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Design of Upper Limb Exoskeleton System Based on sEMG

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Abstract: **The design of the upper extremity exoskeleton system is proposed for the rehabilitation training of stroke patients. This system can help the upper limbs of patients with neuropathy to get efficient and high-quality rehabilitation. The mechanical design of the exoskeleton mainly focuses on the length, shape and motion specification. The use of muscle electrical signals has potential advantages over systems based only on torque and position sensors. An upper limb exoskeleton controlled by surface electromyography (sEMG) signals, which can detect the patient's motor intentions and provide corresponding training movements, establish a rehabilitation robot active-assisted training mode, promote the patient's active participation in rehabilitation treatment, effectively guide the patient to regain self-awareness, and actively assist the patient's rehabilitation.**

Keywords: **EMG signal; extremity exoskeleton; mechanical design; movement intention; rehabilitation training; stroke.**

1. INTRODUCTION

with the increase in the elderly population in most countries of the world, the problem of population aging is becoming more prominent. Stroke, commonly known as stroke, is a major cause of disability, often causing partial destruction of cortical tissue and leading to neurological disorders [1]. A stroke can result in complete or semi-paralysis of the upper limbs [2]. The medical staff needs to provide continuous physical therapy to stroke patients in order to avoid complete loss of muscle strength and muscle atrophy [3]. The number of stroke patients is increasing year by year, but the limited hospital treatment facilities and the small number of health care workers become an urgent problem to be solved.

Exoskeleton is a kind of robot mechanism [4], through controls robotic inputs to help stroke patients regain their motor skills. Many researchers have studied the hu-man lower extremities, but due to the complexity of the joints and muscles in the arms, wrists, and fingers, upper limb exoskeletons are just beginning to be studied in a com-plex and diverse research. Passive movement is useful when a person is unable to generate force in the muscles to cause a limb movement [5], is not able to help patients re-cover. The motor skills cannot be recovered quickly and efficiently only by passive re-habilitation training when the patient has some muscle contraction questions. In general, the exoskeleton is controlled by different types of input signals. In this study, the input signals use surface electromyography (sEMG) signal to identify the user's intention movement, which can realize the user's arm movement rehabilitation and provide an efficient and safe rehabilitation training of the upper limb exoskeleton for the user.

This system is a 5-Degree of freedom Degree of freedom (5-DOF) upper limb exoskeleton rehabilitation device that can help patients complete multi-joint rehabilitation training. The upper extremity exoskeleton includes the shoulder, elbow and wrist and the associated muscles that produce voluntary range of motion.

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2. MATERIALS AND METHODS

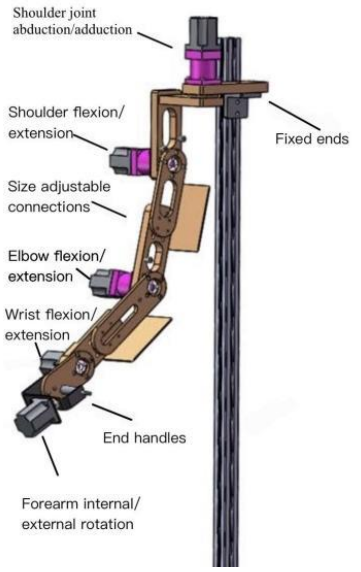
2.1 Upper limb exoskeleton mechanics

Upper limb exoskeleton mechanical structure of 5-DOF, in order to meet the rehabilitation movement requirements for the user's major joints. The mechanical structure was designed by imitating the skeletal structure of human arm. The system of 5 degrees of freedom for it is based on the knowledge of human arm joints and rehabilitation medicine, and considers the experience of medical staff [6]. The upper limb exoskeleton mainly carries out sports training for shoulder, elbow and wrist joints, with natural sagging as the initial state of each joint. Combined with the upper limb exoskeleton structure and the user's training requirements, the range of motion of five degrees of freedom is set. As shown in Table 1.

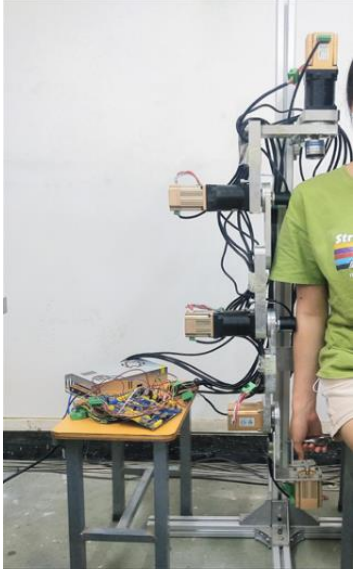
The upper limb exoskeleton was consisted by eight aluminum blocks, each connected to a bearing, which can be completed for a variety of movements. To ensure the overall stiffness of the equipment and reduce the weight of the equipment to a large extent, the main structure of the equipment adopts aluminum profile [7], which enables the overall body of the upper limb exoskeleton to be lightweight. This system includes of a mechanical arm and base. Since the system is designed to achieve 5 degrees of freedom of motion, so 5 servo motors are used to power the arm. The base is used to support the arm and maintain balance, ensuring the stability, reliability and safety of the system. Adjustable structural dimensions of the large arm and forearm, which fully reflecting the adaptability. Although the size of user's upper limb and the location of the lesion vary, it can also meet the needs of the user. The upper limb exoskeleton is shown in Figure 1 (a is the mechanical structure and b is the physical upper limb exoskeleton).

Table 1. Activity training range of upper limb exoskeleton

Each joint degrees of freedom		Range of motion
Shoulder joint	Flex/stretch	0~135°
	Adduction/abduction	0~90°
Elbow joint	Flex/stretch	0~135°
	Inside spin/outside spin	-90~90°
Wrist joint	Flex/stretch	-45~45°



(a) mechanical structure



(b) physical upper limb exoskeleton

Figure 1. Upper limb exoskeleton

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2.2 General scheme design

This system is a myoelectric controlled upper limb exoskeleton, and the overall frame is shown in Figure.2. First, the surface EMG signal of the upper limb is collected by the surface EMG sensor and then transmits them to the computer. Next perform signal processing procedure, which includes pre-processing, feature extraction, upper limb movement classification and finally a command program to control of the motor. Then, the computer sends through the microcomputer STM32F103 command to the motor, which drives the upper limb exoskeleton for active assisted training mode. The flow chart of EMG control program is shown in Figure.3.

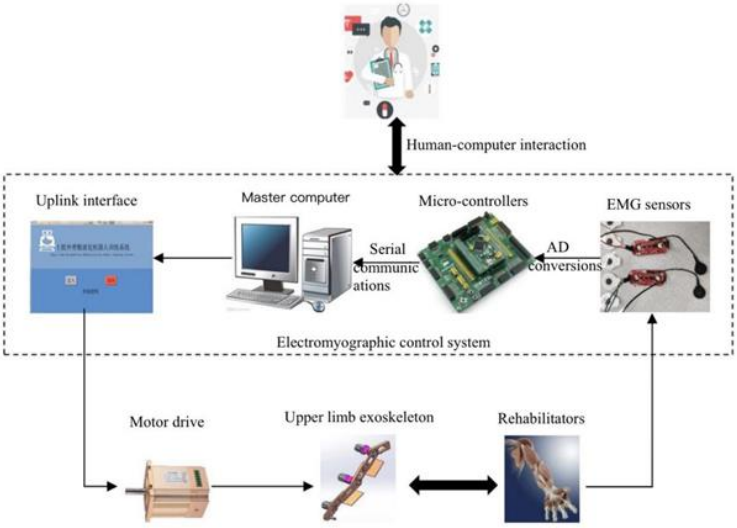

Figure 2. Block diagrams of the general scheme

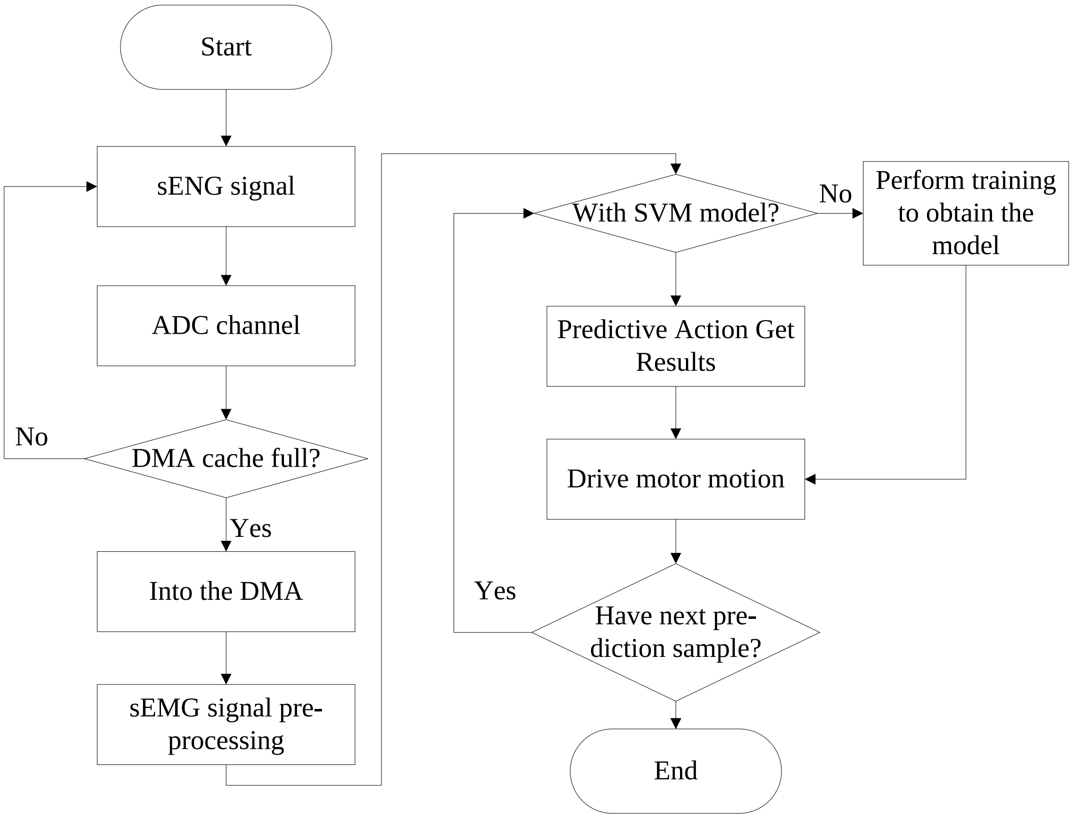

Figure 3. EMG control flow chart

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2.3 EMG acquisition

This system uses disposable silver chloride electrodes equipped with pre-gel, placed approximately 2 cm between the electrodes and aligned with the direction of the muscle, then the electrical signals generated during muscle contraction can be collected. During flexion extension at the shoulder, elbow and wrist of the upper limb, the electrical signals of anterior deltoid, biceps, radial wrist and ulnar wrist flexors [8] are extremely well represented. As shown in Figure 4, a single-channel EMG is measured with two electrodes, and a grounded electrode is placed on a part of the body that is not contacted to the EMG signals, which usually on muscle tendons, main research area, etc.

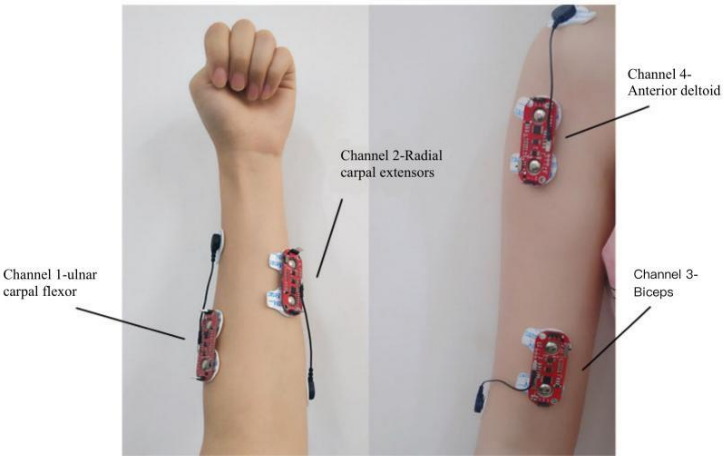

Figure 4. sEMG electrode position

The sampling rate is set to 2000Hz. Since the frequency of sEMG is less than 1000Hz, the energy bandwidth range is 20 to 500Hz, which can transmit important messages and play an important role in identifying actions. According to Nyquist's theorem: when the sampling rate is 2000Hz, to meet the sampling requirements of sEMG [9] the maximum sampling rate is 1000Hz. The ARM microcontroller STM32F103 is used to convert the signals from the EMG sensors to AD and send the conversion results to the computer through the serial port.

2.4 Data Processing

All data processing was performed on Python, and the analysis steps of sEMG signal were shown in Figure 5. The sEMG signal is able to detect the potential generated by muscle cells during activities such as contraction and rest. The signal needs to be pre-processed, which mainly involves noise removal and window segmentation. Split Windows are used to extract function features and process sEMG signals in real time, which allows the data to be split into multiple small Windows. This system uses the split window method as shown in Figure 6 to collect more data samples in less time, using the overlapping split window method to set the window overlap rate to 3/4, and setting the time window to 100ms and the incremental window to 25ms. Frequencies below 20Hz are usually deviated from the baseline, the trajectories can be disturbed moving electrodes and cause noise in the system; When the frequency is higher than 500Hz, less information is contained. Therefore, in this paper, the original sEMG signal will be processed using a fourth-order Butterworth filter with a passband frequency of 20-500Hz in order to achieve noise reduction.

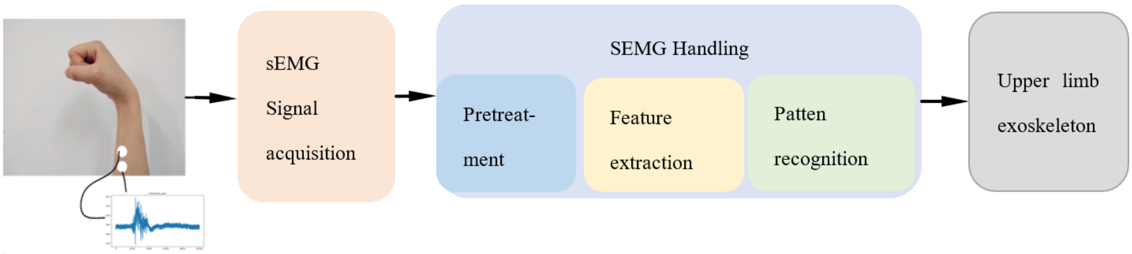

Figure 5. Block diagram of sEMG signal processing

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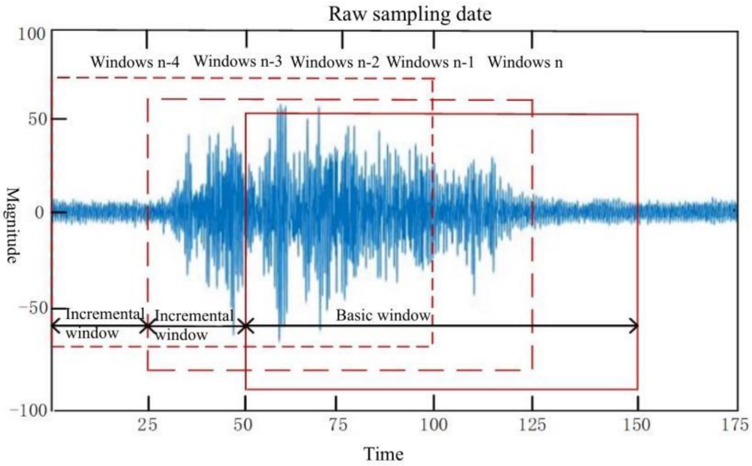
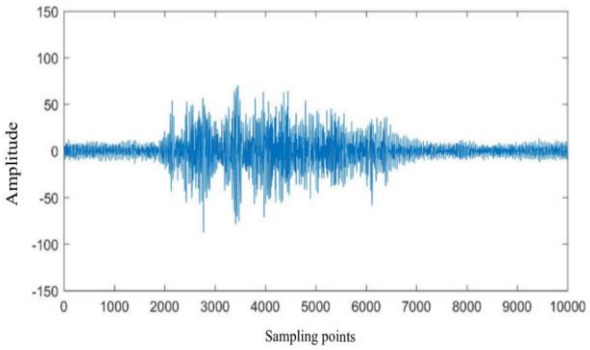
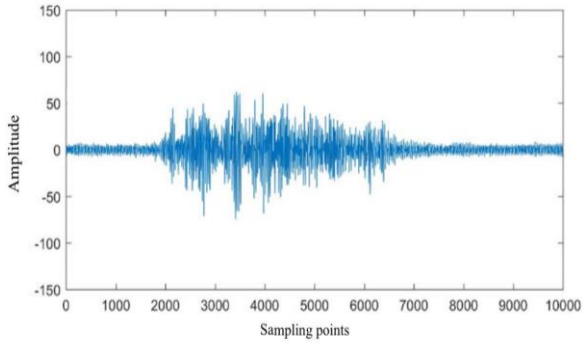


Figure 6. Overlapping segmentation window

The sEMG signal filtering results is shown in Figure 7. The signal before the filter is shown in Figure 7 (a). It can be seen that the waveform tail has obvious baseline drift and a large number of burrs in the resting state. The signal after the filter is shown in Figure 7 (b). The above situation has been improved after filtering.



(a) Primitive EMG



(b) Post-filtered EMG

Figure 7. EMG processing results

In the process of window segmentation, sEMG signal calculates the data of each window and extracts its main features. Transformation of sEMG signal to frequency domain by fast Fourier transform. The waveforms of amplitude and power frequency plots remain relatively stable in the frequency domain analysis. In this paper, 5 time-domain features and 2 frequency-domain features are extracted from sEMG signal to show the important features of the sEMG signal and calculated according to the equations in Table 2, respectively.

According to the purpose of upper limb rehabilitation training and the theory of motor function rehabilitation, the determining factor for proximal joint motion is the correct selection of motor function and upper limb working space, including the movement of the five single joints as shown in Figure 8. The target movements consist of shoulder flexion and extension, extension and contraction, elbow flexion and extension, wrist flexion and extension and forearm rotation movement, and each upper limb movement is performed from a relaxed state.

Support vector machines (SVMs) are a commonly used machine learning technique. SVMs were originally a classical algorithm for solving two classification problems. In this paper, we need to solve the multi-classification problem, so it is necessary to construct a suitable multi-class classifier based on the two-classification SVM. This system uses a decision tree-based classifier (OVR-DT-SVM), which is derived from the theory of OVR.

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Table 2. Feature Publicity Table

Features	Formula
Mean absolute value	$MAV=\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$
Mean absolute value	$RMS=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$
Waveform length	$WL=\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$
IEMG	$IEMG=\sum_{i=1}^{N}\lvert x_i\rvert$
Zero crossing points	$ZC=\frac{1}{N}\sum_{i=1}^{N-1}f(i),\ f(i)=\begin{cases}1, x(i)x(i+1)<0, \lvert x(i)-x(i+1)\rvert>\sigma\\ 0, else\end{cases}$
mean power	$MNP=\frac{1}{N}\sum_{i=1}^{N}p_i$
Median frequency	$MDF=\frac{1}{2}\sum_{i=1}^{N}p_i$

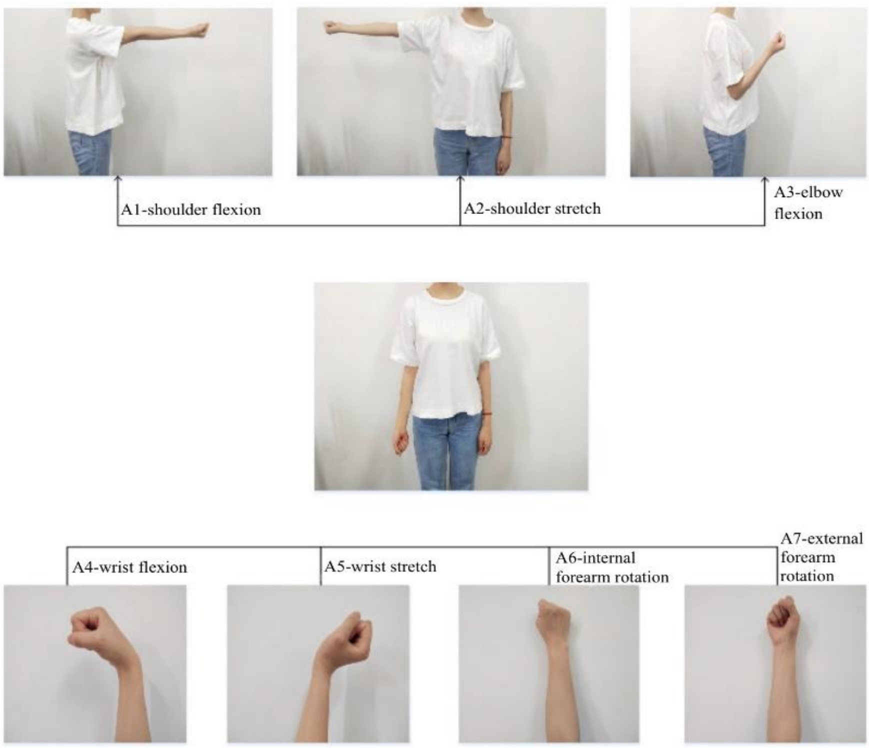

Figure 8. Upper limb rehabilitation training exercises

3. RESULTS AND DISCUSSION

In the analysis of the test data, 7 characteristics were calculated for all tested EMG data. these dates were used to test the effects of single and combined features on the classifications of various actions. The results of the classification of seven single eigenvalues are shown in Figure 9.

As can be seen from Figure 10, the highest recognition error rate was found for forearm external rotation and wrist extension. Better classification results for root mean square (RMS) and median frequency (MFD), among which the error recognition rate of forearm external rotation and wrist extension action was higher, and the classification error rate of MFD was low from the comprehensive observation of seven single features. Combining the two best-performing features, MFD and RMS, with five other features, the average classification error rate when multiple features are combined with each other is shown in Figure 10.

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The above results show that both the time domain characteristic RMS and the frequency domain characteristic MFD can increase the difference of EMG characteristics, thereby improving the action pattern recognition. Since the recognition rate of combined features is much higher than that of a single feature, the combination of multiple features is used to identify upper limb movements. According to the system requirements, the multi-feature combination and OVR-DT-SVM classifier were applied to the upper limb action recognition system, which the experimental results were evaluated using a more general approach, that is, analysis of action selection time, action recognition rate and action completion rate. which results are shown in Table 3.

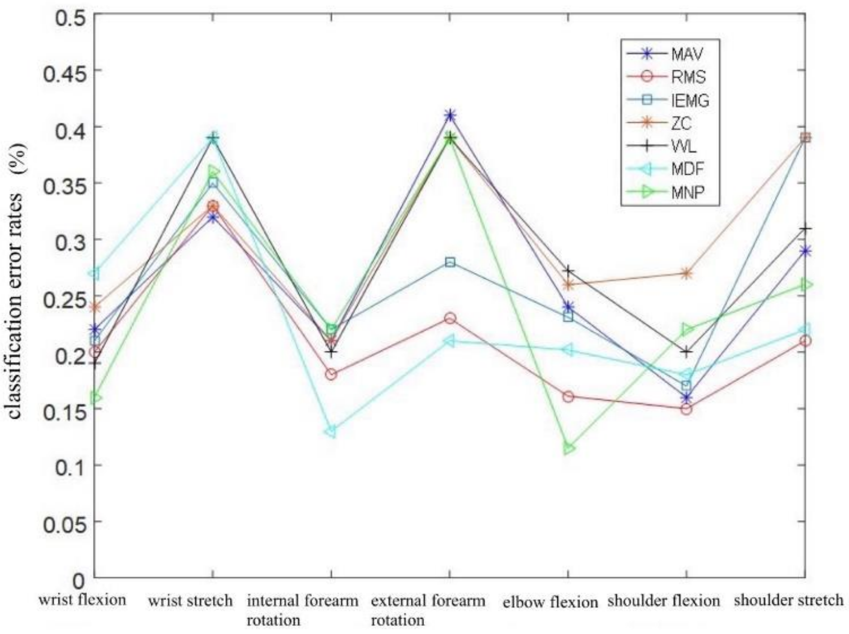

Figure 9. Classification results of seven single eigenvalues

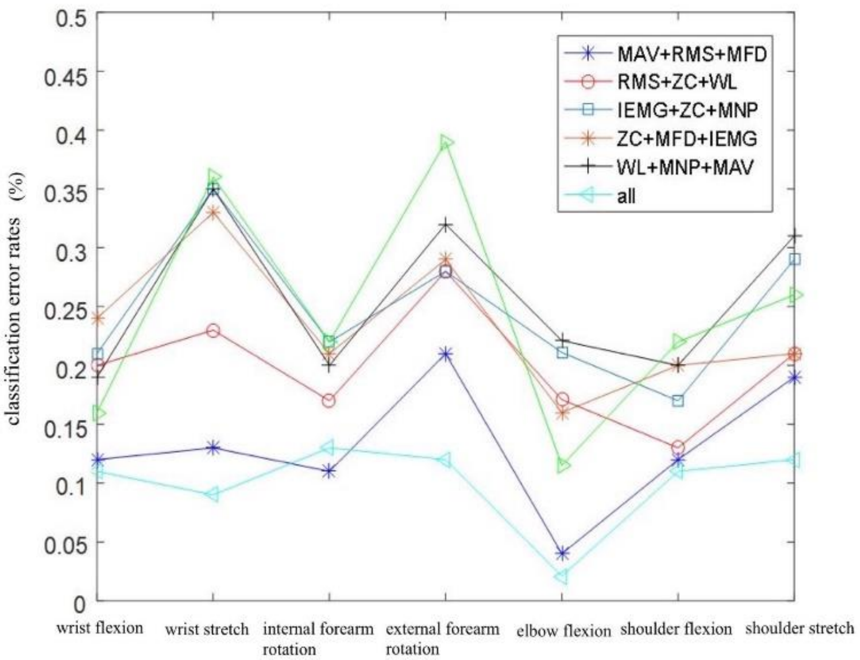

Figure 10. Classification results of multi-feature combinations

Table 3. Results of the evaluation of the three indicators

Target Action/ Evaluation indicators	Action selection time(s)	Action recognition rate (%)	Action completion rate (%)
Wrist flexion	0.33	93	100
Wrist extension	0.36	94	96
turn forearm inward	0.31	94	100
turn forearm outward	0.41	95	98
Elbow flexion and extension	0.19	100	100
Shoulder flexion	0.25	100	100
Shoulder spread	0.22	99	100

The selection time varies for each action, elbow and shoulder performance relatively well, with forearm external rotation and wrist extension muscle performance more similarly, which led to longer selection times for their movements. There are many factors that affect the recognition rate of movement, but the incorrect classification mainly occurs in the stage of category change, which occurs at the beginning and end of movement. The advantage of one-to-many decision tree classification method is that there may be incorrect classification in an action cycle, and the most recognition results are the action classes of the target.

In this system, a construct a three-dimensional drawing of the upper limb exoskeleton with five degrees of freedom was constructed base on SolidWorks, and things were machined. As the exoskeleton is a new technology introduced into the engineering field in recent years, the study of its mechanics part takes a long time. In order to apply to different people in the upper limb exoskeleton production procedures should pay attention to the fit of the exoskeleton joints and size. In this paper, EMG signals are introduced as the control source of the upper limb exoskeleton. Greedy algorithm is used to optimize and update the OVR-DT-SVM classifier to classify the upper limb movements, and experimental tests are conducted on the time of action selection, recognition rate and completion rate of the subjects, to further improve the upper limb exoskeleton system. This system aims to overcome the disability of stroke patients and become an assistive rehabilitation device in the biomedical field.

4. CONCLUSION

This study presents an upper-limb exoskeleton system tailored for post-stroke neurorehabilitation, aiming to facilitate efficient and functionally relevant motor recovery in patients with peripheral or central neural deficits. The mechanical architecture was iteratively designed with anthropometric constraints, including segment length, joint articulation, and kinematic ranges, to ensure biomechanical compatibility with natural upper-extremity movements. In contrast to conventional torque or position sensing approaches, the integration of sEMG offers enhanced capability for decoding volitional motor intent, owing to its direct physiological origin and temporal precedence over mechanical output. The sEMG-driven control scheme enables real time detection of patient-initiated movement commands and subsequently triggers assist-as-needed robotic actions, thereby establishing a closed-loop, active-assisted training paradigm. This paradigm not only augments the patient’s voluntary participation during therapy but also facilitates the reconsolidation of proprioceptive and motor self-awareness, which is critical for cortical reorganization and functional restoration. The synergy between the ergonomic mechanical design and the bio-signal based controller significantly elevates both the proactivity and therapeutic efficacy of the rehabilitation regimen. Experimental validation demonstrates robust system reliability and adaptive responsiveness across diverse clinical scenarios, with marked improvements in human robot interaction fluidity and post-intervention functional outcomes relative to conventional passive-training devices. Collectively, this work offers a stable and clinically practicable upper-limb rehabilitation platform, with promising implications for intelligent rehabilitation frameworks, post-stroke motor recovery protocols, and bio-signal-driven human robot interfacing. Furthermore, it establishes a foundational basis for subsequent investigations into intention-aware control strategies and adaptive autonomy in medical robotic systems.

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