Scholars Journal of Engineering and Technology
OPEN ACCESS
Abbreviated Key Title: Sch J Eng Tech
ISSN 2347-9523 (Print) | ISSN 2321-435X (Online)
Journal homepage: https://saspublishers.com

A Brain-Myoelectric Signal-Based Approach to Hand Rehabilitation in Stroke

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DOI: 10.36347/sjet.2023.v11i06.003 | **Received:** 07.03.2023 | **Accepted:** 18.04.2023 | **Published:** 30.06.2023

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Abstract **Original Research Article**

The existing hand function rehabilitation training model for stroke patients has problems such as single mode, low patient participation, poor rehabilitation effect and long rehabilitation period. In this paper, we propose an active stroke hand rehabilitation training method based on brain EMG signals, including the use of EEG signals to help stroke patients achieve brain neural remodelling and EMG signals to achieve real-time hand function rehabilitation training to assist patients to complete hand rehabilitation. Firstly, a multimodal guided motor imagery experimental paradigm with a mixture of pictures and Chinese characters was designed to improve the stability of the spontaneous motor imagery EEG signals. Then, a gesture acquisition paradigm based on surface EMG signals was designed to exercise the flexibility of stroke patients' arm muscles and fingers. The experimental results showed that the stroke hand rehabilitation training method based on brain-myoelectric signals could achieve better rehabilitation results.
Keywords: Soft Rehabilitation Hand, Flexible Sensing, Perceptive Interaction, Control Strategy.

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1. INTRODUCTION

According to the China Stroke Report 2020 [1], stroke has a distinctly high disabling characteristic, with the overall lifetime risk of stroke in China being 39,9%, the highest in the world, and the proportion of deaths due to stroke is twice as high in China as in the world [2]. Stroke patients do not suffer from limb dysfunction as a result of limb injury, but rather from brain dysfunction resulting in the key to rehabilitation of stroke patients is therefore the ability to restore limb function by remodelling brain function. However, traditional manual rehabilitation and passive rehabilitation devices have a single mode, poor recovery effect, low rehabilitation efficiency and low cure rate, which cannot meet the needs of stroke patients for limb motor function rehabilitation and neuroplasticity [3].

Compared with conventional rehabilitation methods, motor imagery therapy can introduce the patient's active motor intention, which can lead to brain function remodelling and accelerate the recovery of motor function [4-7]. Pfurtscheller *et al.*, were the first to conduct a left/right hand limb EEG analysis by decoding imaginary movements in hemiplegic patients to enable an orthotic device to perform hand grip rehabilitation [8], and Girijesh Prasad *et al.*, combined a motor imagery arm/hand task with a goal-oriented rehabilitation task to help restore paralyzed limb function in stroke patients [9]. These studies suggest that motor imagery therapy can harness the capacity of residual motor neurons to improve cortical connectivity and that motor imagery therapy is effective in the rehabilitation of hand function in stroke patients, and that the earlier a stroke patient is treated with motor imagery interventions, the better the outcome for hand and brain rehabilitation. However, traditional motor imagery brain-computer interfaces still face two technical challenges: firstly, it is difficult to accurately identify motor intent due to the susceptibility of EEG and low signal-to- noise ratio; secondly, most studies have used a single picture modality-guided motor imagery paradigm, which excites a relatively weak EEG signal and has a low accuracy rate of intent recognition. Therefore, it is important to design new motor imagery paradigms and improve the accuracy of intention recognition in order to improve the rehabilitation outcome of stroke patients.

In contrast to weak EEG signals, EMG interaction techniques are more developed and have been widely used in the rehabilitation of stroke patients.

Wang Fengyan *et al.*, used a myoelectric arm ring to acquire nine movements and the average movement recognition accuracy law was 89.81%, demonstrating the feasibility of myoelectric recognition in stroke patients' hand rehabilitation [10], Despite the high recognition rate of EMG-based movement intention, there are still limitations in the application of EMG interaction technology in the rehabilitation training of stroke patients: firstly, patients' muscle atrophy during the flaccid phase, etc. leads to a decrease in EMG intensity and the practicality of EMG interaction is poor; secondly, factors such as stiffness of the affected limb during the spastic phase of stroke patients affect the quality of EMG signals, which in turn affects the effectiveness of EMG rehabilitation training.

To address the above technical problems and challenges, this paper proposes a stroke hand rehabilitation training method based on brain EMG signals and designs an exoskeleton rehabilitation hand system for myoelectric manipulation. To address the situation that stroke patients are unable to move their hands and arms voluntarily during the soft palsy and spasticity periods, a multimodal motor imagery experimental paradigm with a mixture of pictures and additional Chinese characters guided by silent reading is designed to enhance the activation strength of motor imagery EEG signals; to address the problem that patients have insufficient hand strength during the rehabilitation period, motor imagery EEG and surface EMG are used to control the rehabilitation hand system to achieve brain neural remodelling and hand The aim is to achieve neurological remodelling and functional hand rehabilitation.

2 EXPERIMENTS AND METHODS

2.1 EEG data acquisition

In this paper, a multimodal guided EEG signal acquisition for motor imagery was designed with reference to the Graz experimental paradigm used in the BCI Competition IV-2b left- and right-handed motor imagery open dataset, as shown in Figures 1 and 2 respectively, including a picture-guided motor imagery paradigm and an additional Chinese character silent reading-guided motor imagery paradigm. The acquisition was divided into 30 sessions, with each action lasting 5 s. A "-" on the screen indicated a break, and left/right motor imagery was performed according to the picture cues.

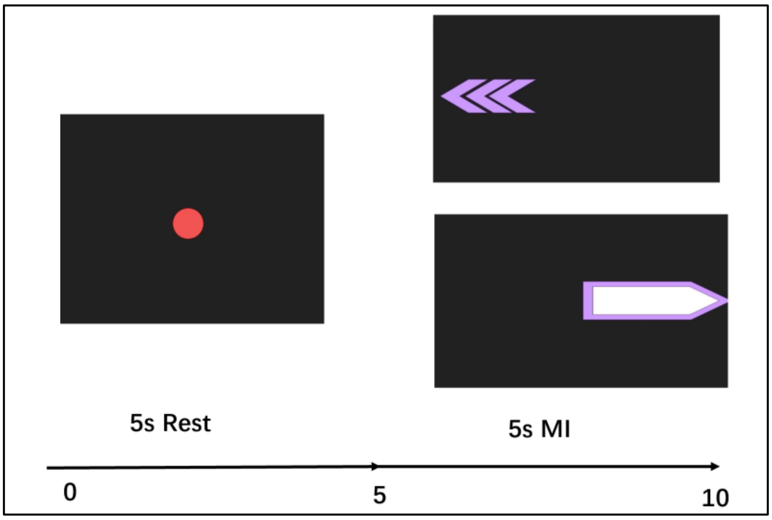


Figure 1: Motion Imagination Collection Process

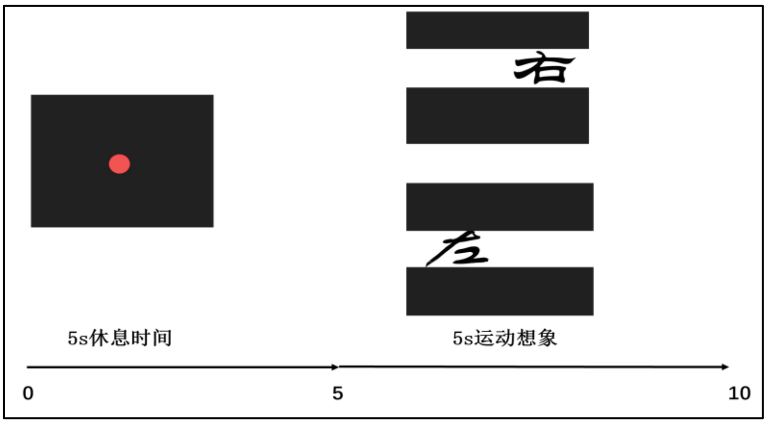
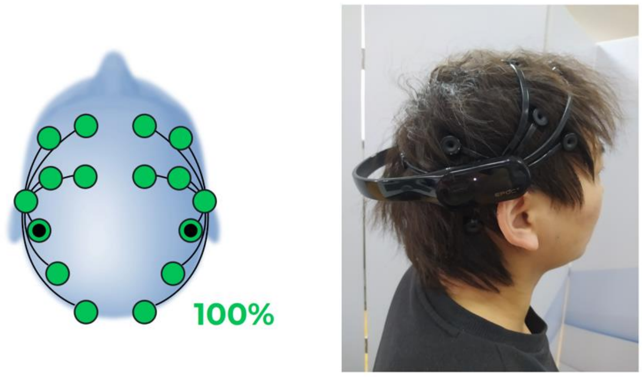


Figure 2: Motion Imagination Collection Process



a) Signal status diagram of the acquisition equipment

b) Diagram of wearing the Emotiv Epoc

Figure 3: Diagram of wearing the Emotiv Epoc

The device used is the Emotiv EpocX, with a sampling rate of 128Hz and electrodes laid out in accordance with the international 10-20 standard electrode position, a 14-channel EEG headset with saline electrodes, lithium batteries to provide 12 hours of continuous use, portable and easy to wear.

2.2 Surface EMG signal acquisition

In this paper, the EMG data acquisition process is set up as follows: the surface EMG data is acquired from the patient through the Myo arm ring, the acquisition process is shown in Figure 4, the movements are selected as open hand, clenched fist, pinched index finger and pinched middle finger, the duration of each of the four movements is 6s, the rest after one movement is acquired is 2s, a total of 4 groups are acquired. The acquisition device Myo has the advantage of being portable and easy to wear, the device and the way it is worn is shown in Figure 5.

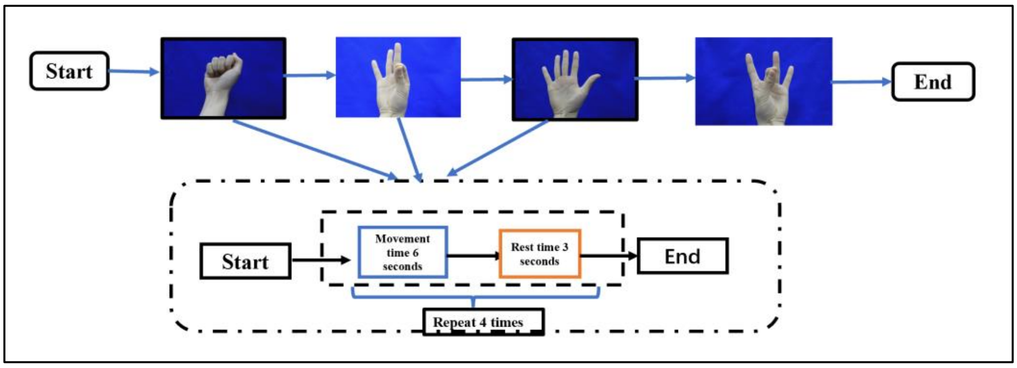


Figure 4: Surface EMG signal acquisition flow chart

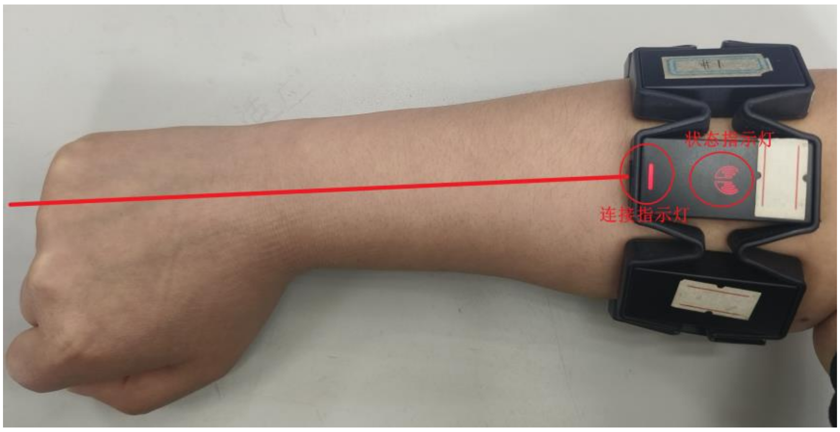


Figure 5: Schematic diagram of wearing an electromyographic armband

2.3 Signal pre-processing

EEG signal pre-processing: As the motor imagery EEG signal is susceptible to interference from the external environment and is mainly generated in the low frequency band, the signal is acquired every 5s, so the data is band-pass filtered from 0 to 30Hz and cut every 500ms.

Pre-processing of the EMG signal: As most stroke patients have manual dexterity and there may be large differences between channels, the 200ms data before and after the start and end of the data were discarded and normalised to be in the range [-1, 1], with the absolute value normalisation equation being:

$$X_{scaled} = \frac{X}{\max(|X|)} \quad (1)$$

3 Feature extraction of brain-myoelectric signals using wavelet transform

EEG signal feature extraction: when a subject imagines a specific action (e.g. left/right hand), different functional areas of the brain will be activated, for example, when a subject imagines a unilateral limb action, the brain will change the frequency band energy in the μ-rhythm and β-rhythm. This is the phenomenon of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS). Wavelet (Wavelet) transforms [11] can combine transient and diffusion phenomena in the data, combining these phenomena into different frequency energies.

Let the total energy after wavelet transform be 1 and the signal in each sub-band segment be $\{S_{i,j,k} | k = 1, 2, \cdots, L\}$, The energy scaling parameter is used to represent the wavelet packet energy spectrum, and the scaling parameter eigenvector is $T = \left(E_{i,0}, E_{i,1}, \cdots, E^{i}_{i,2^i-1}\right)$, Normalized to:

$$E_{i,j} = \frac{\sum_{k=1}^{L} |S_{i,j,k}|^2}{\sum_{j=0}^{2^i} \sum_{k=1}^{L} |S_{i,j,k}|^2} \quad (2)$$

As shown in Figure 6, this paper uses 4th order wavelet decomposition to plot wavelet energy maps by plotting wavelet energy maps for two different patterns of EEG signals, with the additional energy maps for kanji silent reading guided motor imagery showing a significant energy increase.

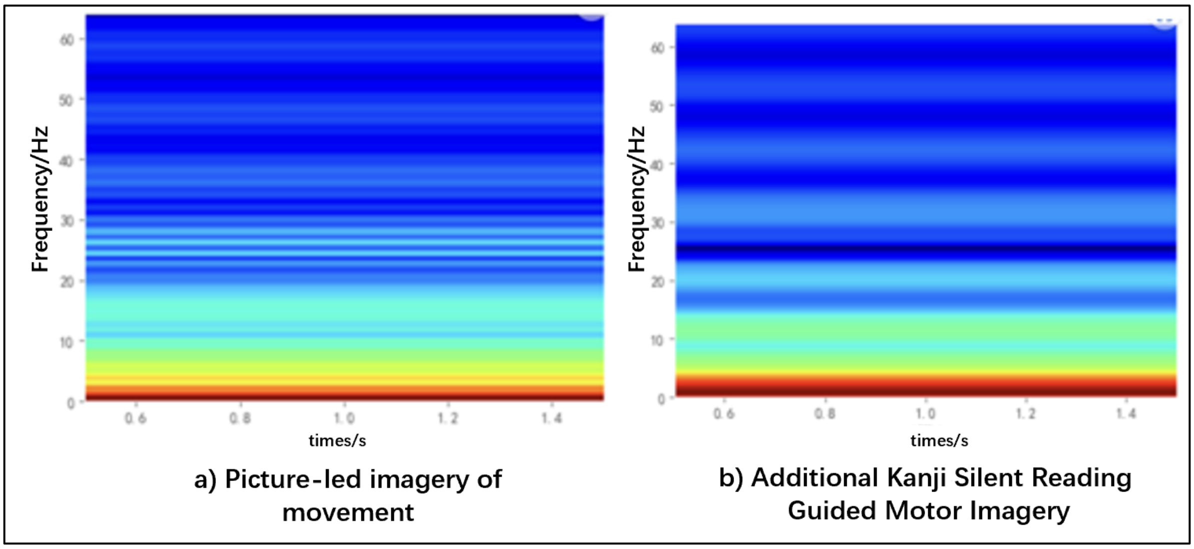


Figure 6: Wavelet energy graph

After slicing the data by data labels, the brain topography maps before and after training in the same category were plotted, as shown in Figures 7 and 8, which are the EEG topography maps of S1 (subject) for the motor imagery by picture, additional Chinese character silent reading guided motor imagery trials for 7 consecutive days, respectively. When the subject was instructed to perform unilateral motor imagery, there was a more pronounced activation of energy in the contralateral brain regions. The results verified that the EEG signals generated by the consciousness task after the additional Chinese character silent reading-guided motor imagery were more stable, demonstrating that its training effect activates the brain of stroke patients and helps them to carry out brain neural remodelling, which has a certain effect on rehabilitation. Moreover, the activation effect was found to be better with increasing training time in the training by brain topography.

EMG signal feature extraction: To improve the feature extraction details of the EMG signal, the acquired surface EMG signal was subjected to four-layer wavelet decomposition using the 'db4' wavelet, and the schematic diagram is shown in Figure 9.

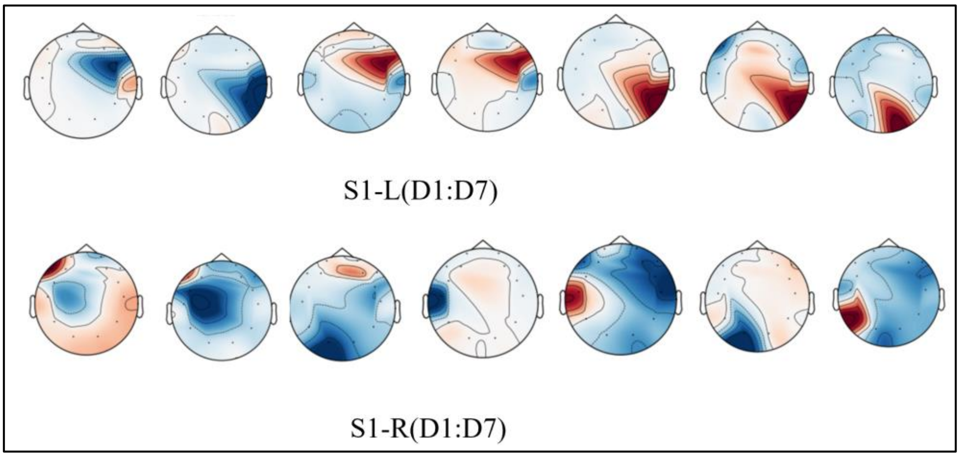


Figure 7: Brain topography of subjects before and after S1 picture-guided motor imagery training

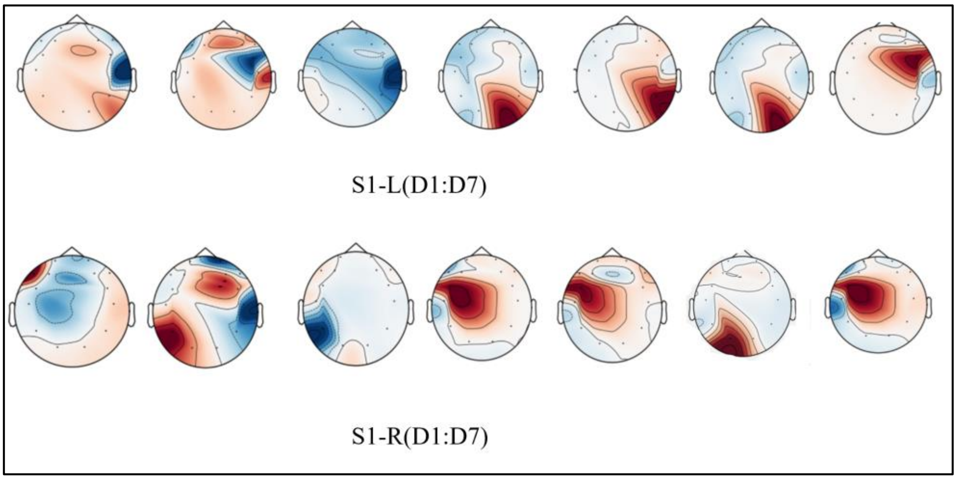


Figure 8: Brain topography of subject S1 before and after additional Chinese character silent reading guided motor imagery training

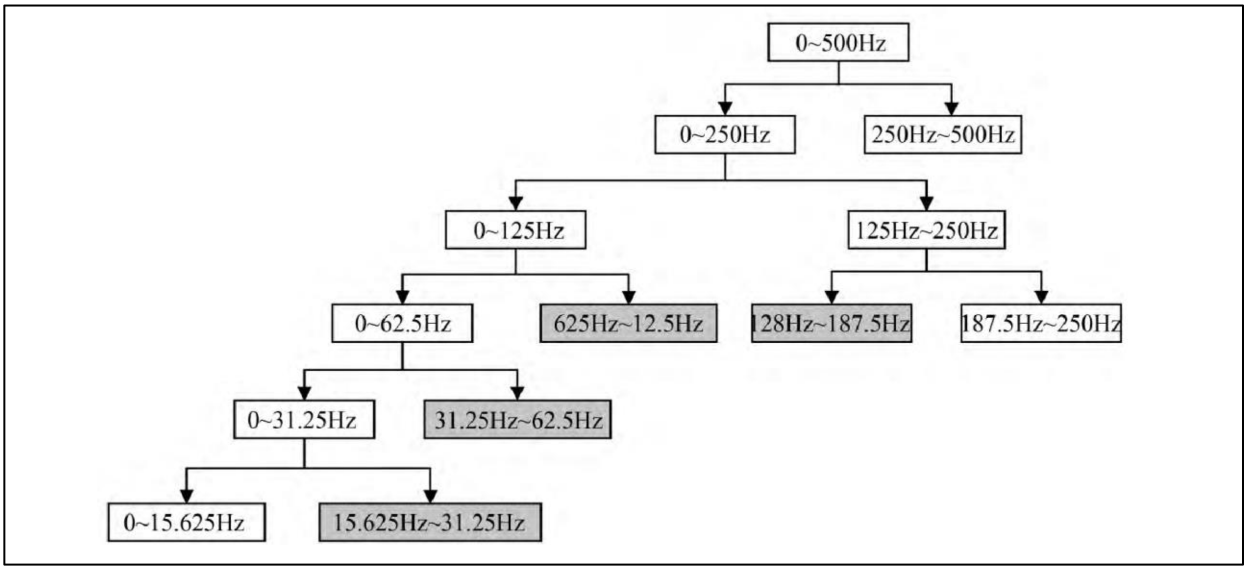


Figure 9: Schematic diagram of EMG signal wavelet decomposition

4. Classification of brain-myoelectric signals using Support Vector Machines

The basic principle of Support Vector Machines (SVM) is to find the optimal classification surface in the feature space by mapping the input feature vectors into a high-dimensional space [12], thus achieving the result of data separation. The 7-day classification results for different modes of motor imagery training are shown in Figures 10 and 11. From the classification results, it can be seen that for untrained subjects, the experimental paradigm of motor imagery with additional Chinese character silent reading guidance has a higher accuracy rate than picture-guided training at the beginning of training, and the accuracy rate improves faster as the number of training days increases, demonstrating that motor imagery with additional Chinese character silent reading guidance has a lower limit of use for non-professionals and is more suitable for stroke patients. It is more suitable for stroke patients to use the training to aid rehabilitation. The results of the classification of surface EMG signals are shown in Table 1:

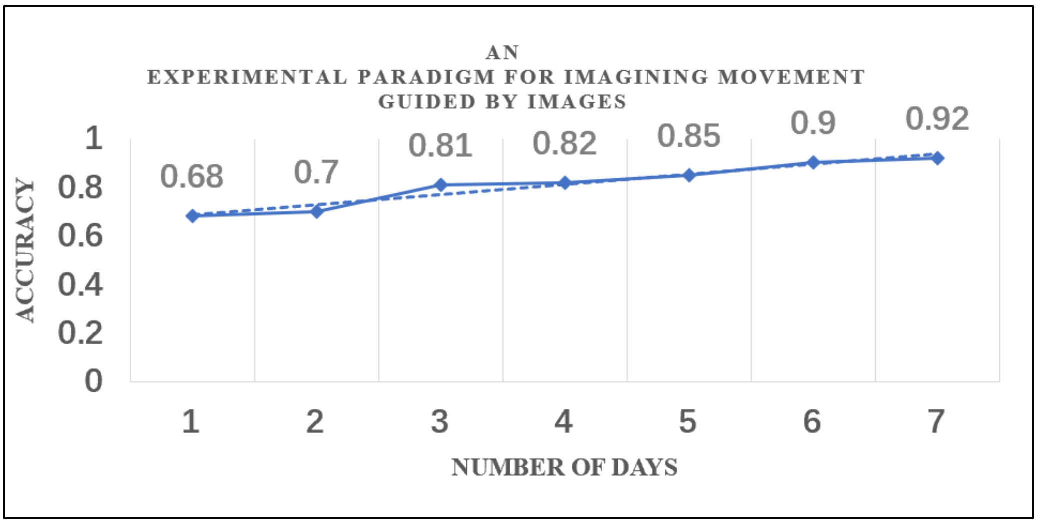


Figure 10: Classification Results of Motion Imagination Based on Images

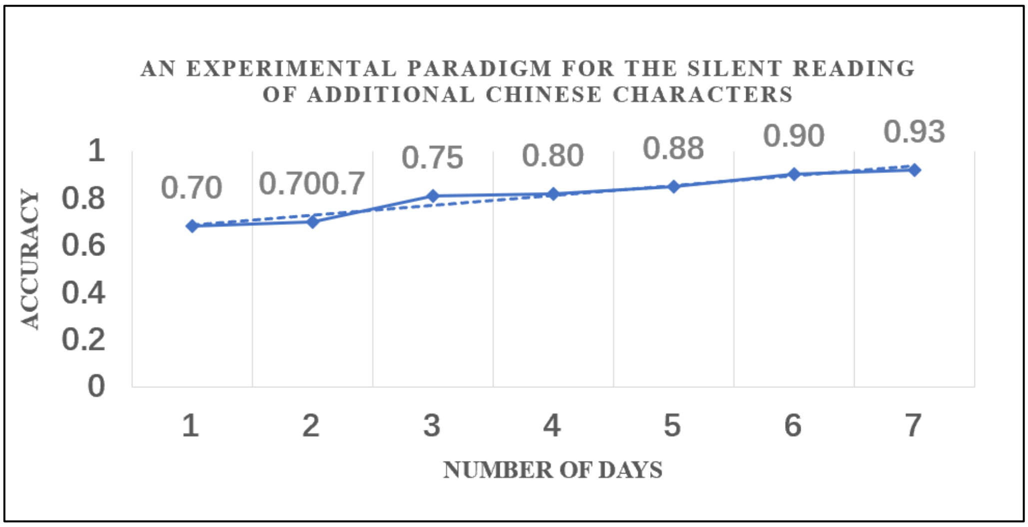


Figure 11: Classification results for additional kanji silent reading guided motor imagery

Table 1: Recognition rate of surface electromyography signals in three subjects

Participants	S1	S2	S3	Average accuracy rate
Classification accuracy	89%	90.1%	92%	90.36%

5 Design of a Multi-Sensor Based Rehabilitation System

5.1 System Test Experiments

Before starting the experiment, the subject is informed of the experimental process and the movements to be performed, and the corresponding motor imagery is done according to the pictures appearing in the screen to generate the raw EEG signals, and the corresponding control commands are output to drive the rehabilitation hand to complete the specified rehabilitation movements through model training of the brain and EMG signals. The overall control strategy is shown in Figure 12.

Experiment 1: Five subjects wore EEG headsets, logged into Emotiv Launcher, confirmed the EEG signal status of Emotiv Epoc, logged into the client software when all the states were good, selected the additional Chinese character silent reading guided motor imagery for data acquisition, read Chinese characters silently while imagining left/right hand movements, performed a total of 20 motor A total of 20 times of motor imagery was performed, with a 5s break after each motor imagery. The correct recognition rate of the rehabilitation hand robot during the motor imagery process was counted, as shown in Table 2, demonstrating the feasibility of the additional Chinese character silent reading-guided motor imagery mode for brain training.

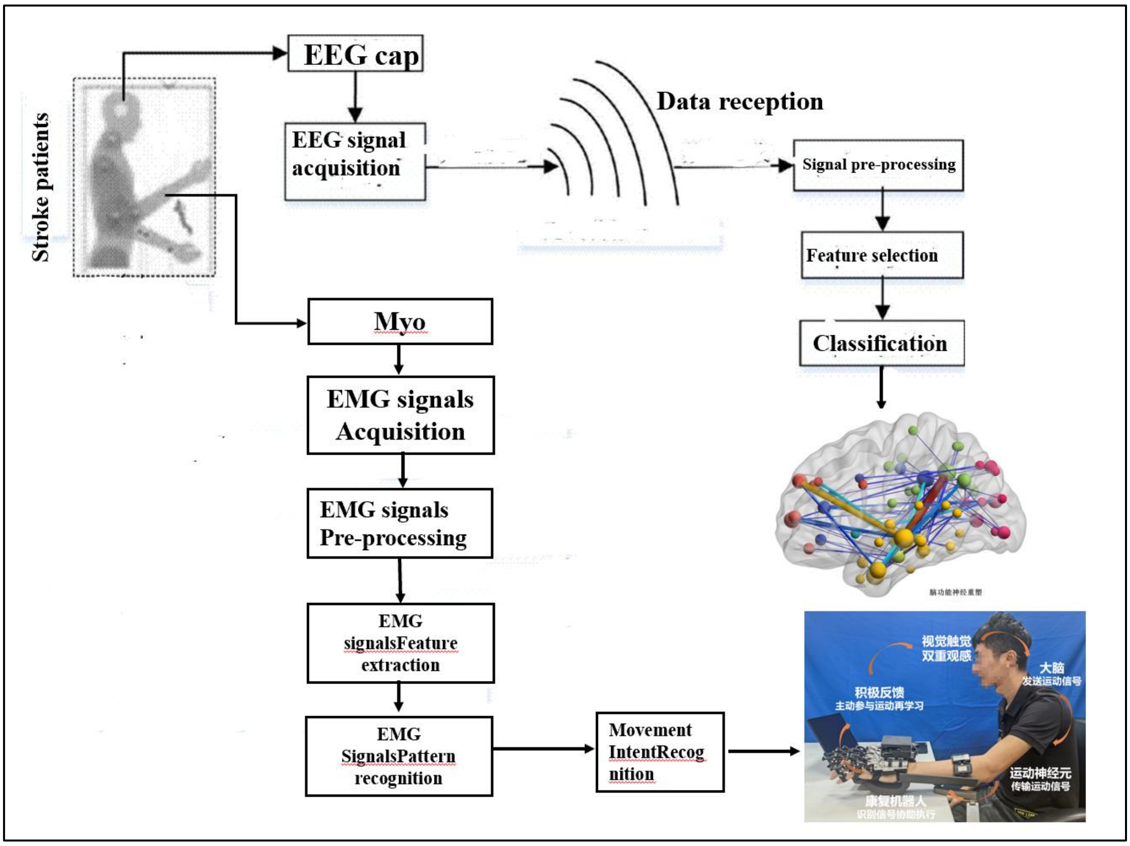


Figure 12: Rehabilitation Strategy Diagram

Table 2: Accurate number of offline EEG controls in 5 subjects

Participants	Number of successful clenched fist recognition	Number of successful open-hand recognition
A	11	12
B	13	11
C	8	15
D	12	12
E	15	10
Total	**59**	**60**

Table 3: Accurate number of online EMG controls in 5 subjects

Participants	Number of successful clenched fist recognition	Number of successful open-hand recognition	Pinch your index finger to identify Number of successes	Squeeze middle finger to identify Number of successes
F	29	25	27	28
G	27	28	25	25
H	26	29	28	27
I	27	29	29	28
J	30	27	28	27
合计	139	138	137	135

Experiment 2: 5 subjects wore the Myo arm ring, confirmed the status of the Myo arm ring, logged into the client software, and selected the active rehabilitation interface for ipsilateral EMG intent-based rehabilitation hand control. The training of surface EMG mainly consisted of four movements: opening the hand, making

a fist, pinching the index finger and pinching the middle finger, and a total of 30 EMG controls were performed, with a single movement duration of 6s and a 2s rest between each movement, after the acquisition was completed Model training was performed, and the rehabilitation hand robot was worn on the ipsilateral hand wearing the Myo arm ring for control of EMG intent. Table 3 shows the number of control accuracies for the subjects, and it can be seen that the surface EMG control of the rehabilitation hand robot was above 90% accuracy in all cases. This indicates that real-time control of the rehabilitation hand can be achieved using surface EMG technology to help stroke patients train muscle and hand strength for effective rehabilitation.

6. CONCLUSION AND FUTURE WORK

This paper proposes a method of hand rehabilitation training for stroke based on brain and EMG signals. An experimental paradigm of motor imagery guided by additional Chinese character mime reading is designed, and the wavelet energy value of the paradigm is found to be significantly increased after the signal is analysed by wavelet decomposition, followed by the analysis of brain topography to prove the feasibility of motor imagery based on additional Chinese character mime reading guidance, which can help patients train to achieve brain neural remodelling The effect of brain and myoelectricity-based rehabilitation training experiments were designed to verify the feasibility of brain and myoelectricity for rehabilitation of stroke patients. In future work, online control of EEG and real-time control of brain-myoelectric fusion will be added to provide more possibilities in the field of rehabilitation.

REFERENCES

1. Wang, C., Li, Z., & Gu, H. (2022). The China Stroke Report Writing Committee. China Stroke Report 2020 (Chinese version) (1) [J]. *China Stroke Journal*, *17*(05), 433-447.
2. GBD 2019 Stroke Collaborators. (2021). Global, regional, and national burden of stroke and its risk factors, 1990-2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet Neurol.*, *20*(10), 795-820.
3. Dimyan, M. A., & Cohen, L. G. (2011). Neuroplasticity in the context of motor rehabilitation after stroke [J]. *Nature Reviews Neurology*, *7*(2), 76-85.
4. Ang, K. K., & Guan, C. (2015). Brain–computer interface for neurorehabilitation of upper limb after stroke [J]. *Proceedings of the IEEE*, *103*(6), 944-953.
5. Chaudhary, U., Birbaumer, N., & Ramos-Murguialday, A. (2016). Brain–computer interfaces for communication and rehabilitation [J]. *Nature Reviews Neurology*, *12*(9), 513-525.
6. Soekadar, S. R., Witkowski, M., Gómez, C., Opisso, E., Medina, J., Cortese, M., ... & Vitiello, N. (2016). Hybrid EEG/EOG-based brain/neural hand exoskeleton restores fully independent daily living activities after quadriplegia. *Science Robotics*, *1*(1), eaag3296.
7. Willett, F. R., Avansino, D. T., Hochberg, L. R., Henderson, J. M., & Shenoy, K. V. (2021). High-performance brain-to-text communication via handwriting. *Nature*, *593*(7858), 249-254.
8. Pfurtscheller, G., Neuper, C., Flotzinger, D., & Pregenzer, M. (1997). EEG-based discrimination between imagination of right and left hand movement. *Electroencephalography and clinical Neurophysiology*, *103*(6), 642-651.
9. Prasad, G., Herman, P., Coyle, D., McDonough, S., & Crosbie, J. (2010). Applying a brain-computer interface to support motor imagery practice in people with stroke for upper limb recovery: a feasibility study. *Journal of neuroengineering and rehabilitation*, *7*(1), 1-17.
10. Wang, F. Y., Zhang, D. F., & Li, F. (2020). An action recognition method based on surface electromyographic signals for patients with different Brunnstrom levels [J]. *Robotics*, *42*(6), 661-671, 685.
11. Slimen, I. B., Boubchir, L., Mbarki, Z., & Seddik, H. (2020). EEG epileptic seizure detection and classification based on dual-tree complex wavelet transform and machine learning algorithms. *Journal of biomedical research*, *34*(3), 151-161.
12. Lingwei, Z., Zhengdong, Z., & Yunfei, X. (2022). Classification of Imagined Speech EEG Signals with DWT and SVM [J]. *Instrumentation*, *9*(02), 56-63.