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Hand Gesture Recognition Based on Deep Neural Network and sEMG Signal*

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***Abstract* - The physiological electrical signal of human body is the direct response from human behavior intention. By analyzing and interpreting the physiological electrical signal of human body, human subject consciousness can be effectively recognized. In order to enable people with physical disabilities to effectively control peripherals according to their own intentions, this research is based on the classification and recognition of sEMG hand movements. The position of sEMG electrode on the muscle is determined. sEMG signals of 8 kinds of common hand movements in daily life are successfully collected and data collection of sEMG signals is completed. The VGG16 is used to construct the convolutional neural network structure suitable for sEMG gesture recognition. At the same time, a highly biomimetic robotic hand is built according to the bone structure of human hand to complete 8 gestures as an actuator, and STM32 microprocessor is used to control it. Through the comparison and analysis with two VGG16 networks with different convolution kernel sizes, the results show that the VGG16 network structure with convolution kernel size of 3×3 adopted by this method has a high accuracy for the recognition of 8 kinds of hand movements.**

Index Terms - CNN; machine learning; sEMG signal; gesture recognition; VGG16.

I. Introduction

In daily life, dexterous hand is the most indispensable part of human beings. Humans can express their thoughts through hand gestures [1-2]. When humans move their hands, the sEMG signal records a muscle’s electrical activity from the surface of the skin and thus reflects the generation [3]. When researchers successfully decipher the information contained in sEMG signal and the motor intentions expressed, they can use this information to guide patients in treatment or develop exoskeletons that enhance human motor abilities [4-5]. The key technology in the application of human-computer interaction is to identify the user's muscle movement intention, and this technology has been widely used in artificial limb control, medical rehabilitation and other fields [6]. At present, researches on medical rehabilitation robot control are mainly divided into two categories. One is motion sensor, such as Andreas, which uses gyroscope sensor and machine learning method to realize gesture recognition [7]. Sawada et al. [8] use acceleration sensor to identify gestures, and conducted in-depth research on three-dimensional spatial interactive mode. Another is the use of sEMG sensors. Reitert et al. [9] first used multichannel sEMG signals to control prosthetic limbs in 1948. In recent years, the control of the multi-channel sEMG researchers have begun to explore for amputation or the possibility to provide better medical rehabilitation in patients with hemiplegia. For example, Carrozza et al. [10] using finite state machine to implement the single degree of freedom (DOF) prosthesis control multi-channel sEMG. Compared with motion sensors, sensors as control source with multi-channel sEMG are not affected by the variations of light, position, and orientation of the hand.

To some extent, CNN algorithm can solve the problem of losing a lot of information in the feature extraction process of traditional machine learning algorithm. But there are still some problems. First of all, a lot of research is to use NinaPro dataset[5,18,19], while the data set is currently the world's largest sEMG signal data sets, but too few repetitions of each action, in DB2 every gesture of every experiment object only repeat 6 times, the sample size is relatively limited, so the data set has some limitations. To solve this problem, we conduct our own experiment and collected data, each gesture of each subject is repeated 70 times. Secondly, the traditional data feature extraction process involves complex computation and a large amount of information loss [20-21]. Our method uses CNN with deep convolution kernel with small size to mine more information of sEMG signal, and the whole sEMG signal will be used as the input of the system. Finally, many researchers employ MYO bracelets as sEMG signal acquisition devices [15,22]. Although the bracelet is portable and easy to collect, its sampling frequency is only 200Hz, and the position of contact between the muscle and the electrode cannot be specified, making it impossible to collect sEMG signals across all relevant muscle surfaces. So, we use a signal acquisition device with a high sampling frequency and the ability to customize the position of the electrode patch.

In this study, a CNN as a gesture recognition classifier is established. The network structure is by Visual Geometry Group with 16 layers (VGG16) [23]. In the design of CNN network architecture, the characteristics of sEMG signals are considered. Unlike the kernel filters commonly used in computer vision, our architecture utilizes smaller sizes and fewer kernel filters, and we improve the original VGG16 network to better adapt to the characteristics of sEMG signals. sEMG information of different channels is fused, and then multiple convolution cores of size 3×3 are repeatedly stacked to dig out deeper information in sEMG signals. Meanwhile,

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the sEMG signal acquisition equipment with sampling frequency of 1500Hz is used to obtain most of the information in sEMG signals, effectively solving the defect caused by the low sampling frequency of MYO bracelet. At the same time, we build a highly biomimetic robotic hand based on the bone structure of human hand as an actuator to perform eight gestures, and STM32 microprocessor to control it. To evaluate the proposed architecture, some reference experiments including some classical methods are implemented.

II. METHODS

A. The data collection

Ten healthy subjects including eight men and two women are recruited in the study. The sEMG data acquisition equipment used in this study is made by Noraxon, USA. The sampling frequency is 1500Hz, and the maximum number of channels is 16, which can meet the requirements of 8-channel data collection in this paper. The entire sEMG signal acquisition equipment is shown in Fig. 1. The system includes eight wireless transmission modules and sEMG signal acquisition module. In the meantime, the computer receives data for direct analysis and processing.

In the study, 8 muscles that are closely related to hand movements are selected, and their corresponding functions are shown in the following TABLE I:

TABLE I
EIGHT RELATED MUSCLES AND THEIR FUNCTIONS

The name of the muscle	**Function**
musculus flexor digitorum superficialis	Flexion middle finger, flexion metacarpophalangeal joint and wrist joint
musculi palmaris longus	Flexion of the wrist, tensing of the palmar aponeurosis
ulnar flexor of wrist	Bend the wrist and draw the hand in
flexor carpi lateralis	Flexion of the wrist and forearm, abduction of the hand
extensor carpi ulnaris muscle	Extend your wrist and bring your hand in
common extensor of fingers	Stretch your wrists and fingers
abductor pollicis longus	Outreach thumb
flexor pollicis longus	Bend your thumb

In the research, 8 kinds of relatively classic gestures are selected, and each gesture is generated by the combined action of each muscle. Therefore, different gestures will generate sEMG signals of different frequencies and amplitudes on the forearm, as shown in the Fig. 1:

Fig. 1 Gesture mode.

B. Data preprocessing

Since sEMG signals are non-stationary some environmental noises and random noises are unavoidable in the collected signals. After collecting the original sEMG data, it should be pre-processed first.

$$F[f(t)] = \int_{-\infty}^{\infty} f(t)e^{-iwt}dt \quad (1)$$

Firstly, the Fourier transform formula shown in (1) is used to convert the time domain sEMG signal of each channel into the frequency domain sEMG signal.

The effective frequency of sEMG signal is mainly concentrated in the range of 10 to 500 Hz [14]. Therefore, a bandpass filter of 10 to 500 Hz is used to filter high frequency noise with frequency higher than 500 Hz and low frequency noise with frequency lower than 10 Hz in order to reduce the influence of noise signal on classifier classification results.

For the filtered data, it cannot be directly used for gesture training and prediction, and needs to go through standardization steps. The main purpose of normalization is to limit the pre-processed data to [-1,1], so as to eliminate the adverse effects of singular sample data on the prediction results.

C. Windowing

The input of CNN is two-dimensional image information [5], so we cannot directly input the sEMG data processed in the previous work into the neural network structure. Before the pre-processed sEMG signal is input into CNN, we need to segment the data to match the input requirements of the algorithm. For each channel, we use a sliding window of L millisecond length to segment the preprocessed data. The increment of sliding window is set to 50 sampling points. Fig. 2 shows the scheme of segmenting and combining the sEMG signals. Each subject's sEMG signal is then converted into multiple 8×200 sEMG image information, of which 8 represents the number of electrode channels and 200 represents the number of sampling points.

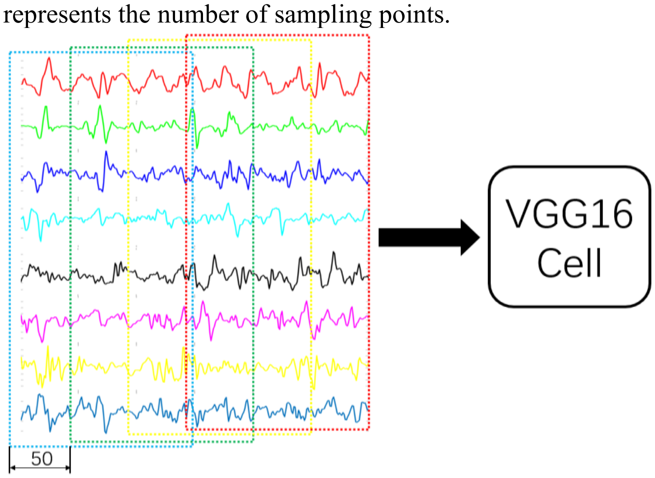

Fig. 2. Converting the sEMG signals to sEMG images by sliding window.

The selection of window length is related to time delay and classification accuracy. The length of the window represents a balance between time delay and classification accuracy. If real-time control is to be achieved, the delay must be less than 300ms [12]. The longer the window length is, the greater the delay of the classifier and the higher the classification accuracy. In order to achieve higher classification accuracy, L must be greater than 100ms. In order to test the performance of the algorithm in this study, L = 133ms is selected and 167ms is reserved for data processing and signal transmission of single image information.

D. Feature Extraction and Classification

CNN can directly input the image information of sEMG signal without designing a feature extractor for it. This is the reason why CNN can solve the problem of large amount of useful information loss in traditional machine learning.

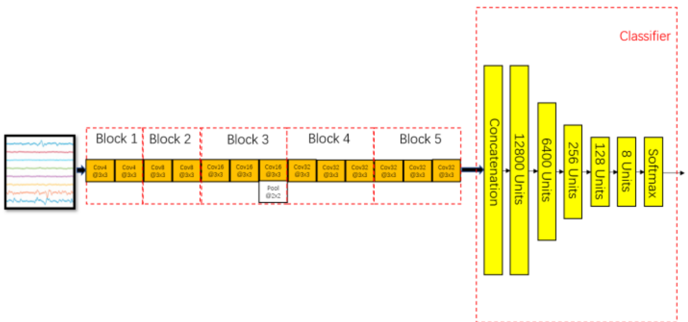

Fig. 3. Schematic of VGG16 used on the sEMG signals.

Fig. 3 shows the network structure of VGG16. The network has 13 convolution layers and 3 full connection layers. All convolution layers contain 2D filters of 3×3 with the stride of 1. Block1 comprises two convolution layers, each of which has four convolution kernels. Block2 comprises two convolution layers, each of which has eight convolution kernels. Block3 comprises three convolution layers, each of which has sixteen convolution kernels. Block4 consists of three convolutional layers, each with thirty-two convolution kernels. Block5 has the same structure as Block4. Each of the first 15 layers employs a relu as an activation function, and the last one utilizes SoftMax to output the final prediction results. Finally, three full connection layers and two dropout with probability of 0.5 are used to reduce the overfitting degree of neural network. In this network structure, information from different electrodes is mixed together to detect correlations between each electrode. In order to improve the robustness of the algorithm, the average pooling layer using the filters of 2×2 is followed by Block3. The local disturbance of sEMG signal caused partly by noise does not affect the classification results.

E. The bionic hand

The process of designing and manufacturing our bionic hand includes laser scanning, 3D printing and component assembly. We use laser/MRI scanner to obtain the shape of the hand bones, by using the method of 3D printing for bionic hand bone, make it have detailed skeleton characteristics, using silicon rubber to instead of the bionic hand soft tissue, after the integration of all the modules of the prosthetic hand, we tested the movement of the fingers and bending effect and bionic hand fetching function.

After the experimenter makes a certain gesture, the sEMG signal of forearm is transmitted to the computer through the wireless transmission module. The computer processes the corresponding data and obtains a classification result, which is then transmitted to the STM32 microprocessor. The bionic hand is controlled by the STM32 microprocessor, which controls 10 servo motors after receiving the corresponding information, so that the bionic hand can successfully complete different gestures. The structure of the bionic hand is shown in Fig 4.

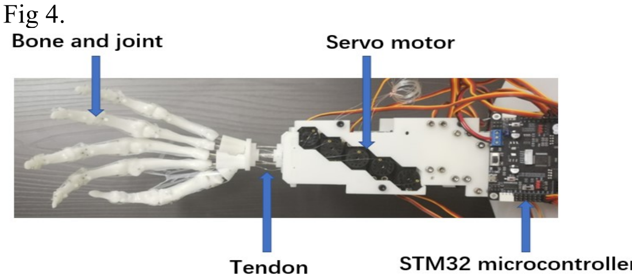

Fig. 4. The structure of the bionic hand

III. Results and Discussion

This study doesn't directly adopt the original structure of VGG16, but make some adjustments to the parameters of the network based on the characteristics of sEMG signals. The first convolution layer of the original VGG16 algorithm has 64 convolution kernels, while the complexity of sEMG signals is not as complex as image data. Therefore, in this study, there are 4 convolution kernels in the first convolution layer, which can greatly reduce the training time on the premise of ensuring classification accuracy. In combination with several reference experiments, the performance characteristics of VGG16 network structure with convolution kernel size of 3×3(VGG16-3×3) is evaluated. The network structure of VGG16-3×3 is shown in TABLE II, which has 13 convolution layers and 3 full connection layers.

$$accuracy = \frac{CPS}{TS} \tag{2}$$

where CPS represents the number of correctly predicted samples, and TS represents the total number of samples.

After the model is trained, it is automatically saved in the corresponding folder. When we test the model with the data of the test set, the system will load the model file in the corresponding folder, and then predict the data in the test set, judge their corresponding gestures, and then compare with the label of the test set to get the test accuracy of the model on the test set. The mathematical expression of accuracy is shown in equation (2).

TABLE Ⅱ
NETWORK STRUCTURE OF VGG16-3×3.

Block	Size of Convolutional Kernels	Number of Convolutional Kernels
Block 1	3×3	4
	3×3	4
Block 2	3×3	8
	3×3	8
Block 3	3×3	16
	3×3	16
	3×3	16
Block 4	3×3	32
	3×3	32
	3×3	32
Block 5	3×3	32
	3×3	32
	3×3	32
Full Connection Layer		

- VGG16-2×2

The structure of this network is very similar to VGG16-3×3, except that the size of all convolution kernel is changed to 2×2.

- VGG16-4×4

In the structure of the network, the size of convolution kernel is changed to 4×4.

All three VGG16 networks are trained using the same training set and test set on a computer with a GeForce GTX 1050 GPU. Their average training time is shown in TABLE IV. The average classification accuracy of their trained model on the test set is shown in TABLE III.

TABLE III
TRAINING TIME FOR 50 ITERATIONS

Network	Training time for 50 iterations
VGG16-2×2	6983s
VGG16-3×3	7661s
VGG16-4×4	13896s

Table IV
Accuracy of the test

Network	Accuracy of test set
VGG16-2×2	88.87%
VGG16-3×3	93.83%
VGG16-4×4	93.91%

By TABLE III and TABLE IV, you can see that although VGG16-2×2 has the shortest training time and only 6983s are used in 50 iterations, but the average classification accuracy is only 88.87%, simultaneously, although the training time of VGG16-3×3 is 7661s, almost 1.1 times that of VGG16-2×2, but the average classification accuracy reached 93.83%, which is significantly improved compared with the former. The gap of training time can be shortened by increasing the computing speed of computer, but the difference of testing accuracy is difficult to change. Although VGG16-4×4 model has the highest average test accuracy, its calculation amount is also the highest among the three networks, whose average training time reaches 13896s, and its training time is nearly twice as long as that of VGG16-2×2. Meanwhile, the test accuracy of this network is not significantly improved compared with the former, only 93.91%. It can be seen that although too small convolution kernel size can reduce training burden, it will also reduce accuracy. This may be because the smaller size of the convolution kernel cannot extract more global features of sEMG signals, while the larger size of the convolution kernel will increase the computation. Therefore, it is very essential to choose an appropriate convolution kernel size to improve the performance of the network. Based on the comparison mentioned above, VGG16 network with size of 3×3 is adopted in this study.

The changes of the loss function, training accuracy and test accuracy in the training process of VGG16-3×3 are shown in Fig. 5.

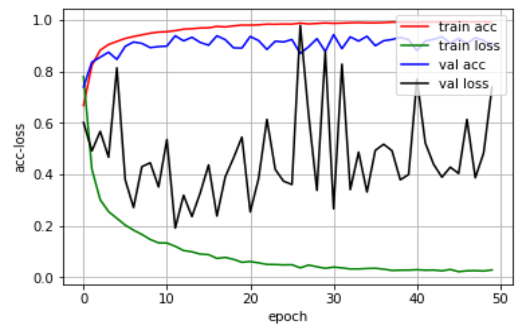

Fig. 5. VGG16-3×3 training process diagram. train acc: The training accuracy; train loss: Loss function of training set; val acc: Accuracy of the test set; val loss: Loss function of test set.

Since there may be differences in physiological electrical signals between individuals, this study collected the sEMG signals of 10 subjects of different ages, genders and sizes, and used their sEMG training models to calculate the average recognition accuracy of 10 subjects on 8 gestures in the following TABLE V. The average accuracy rate of No. 7 object is the lowest, 92.03%, and that of No. 10 object is the highest, 94.95%. Although there are some individual differences between different individuals, the overall accuracy rate is more than 92%. At the same time, the average accuracy rate of 10 research objects is 93.83%, which can meet the needs of human-computer interaction.

TABLE V
CLASSIFICATION RESULTS OF VGG16 NETWORK.

Subject	Accuracy
1	93.55%
2	93.72%
3	93.89%
4	94.03%
5	93.93%
6	94.53%
7	92.03%

8	94.13%
9	93.96%
10	94.95%
Average	93.83%

In the experiment, VGG16 network structure achieves 73.93% classification accuracy at the end of the first iteration. Start with the seventh iteration, the recognition accuracy of the test set is stable above 90%, indicating that the algorithm has a fast iteration speed. By comparison with the other two VGG16 networks, it can be clearly seen that the VGG16 network we used maintained high-test accuracy without increasing too much training time. At the same time, because the original VGG16 appeared over-fitting phenomenon in the training process, this study improved the network structure of VGG16, after first and second fully connected layers, the dropout with a probability of 0.5 is adopted. The experimental results show that VGG16 is effective in gesture recognition based on sEMG.

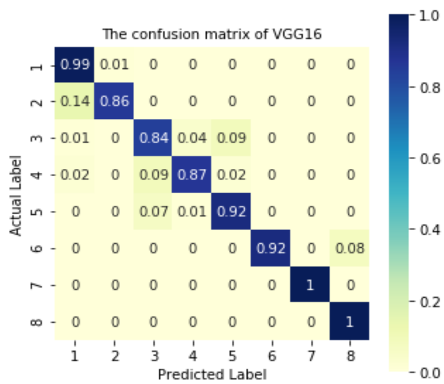

Fig. 6. Confusion matrix of VGG16 structure.

As described in [10], sEMG signals from different muscles are statistically independent of each other. There are different movements between muscles when using different gestures. This algorithm integrates the information of each channel and uses deep network structure to mine the deep information in the data. Compared with other fusion methods, this method uses convolution kernel with smaller size, which can effectively reduce the computation amount, shorten the training time, and obtain better fusion effect. As shown in TABLE VI, the average recognition rate of VGG16 network for 8 gestures reaches 93.83%.

TABLE VI
CLASSIFICATION ACCURACY OF EIGHT GESTURES.

Gesture	Accuracy
1	98.81%
2	86.04%
3	84.46%
4	87.12%
5	91.75%
6	91.97%
7	100%
8	99.85%

Compared with the existing research results, we find that although our recognition accuracy is not the highest, we don't need to design the steps of extracting features manually. The experimental scheme is relatively simple, and the raw data after pre-treatment can be directly used as the input of the neural network. Secondly, the gestures studied in this paper are mainly finger gestures. As shown in TABLE VII, Ding et al. [5] directly use data from the NinaPro data set, but don't collect data from sEMG signals themselves. Although the data set is the largest data set of sEMG signals in the world, the environment of the data set collection is different from that of our data collection. Meanwhile, the number of repetitions of gestures in the data set is too small and the sample size is relatively small, which has certain limitations.

TABLE VII
PERFORMANCE COMPARISON WITH OTHER STUDIES.

works	**Gestures**	**Electrode**	**Sample Rate**	**Method**	**Accuracy (%)**
(Ding et al., 2018) [5]	50	SA-B	2000Hz	CNN	78.86
(Shi et al., 2018) [16]	4	SA-B	1000Hz	*k*-NN	94
(Benalcázar et al., 2017) [22]	5	D-B	200Hz	*k*-NN	86.41
(Hassan et al., 2019) [17]	5	SA-B	1000Hz	SVM	90
(Manfredo et al., 2016) [18]	50	SA-B	2000Hz	RF	75.32
(Hudgins et al.,1993) [24]	4	SA-B	1000Hz	ANN	91
This study	8	SA-B	1500Hz	CNN	93.83

Note: D-B (dry bipolar electrode); SA-B (self-adhesive bipolar electrode)

As can be seen from TABLE VII, although the accuracy of this study is slightly lower than that of Shi et al. [16], there are 8 gestures in our study, including some finger gestures with small differences. Benalcázar et al. [22] adopt the method of *k*-NN and the dynamic time warping algorithms and use MYO armband to recognize 5 gestures, and the recognition rate reach 86%. Hassan et al. [17] study the recognition of seven different gestures and achieve classification accuracy of 90%. However, the feature extraction used in their study is complex, and the seven gestures they study are wrist movements, not finger movements that also play a very essential role in real life. Benalcazar et al. [13,22] apply a MYO armband with eight dry bipolar electrodes. Although the armband is convenient to use, it is unable to place the electrode in the exact position of the muscle, and can only collect sEMG signals in the upper part of the forearm.

Meanwhile, the useful information of the sEMG signals of the arm mainly focuses on 10-500Hz, and the sampling frequency of 200Hz will inevitably lose the relevant frequency components of 200-500Hz.

Gesture selection affects classification accuracy [10,11,16]. It can be seen from the confusion matrix (Fig. 6) that the recognition accuracy of gesture 2, 3, 4 and 5 is low. These four gestures only involve the movements of the index finger, middle finger, ring finger and little finger. The difference between them is relatively small and the recognition difficulty is relatively large.

IV. Conclusions

Regarding of gesture recognition multi-channel sEMG, most researchers focus on looking for more representative features. However, the traditional machine learning algorithm in the extraction of characteristic value tend to cause more information loss. To solve this problem, we introduce CNN, whose input is after pre-processed data, won't cause information loss while can produce high precision. In this study, we used bandpass filtering and normalized data pre-processing methods, and build a 16-layer deep network structure based on the well-known VGG16 network structure to solve the above problems, and verify it by collecting data, and obtain relatively accurate accuracy, and compare it with VGG16 networks with different convolution kernel sizes. The experimental results show that the VGG16 network with convolution kernel size of 3×3 has the best performance and can still ensure high classification accuracy under the condition of less training time. At the same time, we build a highly biomimetic robotic hand to complete 8 gestures, and used STM32 single-chip microcomputer to control it. The future work will focus on reducing the structure complexity of CNN and shortening the training time in order to achieve real-time control of the manipulator.

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