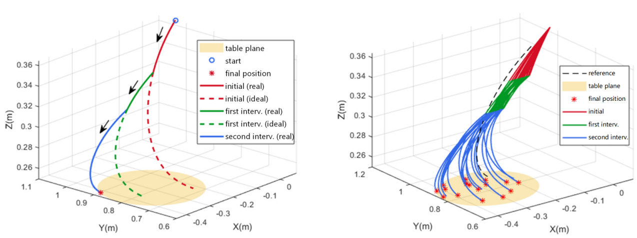
Fig. 8. Spatial trajectory imitation of catching a water cup generated by (a) DMP; (b) CP-DMP.

Second stage. To further validate the collaboration strategy with the participation of the affected side, after the two arms hold the cup together, an imitation trajectory of the cup transfer is generated by setting a predefined target position. During the experiment, we ask the subject to intervene with the affected limb. As shown in Fig.9(a), the initial motion trajectory is plotted in the red line, and the green and blue lines indicate the motion trajectories planned by the system under the two active interventions in an online fashion. The solid line is the trajectory of the actual motion, while the dashed line is the unexecuted trajectory. We performed 20 different tests for this experiment, and the experimental results are shown in Fig.9(b). All the interventions successfully changed the desired positions and moved the limb to new ones. Muscle activation intensity is also collected to assess

TABLE I

MEANS OF MUSCLE ACTIVATION INTENSITY (UNIT: μV)

Method	Posterior deltoid	Lateral deltoid	Biceps
Passive	2.40	2.54	7.29
Collaborative	8.73	5.89	35.52



(a) (b)

Fig. 9. Collaborated trajectory generation.

the active involvement of the affected limb. We evaluate three representative muscles in the upper limb, i.e. posterior deltoid, lateral deltoid and biceps. The location of the sEMG (surface electromyography) sensors and the sEMG signal acquisition setup are shown in Fig. 10. We record the sEMG signals for passive cup catching in the first stage and for cooperation in the second stage, as shown in Fig. 11. Since the sEMG signal is sensitive to perturbations, we conduct another experiment in which the subject is asked to intervene actively once during the passive training. In the control experiment, the passive training is activated with the robot moving the affected limb along the same trajectory. Referring to the quantitative analysis in Table I, the collaborative strategy witnesses a significant muscle activation intensity compared to the passive one, indicating that our proposed DPC considers the human intention while performing the customized upper limb rehabilitation.

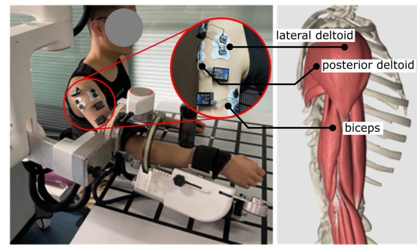


Fig. 10. Location of sEMG sensors and signal collection setup.

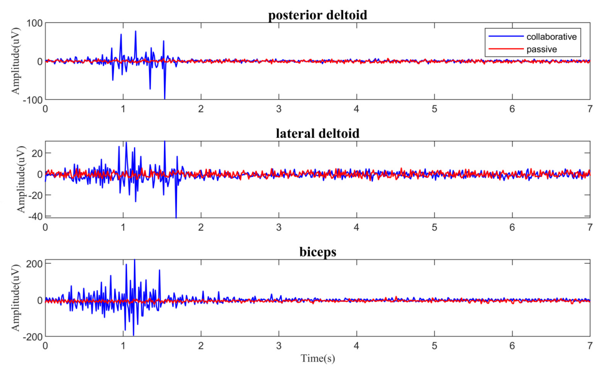


Fig. 11. Comparison of upper limb muscle activation intensity by sEMG signals.

V. CONCLUSION

We propose a new human-robot collaboration framework for hemiplegic patients that integrates the collaboration of the healthy/affected limb and the robot to improve the participation of the affected side during occupational therapy. We have addressed the two main issues: motion parameterization and trajectory modulation. For the first issue, we present an upper limb motion parameterization method for upper limb posture estimation with two wearable IMU sensors. By adding a force coupling term to the imitation learning method, the rehabilitation trajectory can be modulated by the interaction between the affected side and the robot. The resulting trajectory encapsulates the adaptive capability that includes the imitation of the healthy limb and the participation of the affected limb in the collaboration with the robot.

Nevertheless, the main caveat of the current work is the lack of clinical trials. It is expected that when clinical trial data become available, the efficacy of our collaborative strategy in restoring motor function in hemiplegic patients will be further confirmed.

REFERENCES

[1] B. Nätterlund and G. Ahlström, "Activities of daily living and quality of life in persons with muscular dystrophy," *Journal of Rehabilitation Medicine*, vol. 33, no. 5, pp. 206–211, 2001.

[2] S. M. Waller and J. Whitall, "Bilateral arm training: Why and who benefits?" *NeuroRehabilitation*, vol. 23, no. 1, pp. 29–41, 2008.

[3] A. A. Blank, J. A. French, A. U. Pehlivan, and M. K. O'Malley, "Current trends in robot-assisted upper-limb stroke rehabilitation: promoting patient engagement in therapy," *Current Physical Medicine and Rehabilitation Reports*, vol. 2, no. 3, pp. 184–195, 2014.

[4] J. Bai, A. Song, B. Xu, J. Nie, and H. Li, "A Novel Human-Robot Cooperative Method for Upper Extremity Rehabilitation," *International Journal of Social Robotics*, vol. 9, no. 2, pp. 265–275, 2017.

[5] H. M. Qassim and W. Z. Wan Hasan, "A review on upper limb rehabilitation robots," *Applied Sciences (Switzerland)*, vol. 10, no. 19, pp. 1–18, 2020.

[6] J. Hunt and H. Lee, "Development of a low inertia parallel actuated shoulder exoskeleton robot for the characterization of neuromuscular property during static posture and dynamic movement," in *International Conference on Robotics and Automation*, 2019, pp. 556–562.

[7] R. Mallat, M. Khalil, G. Venture, V. Bonnet, and S. Mohammed, "Human-Exoskeleton Joint Misalignment: A Systematic Review," in *2019 Fifth International Conference on Advances in Biomedical Engineering (ICABME)*, Tripoli, Lebanon, 2019, pp. 1–4.

[8] S. H. Lee, G. Park, D. Y. Cho, H. Y. Kim, J. Y. Lee, S. Kim, S. B. Park, and J. H. Shin, "Comparisons between end-effector and exoskeleton rehabilitation robots regarding upper extremity function among chronic stroke patients with moderate-to-severe upper limb impairment," *Scientific Reports*, vol. 10, no. 1, pp. 1–8, 2020.

[9] H. Wu, Y. Wang, J. Qiu, J. Liu, and X. L. Zhang, "User-defined gesture interaction for immersive VR shopping applications," *Behaviour and Information Technology*, vol. 38, no. 7, pp. 726–741, 2019.

[10] F. Negro, S. Muceli, A. M. Castronovo, A. Holobar, and D. Farina, "Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation," *Journal of Neural Engineering*, vol. 13, no. 2, pp. 1–17, 2016.

[11] A. Gupta, M. K. O. Malley, V. Patoglu, and C. Burgar, "Design, Control and Performance of RiceWrist: A Force Feedback Wrist Exoskeleton for Rehabilitation and Training," *The International Journal of Robotics Research*, vol. 27, no. 2, pp. 233–251, 2008.

[12] A. J. Ijspeert, J. Nakanishi, and S. Schaal, "Learning Rhythmic Movements by Demonstration using Nonlinear Oscillators," in *Proceedings of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Lausanne, 2002, pp. 958–963.

[13] S. M. Khansari-Zadeh and A. Billard, "Learning stable nonlinear dynamical systems with Gaussian mixture models," *IEEE Transactions on Robotics*, vol. 27, no. 5, pp. 943–957, 2011.

[14] A. Paraschos, C. Daniel, J. Peters, and G. Neumann, "Probabilistic Movement Primitives," in *Proceedings of the 26th International Conference on Neural Information Processing Systems*, ser. NIPS'13, Red Hook, NY, USA, 2013, pp. 2616–2624.

[15] Y. Huang, L. Rozo, J. Silvério, and D. G. Caldwell, "Kernelized movement primitives," *International Journal of Robotics Research*, vol. 38, no. 7, pp. 833–852, 2019.

[16] C.-h. Lai, W.-h. Sung, S.-l. Chiang, L.-h. Lu, C.-h. Lin, Y.-c. Tung, and C.-h. Lin, "Bimanual coordination deficits in hands following stroke and their relationship with motor and functional performance," *Journal of NeuroEngineering and Rehabilitation*, vol. 4, pp. 1–14, 2019.

[17] A. Gams, B. Nemec, A. J. Ijspeert, and A. Ude, "Coupling movement primitives: Interaction with the environment and bimanual tasks," *IEEE Transactions on Robotics*, vol. 30, no. 4, pp. 816–830, 2014.