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A phase-dependent and EMG-driven variable stiffness control strategy for upper limb rehabilitation robot

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***Abstract*— Bilateral training is a widely adopted approach in upper limb rehabilitation due to its effectiveness and ease of implementation. Variable stiffness actuators enhance this approach by facilitating compliant human-machine interaction, ensuring both comfort and safety. However, optimizing stiffness levels for individual subjects to maximize training effectiveness remains a significant challenge. The difficulty of different task phases varies across subjects, necessitating customized robotic assistance. This paper proposes an adaptive stiffness modulation strategy that leverages the cyclic nature of rehabilitation tasks. An adaptive frequency oscillator is employed for real-time phase detection, while a tuning rule, based on motion tracking error and muscular activation, dynamically adjusts stiffness levels. Experimental validation with two participants demonstrated that the proposed strategy effectively promotes affected arm motion and tailors assistance to the user's specific needs.**

I. Introduction

Stroke has become a major global health threat, affecting millions of people worldwide [1]. Most stroke survivors experience neurological impairments, particularly hemiplegia. Rehabilitation training with physical therapists (PTs) is crucial for restoring upper limb function in stroke survivors. However, the repetitive and cyclic nature of these exercises places a significant physical burden on PTs [2]. Consequently, there is a growing trend toward utilizing rehabilitation robots to assist PTs in delivering physical therapy.

Robot-assisted rehabilitation can be divided into two types: passive and active training strategies [3]. The passive training strategy assists movement along a predefined trajectory, helping to improve motor abilities, while the active training strategy encourages patients to exercise voluntarily, with the robot providing only the necessary assistance. Active training has shown greater effectiveness in rehabilitation, as it promotes patient engagement, enhances neuroplasticity, and improves motor control in people who suffered from neuromuscular impairments [4]. A major challenge in robot-assisted active rehabilitation, however, is accurately detecting the patient's motion intentions during therapy. Bilateral training addresses this challenge by using the motion of the healthy limb as a reference for training the affected limb, providing an intuitive and effective approach that enables users to control the robot's movements naturally [5][6].

Electromyography (EMG) is a bio-electrical signal that reflects the activation level of muscles [7]. EMG-driven control for rehabilitation robots has been widely explored by researchers to estimate joint motions [8][9], movement intentions [10] and muscle force [11]. EMG can also be used to estimate joint stiffness, which plays a key role in safe and effective therapy. To ensure safety during physical therapy with rehabilitation robots, compliant mechanisms have been incorporated into their designs, with variable stiffness actuators being among the most popular [12]. Unlike traditional stiff actuators, which hold a fixed position or follow a trajectory with high rigidity, variable stiffness actuators enable compliant and safe human-machine interaction by avoiding confrontation between the user and the machine. Variable stiffness control can mimic the stiffness of a human joint [11] or enhance voluntary patient participation [13][14], based on EMG signals from the contralateral side or motion errors.

Given that each patient has unique needs, the required assistance during training varies accordingly. The concept of assist-as-needed (AAN), which provides minimal assistance to maximize patient effort and enhance training effectiveness, has gained considerable attention [15]. Although the motion error has been used to adjust the level of resistance to iteratively achieve the AAN, this approach is not

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optimal, as adjustments occur only after the error is detected, resulting in a time delay in assistance modulation. To effectively implement AAN, it is essential to consider the cyclic nature of movements during rehabilitation. This paper proposes an EMG-driven, phase-dependent variable stiffness controller designed to enhance the effectiveness of bilateral upper limb rehabilitation by employing an AAN strategy. The healthy limb's motion trajectory is used as the reference for the affected limb. During training, the frequency and phase of the task are extracted using an adaptive oscillator (AO), while the initial stiffness profile is determined by an EMG-based arm model. The stiffness is then dynamically adjusted throughout the task based on the motion error between the two arms at the same task phase. The contributions of this paper are outlined as follows:

1) A phase-dependent stiffness modulation strategy for bilateral upper limb rehabilitation is proposed, which adjusts the level of assistance based on the user's muscular activation and performance from previous tasks.

2) Through experimentation, it was validated that the proposed modulation strategy can adaptively adjust stiffness levels to provide appropriate assistance, thereby facilitating bilateral arm rehabilitation.

II. PVSED

The propose control strategy for bilateral upper limb rehabilitation is evaluated by using an upper limb rehabilitation robot, named as powered variable stiffness exoskeleton device (PVSED), as shown in Fig. 1.

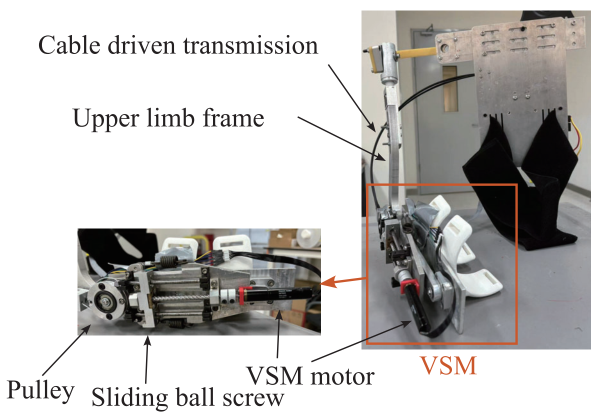

Fig. 1. PVSED with integrated VSM·.

The PVSED is designed as a portable, wearable robot for upper limb rehabilitation. It features three passive degrees of freedom (DoF) at the shoulder joint and one active DoF at the elbow joint. The elbow joint is connected to a pulley system driven by a direct-current brushless motor via cables, allowing the robot to assist with both elbow flexion and extension movements. Additionally, a variable stiffness mechanism (VSM), illustrated in Fig. 2, is integrated into the elbow joint. This mechanism is actuated by a compact direct-current brushless motor, enabling the stiffness of the elbow joint's movement to be adjusted by altering the position of the spring.

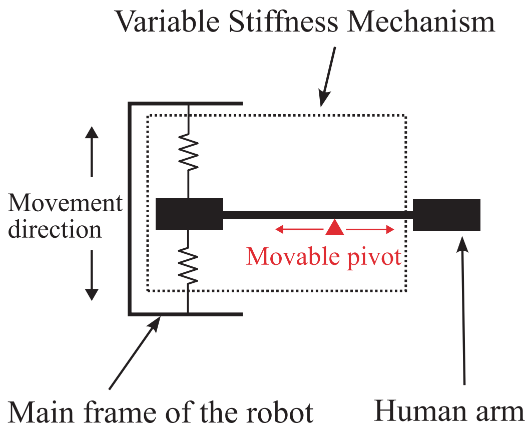

Fig. 2. The model of the variable stiffness mechanism.

III. Adaptive stiffness control

A. Control strategy

Bilateral upper limb rehabilitation uses the motion of the healthy arm as a reference trajectory for guiding the affected arm. Rehabilitation robots provide assistance to help the affected arm mirror the healthy arm's movements, thereby promoting motor relearning. This approach effectively utilizes the remaining motor ability of individuals with hemiplegia, offering a straightforward yet effective training strategy. Variable stiffness actuators are particularly well-suited for this rehabilitation method, as they enable compliant human-machine interaction and allow the level of assistance to be adjusted according to the needs of different users.

In this section, a EMG-driven and adaptive oscillator-based stiffness modulation strategy for robot-assisted bilateral upper limb rehabilitation is presented. The flow chart of the control system is presented in Fig. 3. The movement of the healthy side is used as the reference trajectory for the PSVED through a PID controller to achieve the position tracking. The PSVED provides assistance to affected side of arm with a specific stiffness. The stiffness of

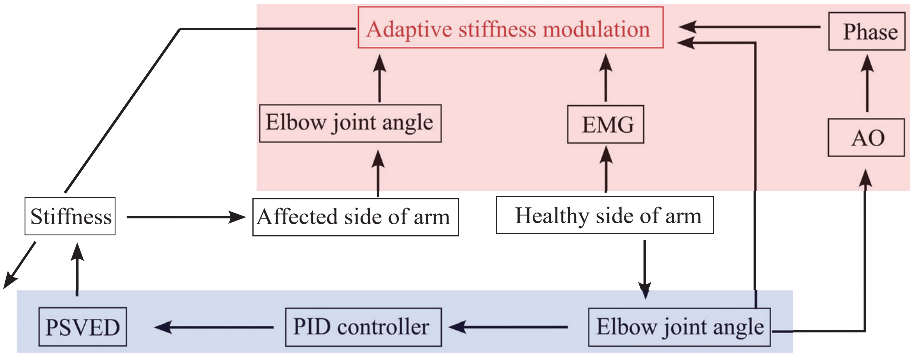

Fig. 3. The flowchart of the proposed control strategy.

the PVSED is determined by an adaptive stiffness modulation which is adjusted by the motion error between two arms and the sEMG signal from the healthy side at the phase of previous cycles.

B. EMG-based muscular stiffness model

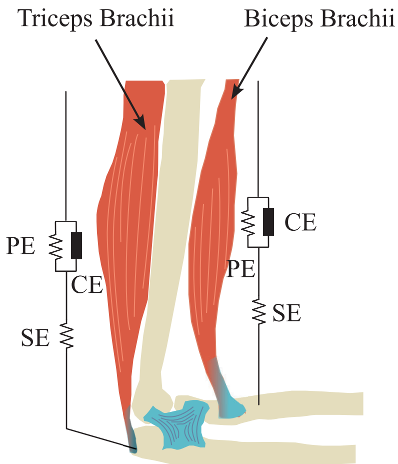

Fig. 4. The musculoskeletal model of elbow joint.

In this paper, muscles are considered as a serially connected spring-damper combination and a spring, representing the active force generated by the muscle and the passive force by the muscle/tendon structures, respectively [16]. For the joint of elbow, there are two main muscles, namely biceps brachii (BB) and triceps brachii (TB). And the upper limb equivalent model is shown in Fig. 4. These two agonist and antagonist cooperated together to achieve flexion and extension of elbow joints. Moreover, the stiffness of the elbow joint is associated with the sum of the torques generated by the agonist and antagonist.

The stiffness of the joint is linearly correlated with the sum of the torque applied on the joint, therefore the stiffness of the joint can be represented as:

$$K_{joint}(\varphi) = \alpha \cdot \sum_{i=0}^{n} |\tau_i| + \beta \tag{1}$$

where α and β are two constants which depends on the intensity of the task and the subjects, τ is the torque generated by the muscle. The calculated stiffness by using the above method is used to generate a reference stiffness profile in a task. This model and its parameters have been investigated in a previous research by our team [5].

C. AO-based frequency and phase estimation

In order to generate a phase-based stiffness profile and adjust the stiffness level based on the phase of the task. It is necessary to detect the frequency and phase of a task in real time. AO was proposed by Righetti [17] and it was widely used to extract the amplitude, phase and frequency of quasi-periodic signals for control of lower limb robots and cancelling tremors of surgeons. The AOs can synchronize with periodic signals and track the frequency and phase of the target signal without delay. The estimated parameters were used to reconstruct an approximate signal. The residual between the estimated and target signal are used to adjust the parameters of the AO to adapt to the target signal. An AO can be described by the following formulas:

$$\dot{r} = (\mu - r^2) \cdot r + \sigma \cdot F \cdot \cos\varphi \tag{2}$$

$$\dot{\varphi} = \omega - \frac{\sigma}{r} \cdot F \cdot \sin\varphi \tag{3}$$

$$\dot{\omega} = -\varepsilon \cdot F \cdot \sin\varphi \tag{4}$$

$$\dot{a} = \delta \cdot F \cdot r \cdot \cos\varphi \tag{5}$$

$$y = a \cdot r \cdot \cos\varphi \tag{6}$$

where r, φ, and ω are the amplitude, phase and frequency of the oscillator, respectively. $a \cdot r$ is the amplitude of the reconstructed signal. F is the difference between the reconstructed signal and target signal. y is the reconstructed signal by the AO. The learning speed is adjusted by the constants of μ, ε, σ, and δ.

A single AO is used in this research to track the frequency and phase of the task, which involves only elbow flexion and extension movements, as the elbow angle profile approximates a sinusoidal wave. In the model, r represents the amplitude of elbow joint angle, φ represents the phase of a curl movement, and ω represents the frequency of a curl movement of elbow joint, y represents the elbow joint angle.

D. Stiffness adaptation rule

In order to adapt to the need of users and the intensity of the task, a stiffness adaptation rule is proposed in this paper. And the stiffness of the robot can be represented as:

$$\bar{K}_{joint}(\varphi) = K_{joint}(\varphi) + E \cdot \sum_{i=n-m}^{n} e(i) \tag{7}$$

where $\bar{K}_{joint}(\varphi)$ is the actual stiffness of the robot at the phase of φ. $e(i)$ is the motion error in the i-th cycle of the task at the phase of φ. R is a constant which can adjust the change ratio of the adaptation.

The stiffness corresponding to a gait phase is adjusted by the motion errors, which is defined as the elbow joint angle difference between the reference trajectory and the actual trajectory, in the past three cycles of the task.

IV. Evaluation with an Experiment

A. Experimental protocol

Two subjects joined the experiment for the evaluation of the proposed adaptive stiffness modulation bilateral training strategy. In this experiment, the PVSED was attached to the users' right arm. The right arm of users is considered as the affected side of arm and the left arm is the healthy side in this bilateral training experiment.

The overall experimental set up is presented in Fig. 5. The EMG signal was captured by using the electrodes and a sEMG device from the BB and TB of the left arm. The EMG signals were processed on-line and were used for generating a reference elbow joint stiffness profile by using the same method proposed in a previous research [5]. Three IMU sensors (GY 25T) were attached to the right and left wrist of a subject respectively for obtaining the motion trajectory of forearm during the experiment. The stiffness of the VSM device integrated into the PVSED device was calculated by using a curve from the position of the pivot and the stiffness of the VSM which was proposed in a previous research of our group [5].

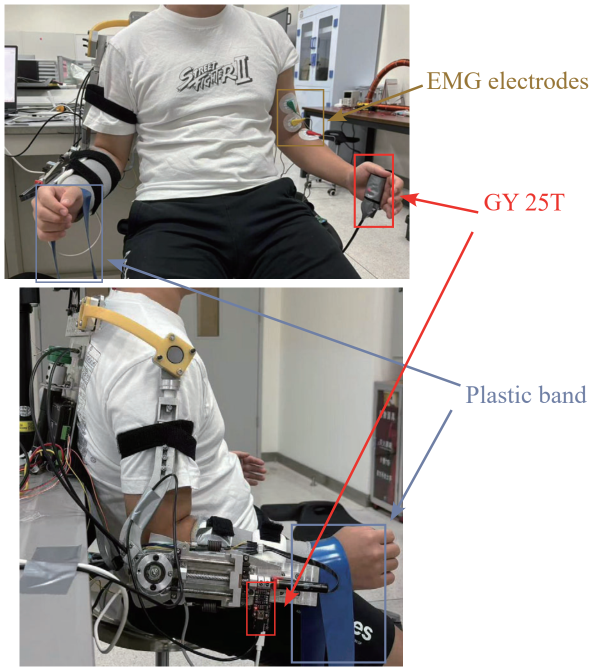

Fig. 5. The experimental setup.

Subjects were instructed to perform elbow flexion and elbow extension movement with their both arms. In order to examine the adaptive stiffness modulation strategy, a plastic band was attached to the right wrist of the user and the plastic band was exerting pulling force when the elbow joint angle was less than 0°. Therefore, the varying need for the stiffness of the elbow joint was generated within in a curl task.

B. Experimental results

The stiffness determines the level of freedom of the movement during the curl movement. The movement of the affected side of the user can be different from that of the healthy side with a low stiffness, while the bilateral movement are almost identical with a high stiffness. The low stiffness allows the user to complete the curl movement with their own effort. The average tracking error and the maximum flexion angle of the affected arm are shown in TABLE I.

The movement profile of the healthy side of arm (HS), the main frame of PVSED, and the affected side (AS) in the case of low stiffness are shown in Fig. 6. The difference between the robot's main frame and the affected limb was considerably larger than under other conditions. Around the 13-second and 26-second marks, the maximum elbow flexion angle is approximately 4° lower than that of the healthy arm. This reduced range of motion during rehabilitation can lead to less effective training, especially for post-stroke patients suffering from a stiff elbow joint.

In contrast, the high stiffness mode, as shown in Fig. 7, kept the affected arm closely aligned with the reference trajectory, ensuring the full range of motion during training. However, in this mode, the robot operated in a passive manner, with the affected arm merely following the robot's movements without active participation in the training.

As for the proposed method, as shown in Fig. 8, it kept a balance by using adjustable stiffness. It ensured the necessary range of motion during training while reduced stiffness when appropriate to achieve an AAN rehabilitation strategy.

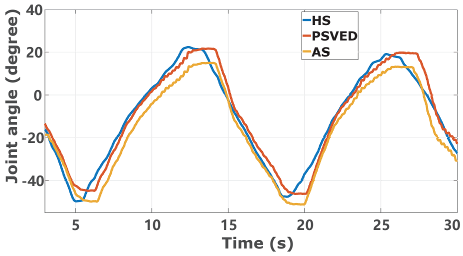

Fig. 6. Position tracking with low stiffness

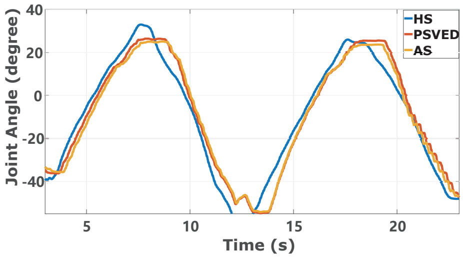

Fig. 7. Position tracking with high stiffness

TABLE I
EXPERIMENT RESULTS

	Ave. tracking error (°)	Max. flexion angle (°)
High stiff.	6.13 ± 3.47	14.96
Low stiff.	2.89 ± 2.11	25.05
Proposed	3.43 ± 2.66	25.33

V. DISCUSSION

The proposed variable stiffness control method adjusts the stiffness of an upper limb wearable robot

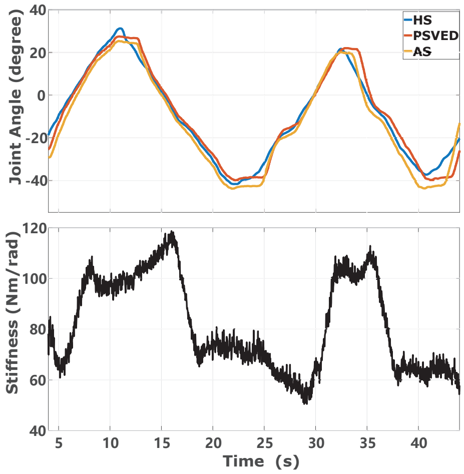

Fig. 8. Position tracking with the proposed strategy

to implement an AAN rehabilitation strategy. While previous research, such as the task performance index (TPI) proposed by Yang et al. [13], has also explored tuning stiffness to achieve AAN, our method introduces a key distinction by leveraging the cyclic nature of rehabilitation motions to adjust the level of assistance. Unlike previous approaches that react to the user's performance in real-time, our method proactively adjusts the assistance level before motion errors escalate, ensuring a smoother and more precise level of support.

Although the proposed method may appear similar to those that adjust stiffness based on joint angles, there are fundamental differences. Firstly, the proposed method adjusts stiffness based on the phase of movement, independent of the actual range of motion. This phase-based approach offers greater robustness during training, allowing the system to adapt even when the user's range of motion changes due to fatigue or other factors. Secondly, in the context of multi-joint upper limb rehabilitation, movements are often complex, and the phase of movement provides a more accurate indicator than joint angles alone. This enhanced accuracy improves the overall effectiveness of the rehabilitation process.

In this research, stiffness profiles are tuned at different phases, which can lead to abrupt changes in assistance, causing rapid shifts in assistance. This discontinuity may be uncomfortable or even harmful to users in certain scenarios. As a next step, a continuous function will be developed to represent the stiffness profile. The motion errors and EMG signals of users will be used to dynamically shape this continuous function [18], allowing smooth transitions in assistance. Additionally, the current stiffness tuning method has been applied only in a one-dimensional setting. Expanding its application to multi-degree-of-freedom rehabilitation robots remains a challenge but is crucial for advancing the effectiveness of upper limb rehabilitation. In the multi-joint rehabilitation scenarios where the joint angle profiles are not sinusoidal, the single AO used in this study is insufficient; thus, a multi-AOs approach will be required.

VI. Conclusions

This paper presents an adaptive stiffness modulation strategy that leverages muscular activation and motion errors from previous movement cycles to achieve assist-as-needed (AAN) rehabilitation. In rehabilitation sessions, movements or tasks are often cyclic, designed to enhance joint movement abilities or task performance. The proposed strategy determines the required level of assistance by analyzing performance in prior cycles. A preliminary experiment involving two subjects demonstrated that this stiffness modulation method effectively adjusts stiffness levels according to the user's needs, thereby facilitating AAN rehabilitation.

This study represents a significant advancement in the development of adaptive stiffness control strategies for upper limb rehabilitation robots. In future work, the proposed method will be applied to robots with higher degrees of freedom and more complex rehabilitation tasks.

Acknowledgment

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