The Design of Rehabilitation Glove System Based on sEMG Signals Control

Qing Cao[1], Mingxu Sun[1], Ruiyun Li[1], and Yan Yan[2](✉)

[1] University of Jinan, Jinan 250022, China
[2] Shandong Guohe Industrial Technology Institute Co., Ltd., Jinan 250098, China
yanyan@china-csi.com.cn

Abstract. Stroke is a sudden disorder that causes impaired blood circulation to the brain, and resulting in varying degrees of impairment of sensory and motor function of the hand. Rehabilitation gloves are devices that assist in the rehabilitation of the hand. The sEMG (Surface Electromyography) is a bioelectrical signal generated by muscle contraction. It is rich in physiological motor information and reflects the person's motor intention. That means sEMG signals is an ideal signal source for rehabilitation glove system. This paper describes the design of a rehabilitation glove system based on sEMG signals control. The system controls the movements of the rehabilitation glove by collecting and analyzing the sEMG signals, and is used to achieve the purpose of rehabilitation training. This system includes a rehabilitation glove system and a host computer. The rehabilitation glove system is used to control the rehabilitation glove to achieve rehabilitation movements, to perform rehabilitation training for patients and to collect sEMG signals. The host computer is used to receive signals and perform gesture classification by CNN (Convolutional Neural Network) to recognize the movement intention.

Keywords: Surface Electromyography(sEMG) · Convolutional Neural Network (CNN) · Pneumatic rehabilitation gloves · Hand rehabilitation

1 Introduction

With over 10 million new strokes worldwide each year [1], stroke is remain the main cause of death and disability in adults [2]. Stroke is a sudden disorder that causes sensory and motor functions of the hand are impaired to varying degrees [3]. The clinical manifestations are usually involuntary muscle contraction caused by finger flexor spasm, decreased muscle strength and abnormal muscle tension [4]. Decreased flexibility of fingers, numbness of limbs, and reduction of thumb movement range are also common disabling symptoms after stroke [5]. About 30% of patients will have spasms in the first few days or weeks [6]. The wide distribution of joint nerves and the large number of blood vessels in the hand. Effective nerve stimulation of the hand can promote the rehabilitation of the upper extremity.

B. Wang et al. (Eds.): ICMTEL 2023, LNICST 535, pp. 248–256, 2024.
https://doi.org/10.1007/978-3-031-50580-5_21

Bioelectrical signals recognize and classification have become an important role in wide applications, including magnetoencephalography (MEG), electroencephalogram (EEG), electrocorticogram (ECoG) and electromyography (EMG) [7]. Nowadays, bioelectrical signal-based recognition technologies have gained widespread attention in various fields such as virtual reality, motion sensing games and medical rehabilitation training [8]. In this paper, EMG is selected as the bioelectrical signal for motion recognition.

The EMG is a bioelectrical signal generated by muscle action, and include needle in electromyography (nEMG) and surface electromyography (sEMG). It contains rich physiological motor information [9]. Compared to nEMG, sEMG has the advantages of non-invasive and easy operation. The sEMG-controlled rehabilitation gloves and real human hands belong to the same family of control [10]. By analyzing the sEMG signals, the movement patterns of the hand can be recognized [11]. The sEMG is able to sense and decode human muscular activity directly [12], so sEMG signals are the ideal signal source for human-machine interaction systems [13].

For patients, sEMG signals can be collected from either the unaffected hand or the affected hand. Since most stroke patients have functional impairment in one arm and the sEMG signals from the affected hand is very weak or nearly absent [14]. Therefore, the sEMG signals of the unaffected hand are used as control signals [15]. The movements of the unaffected hand are copied to the affected hand for bimanual training.

Bimanual training is a rehabilitation strategy based on natural coordination between limbs [16]. Performing bimanual training on patients improves the efficiency of movements on the affected hand [17].

Machine-assisted hand rehabilitation has been shown to reduce injuries and improve motor function [18]. During the early rehabilitation and spontaneous recovery of the patient's limbs, the patient's symptoms can be greatly improved by driving the finger joints and thus assisting in the motor rehabilitation of the hand, and by implementing continuous passive movements to compensate for the lack of active movements [19].

At present, the popular hand rehabilitation equipment can be divided into rigid mechanical exoskeleton rehabilitation equipment [20] and flexible pneumatic rehabilitation gloves. A major limitation of rigid mechanical hand exoskeleton rehabilitation robot is that most are based on rigid linkages and are overall bulky and heavy. This makes them unsuitable for patients to wear them for activities of daily living [21]. Compared with rigid mechanical exoskeleton rehabilitation robot, flexible pneumatic rehabilitation glove has some advantages, including good flexibility, small size, easy to move, safety and reliability [22].

For this purpose, in this paper used a flexible pneumatic rehabilitation glove, and used a CNN classification method. The sEMG from the unaffected hand of the patient are used to classify and identify hand gestures by CNN classification method, to control the movement of the rehabilitation glove and help the patient's affected hand function recovery.

2 Design of Rehabilitation Gloves System

The pneumatic rehabilitation glove system consists of pneumatic gloves, air pump, Stm32 microprocessor, sEMG sensor, solenoid valve, gas pressure sensor and host computer. The composition of the rehabilitation glove system block diagram is shown in Fig. 1

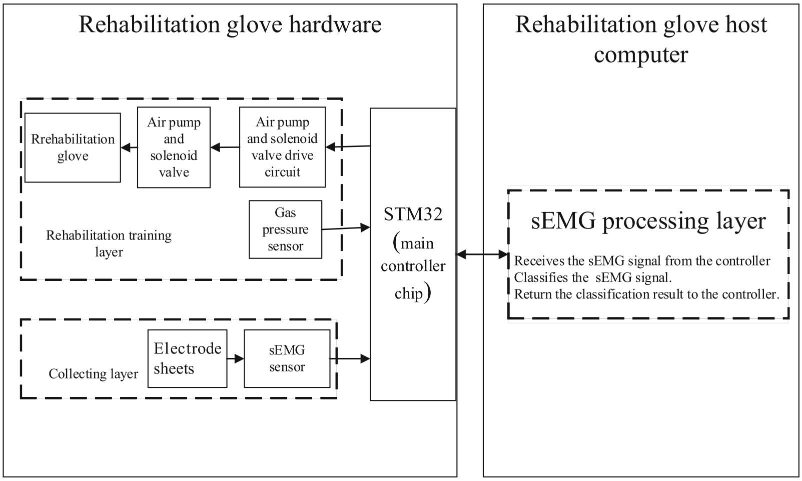


Fig. 1. The rehabilitation glove system block diagram.

The rehabilitation training layer including pneumatic rehabilitation glove, air pump, solenoid valve and gas pressure sensor. The pneumatic rehabilitation glove covers well around the patient's fingers and back of the hand. The pneumatic gloves are powered by the air pump, air pump can inflate and suctioned to allow finger flexion and dorsiflexion. The solenoid valve is used to achieve the movement of the selected finger to completed different rehabilitation exercises. The collecting layer use the sEMG sensor to collect the sEMG signals from the unaffected hand of the patient.

The host computer is used to process the sEMG data and is developed using PyCharm software as the development environment. It performs gesture classification recognition by analyzing the sEMG signals data. The classification results obtained are sent to the microcontroller.

Firstly, the unaffected hand makes a fist-clenching action, and then the sEMG signals is collected through the sEMG sensor. Then the signal is sent to the host computer, which further identifies the signals and classifies it to get the corresponding gesture action. After that, the obtained action commands are sent down to the rehabilitation glove, and use the microcontroller controls the air pump. Then driver the action of the pneumatic rehabilitation glove. The rehabilitation glove drives the affected hand to perform rehabilitation movements and complete rehabilitation training to achieve the purpose of bimanual training.

3 Hardware Design of Rehabilitation Glove

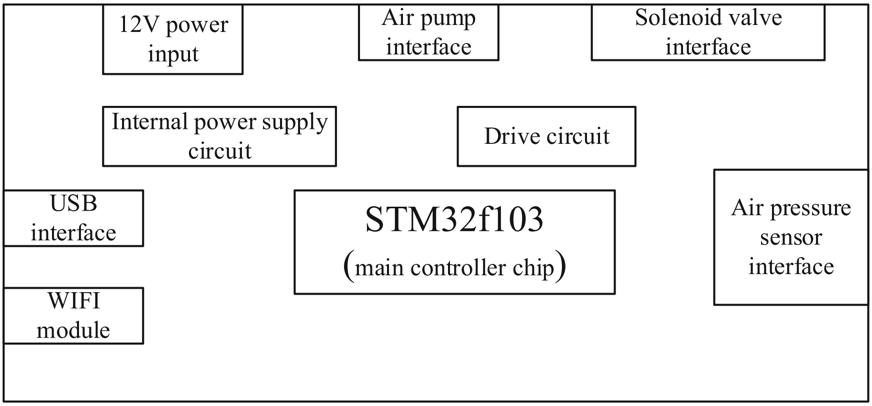


Fig. 2. The hardware design of the rehabilitation glove.

The block diagram of the hardware design of the rehabilitation glove is shown in Fig. 2. The rehabilitation glove controller is stm32 microprocessor for the main control of the system. 12V system power input, which is used to supply power to the whole system. Through the internal power conversion circuit, the 12V power supply is converted into the 3.3V required by the chip.

The air pump interface and solenoid valve interface are used for connect external air pump and solenoid valve. The Stm32 microprocessor controls the switching of the solenoid valve and the air pump through the driver circuit. By controlling air pump inflated and suctioned to allow finger flexion and dorsiflexion. By controlling different combinations of switches of the solenoid valve to achieve the purpose of completing different rehabilitation gestures.

The USB interface and WIFI module are used to connect the controller to communicate with the host computer software. The difference is that the USB interface is connected through a data line and the WIFI module is for wireless communication.

The gas pressure sensor interface is used for connect gas pressure sensor. The gas pressure sensor built into the air circuit of the glove to monitor the gas pressure in real time. Prevent injuries caused by excessive air pressure when the air pump inflation and deflation. When the gas pressure exceeds a predetermined pressure value, an alarm will be triggered and the solenoid valve will open immediately to release the gas in the air circuit to avoid injury.

The dual-channel sEMG sensors is used to collected original sEMG signals from the unaffected hand of the patient. Using sEMG sensors, the sEMG signals are digitally filtered, amplified and rectified then transmit the to the host computer. The sensor collects sEMG signals of patients with a sampling frequency of 500 Hz. Each sEMG sensor channel has two detection electrodes (yellow and green) and one reference electrode(red). The sEMG sensor is shown in Fig. 3.

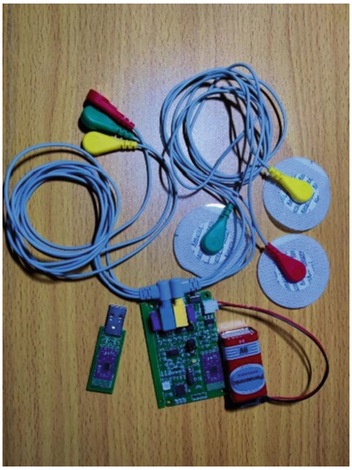
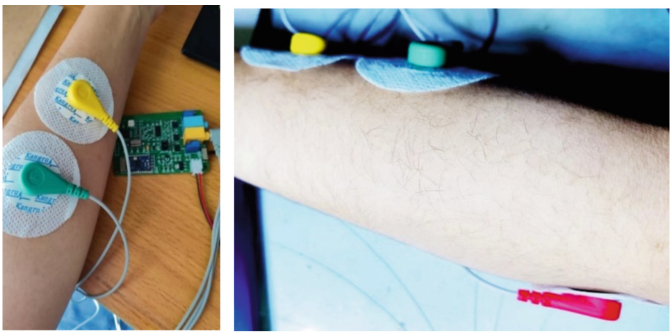


Fig. 3. sEMG sensor

Subject: A healthy young people were selected to participate in this experiment, and the subject were free from upper limb muscle diseases and skeletal disorders. Because the sEMG signals is unstable and susceptible to interference on the skin surface, the skin on the arm muscles needed to be cleaned and disinfected with alcohol before collecting the sEMG signals.

Electrode sheet location: electrode sheets are used to collect sEMG signals. To have an effectively collect the sEMG signals, it is generally placed at the location where the muscle contraction is strong, and the detection electrode sheets is placed at the muscle of the subject's forearm as shown in Fig. 4 (a). The reference electrode sheet is usually placed at a location where the number of muscles is low. In this experiment, the reference electrode sheet was chosen at the elbow, as shown in Fig. 4 (b).



(a) (b)

Fig. 4. Electrode sheet location

The sEMG signals data of the subject's hand in the calm state and in the clenched fist state were collected as the test data. The sEMG signals was collected with the subject's one side hand palm facing upward and flat on the table. The duration of each set of movements was 2s. When the subject finished a gesture, should rest for 4s. When the gesture returns to resting state, repeat the previous gesture again.

30 sets of sEMG signals were collected from the subject's hand in the calm state and 30 sets of sEMG signals from the clenched fist state, which were used as the original data set. The one set of the calm and clenched fist states data are shown in the Fig. 5.

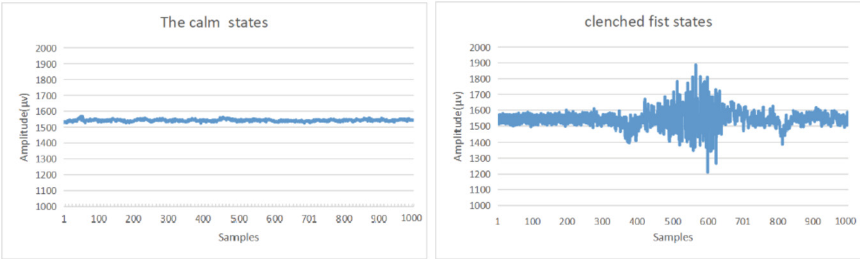


Fig. 5. The signals collected in the calm and clenched fist states.

4 Design of sEMG Classification Recognition

Build a training model structure for real-time recognition of sEMG signals and save the parameters of the model. The classification method of this study [23], We use a classical signal classification method based on CNN to classify sEMG signals [24].

Feature extraction is performed on the original data set of each gesture, and 80% of the extracted data is randomly selected as the original training set and the remaining part as the original test set, with no crossover between the training set and the test set.

The model is first trained with the data from the training set, and then the accuracy of the model is tested using the test set. If the expected accuracy is not achieved, the model continues to be trained. If the expected accuracy is achieved, the training is stopped and the model parameters are saved. The flow chart to save the model is shown in Fig. 6.

In order to verify the feasibility of the system, a preliminary binary classification network model was constructed. The model will be further optimized later to achieve more and more accurate classification and recognition of hand gesture actions.

The flow chart of real-time sEMG signals recognition is shown in Fig. 7. After initialization, the host computer receives the sEMG data transmitted in real time from the sEMG sensor and performs feature extraction on it. A pre-saved model is used to classify the collected sEMG signals and the classification results are sent to the controller of the rehabilitation glove. The controller outputs the corresponding switch control signal to control the glove to complete the action.

The confusion matrix for this network for data set as shown in Fig. 8, which shows all the gestures are classified accurately with low error. From the confusion matrix, this classification method gave 100% validation accuracy for the classification of the two gestures. This lays a good foundation for future extension to multi-gesture classification.

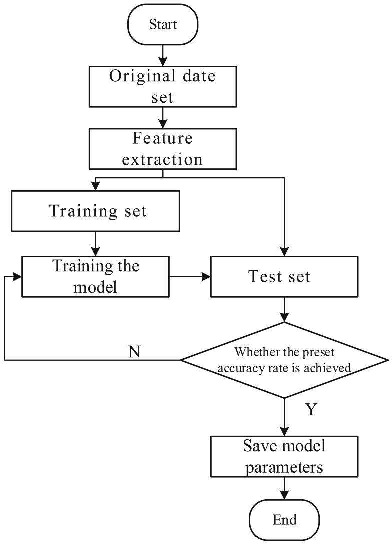


Fig. 6. The flow chart of save model parameters

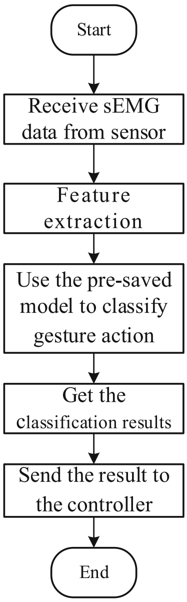


Fig. 7. The flow chart of real-time sEMG signals recognition

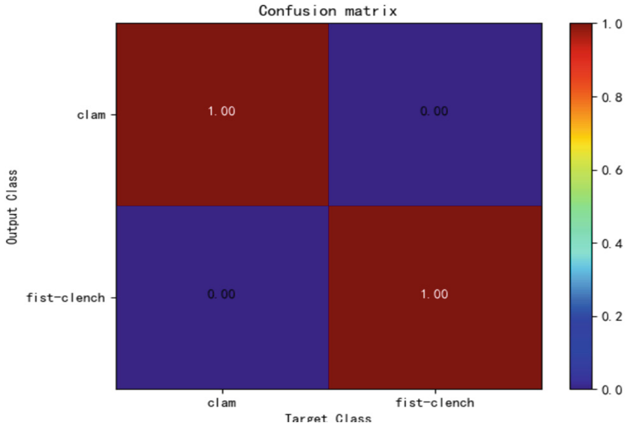


Fig. 8. The confusion matrix for this network for data set

5 Conclusions

In this paper we collect sEMG signals from patients through sEMG sensor and use a CNN classification method to recognize hand gestures and control the movement of rehabilitation gloves to help patients recover hand function. The classifier can maintain a high accuracy rate in recognizing hand movements in real time. The motion control of the rehabilitation glove based on the recognition of sEMG signals is verified. Experiments on gesture motion control of rehabilitation gloves were designed. The feasibility of the CNN classification method for controlling rehabilitation gloves is illustrated. It lays the foundation for further research on intelligent rehabilitation gloves.

References

1. Pandian, J.D., Gall, S.L., Kate, M.P., et al.: Prevention of stroke: a global perspective. Lancet **392**(10154), 1269–1278 (2018)
2. Ferrarin, M., Palazzo, F., Riener, R., Quintern, J.: Model-based control of FES-induced single joint movements. IEEE Trans. Neural Syst. Rehabil. Eng. **9**(3), 245–257 (2001)
3. Johnston, S.C., Mendis, S., Mathers, C.D.: Global variation in stroke burden and mortality: estimates from monitoring, surveillance, and modelling. Lancet Neurology **8**(4), 345–354 (2009):
4. Marciniak, C.: Poststroke hypertonicity: upper limb assessment and treatment. Top. Stroke Rehabil. **18**(3), 179–194 (2011)
5. Dietz, V., Sinkjaer, T.: Spastic movement disorder: impaired reflex function and altered muscle mechanics. Lancet Neurol. **6**(8), 725–733 (2007)
6. Mayer, N.H., Esquenazi, A.: Muscle overactivity and movement dysfunction in the upper motoneuron syndrome. Phys. Med. Rehabil. Clinics **14**(4), 855–883 (2003)
7. Feng, Y., et al.: Active triggering control of pneumatic rehabilitation gloves based on surface electromyography sensors. Peer J Comput. Sci, **7**, e448 (2021)
8. Wang, Y., et al.: Deep back propagation–long short-term memory network based upper-limb sEMG signal classification for automated rehabilitation. Biocybern. Biomed. Eng. **40**(3), 987–1001 (2020)

9. Qi, J., et al.: Intelligent human-computer interaction based on surface EMG gesture recognition. IEEE Access **7**, 61378–61387 (2019)
10. Ahanat, K., Juan, A.C.R., Veronique, P.: Tactile sensing in dexterous robot hands-Review. Rob. Auton. Syst. **74**, 195–220 (2015)
11. Li, G., et al.: A novel feature extraction method for machine learning based on surface electromyography from healthy brain. Neural Computing and Applications **31**(12), 9013–9022 (2019)
12. Fang, Y., et al.: A multichannel surface EMG system for hand motion recognition. Inter. J. Humanoid Robot. **12**(02), 1550011 (2015)
13. Kamavuako, E.N., et al.: Estimation of grasping force from features of intramuscular EMG signals with mirrored bilateral training. Annals Biomed. Eng. **40**(3), 648–656 (2012)
14. Zou, Z., et al.: Analysis of EEG and sEMG during upper limb movement between Hemiplegic and normal people. In: 2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), vol. 4. IEEE (2021)
15. Leonardis, D., et al.: An EMG-controlled robotic hand exoskeleton for bilateral rehabilitation. IEEE Trans. haptics **8**(2), 140–151 (2015)
16. Luft, A.R., et al.: Repetitive bilateral arm training and motor cortex activation in chronic stroke: a randomized controlled trial. Jama **292**(15), 1853–1861 (2004)
17. Waller, S.M., et al.: Temporal coordination of the arms during bilateral simultaneous and sequential movements in patients with chronic hemiparesis. Experim. Brain Res. **168**(3), 450–454 (2006)
18. Frisoli, A., et al.: Positive effects of robotic exoskeleton training of upper limb reaching movements after stroke. J. Neuroeng. Rehabil. **9**(1), 1–16 (2012)
19. Boake, C., et al.: Constraint-induced movement therapy during early stroke rehabilitation. Neurorehabil. Neural Repair **21**(1), 14–24 (2007)
20. Agarwal, P., et al.: An index finger exoskeleton with series elastic actuation for rehabilitation: Design, control and performance characterization. Inter. J. Robot. Res. **34**(14), 1747–1772 (2015)
21. Laschi, C., Cianchetti, M.: Soft robotics: new perspectives for robot bodyware and control. Front. Bioeng. Biotechnol. **2**, 3 (2014)
22. Heung, K.H.L., et al.: Robotic glove with soft-elastic composite actuators for assisting activities of daily living. Soft Robotics **6**(2), 289–304 (2019)
23. Atzori, M., Cognolato, M., Müller, H.: Deep learning with convolutional neural networks applied to electromyography data: A resource for the classification of movements for prosthetic hands. Front. Neurorobot.Neurorobot. **10**, 9 (2016)
24. Bakircioğlu, K., Özkurt, N.: Classification of EMG signals using convolution neural network. Inter. J. Appli. Mathem. Electron. Comput. **8**(4), 115–119 (2020)