Data Analysis of MYO Signals during Upper Limb Movements of Enhanced Exoskeleton

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Abstract. Equipped with enhanced exoskeleton in the individual combat system can effectively enhance the soldiers’ long-term load-bearing capacity and enhance the combat effectiveness of the army. In the exoskeleton control system, accurate recognition of human movement intentions plays an important role as upper-level control. This paper uses MYO armband as a sEMG sensor to collect 8 channels sEMG signals. Neural network method is applied to estimate the joint angles during arm movement. Motion capture system is used to verify the estimation accuracy. PCA (Principle Component Analysis) method is performed on the 8 channels data collected by MYO and processed dimensions were selected by experiments to make the estimation accuracy the highest. The results show that when the principal component dimension is selected as 8, which makes the estimation accuracy of the joint angles the highest.

1. Introduction

There is a limit to the physical energy of human. When engaged in manual labour, it is unavoidable to feel tired when carrying objects and operating machines for a long time. Exoskeleton is a wearable robotic device developed that can solve such problems. Exoskeleton is gradually being adopted to provide support for their work or daily life. With the deepening of the research, exoskeletons are continuously advancing to the intelligent level.

In the military, the use of exoskeleton can greatly improve the combat performance of individual soldiers and reduce casualties. Soldiers can carry more weapons and equipment that can increase their mobility and reduce physical energy consumption [1-5]. In addition, rescue, factory and other fields are also important applications for exoskeleton development. Therefore, the study of exoskeleton system has important research value and significance.

There is an inevitable human role in the exoskeleton system. It plays an important role in the intelligent exoskeleton control system [6]. The purpose of human intention estimation is to detect the occurrence of actions accurately in real time and to simulate the information of human nerve central motion intention. The underlying controller of the exoskeleton system selects the corresponding control strategy based on the estimated intent information.

There is information exchange and energy exchange between human and robots. Therefore, it is necessary to obtain accurate and efficient recognition of human motion intention.
Normally, kinematics, dynamics and EMG signals can be the sources to estimate the MI. Force or position signals are commonly used in current commercial products [7][8], but they usually hide the subjective initiative of human motion. In the face of relatively complex motion conditions or with an accelerated motion speed, it is difficult to ensure the desired accuracy and response speed. In essence, these signals have hysteresis characteristics so that cannot be consistent with movement. Fortunately, using EMG or EEG (Electroencephalogram-graph) signals prior to the generation of motion can make up for the delay of the control system. Besides, they can reflect the subjective initiative of the human body to a certain extent. The generation of EMG precedes movement. There are two acquisition approaches [9]. One is to insert needle electrodes into muscle for detection. This kind of EMG signals have small interference, good localization and are easy to be recognized. The other is to detect the EMG of human skin through surface electrodes. This method is prone to interference, while it is widely used because of its simple operation and non-invasive characteristics. Some studies have established the relationship between EMG and human joint angle, force or torque to observe human motion intention.

This paper analyses the selection of the number of sEMG signal channels in intention recognition of upper limb. BPNN (Back propagation Neural Network) is used as the joint angle estimation algorithm to judge the accuracy. The second chapter introduces the myoelectric sensor MYO armband used in this article and the original sEMG pre-processing method; the third chapter introduces the overall algorithm of intention recognition, including the establishment of the upper limb coordinate system, the data dimension reduction method and the neural network used to estimate joint angles; chapter 4 and chapter 5 are experimental design and experimental results respectively; the last chapter is the conclusion.

2. Acquisition and pre-processing of sEMG

2.1. Introduction of MYO armband

MYO, as shown in figure 1, is released by Thalmic Labs, a Canadian company. It uses 8 electrodes to detect muscle activities and arm movements, gestures and even finger movements through the detection of biological electrical signal changes of the forearm [10]. The signals are transmitted through low-power Bluetooth with low interference, high quality and low price.

![Photo of MYO armband]

Figure 1. Photo of MYO armband

In this paper, the MYO armband is used to detect sEMG signals during arm movement. In the experiment, MYO is worn in the middle of the big arm with the indicator light pointing toward the middle finger. The original sEMG collected by MYO contains 8 channel data (channel starting from the indication pole is set as channel 0, and arranged anticlockwise to channel 7).

2.2. sEMG preprocessing method

Because the original collected sEMG signals have noise interference, the sEMG signals are relatively weak, so it is hard to extract effective signals related to motion. The original sEMG needs a series of processing before it can be used for subsequent analysis. The general processing steps are shown in figure 2. After going through the high-pass filter, full-wave rectifier, low-pass filter, and normalization,
the muscle activity is obtained. The muscle activity is distributed between 0 and 1 after processing, which is also smoother and the features are more obvious and easier to be extracted.

According to the frequency characteristics, sEMG signals is usually distributed between 20 and 500Hz. Besides, sEMG is mixed with low-frequency or high-frequency noise signals. Therefore, low-frequency noise must be removed by a high-pass filter. The signal can be rectified by taking the absolute value simply. And then a low-frequency filter is used to filter out high-frequency interference signals.

3. Establishment of upper limb motion model

3.1. Upper limb motion coordinate system

The structure of the human upper limb is abstracted as shown in figure 3, in which point A represents the shoulder joint, and B and C are the elbow joint and the wrist joint respectively. The big arm AB and the forearm BC are abstracted as a 2-link model that rotates around a fixed point, and the mass and volume are evenly distributed. The angle between AB and y axis, x axis, and z axis are defined as $\theta_1$, $\theta_2$ and $\theta_4$ separately. The angle between BC and the extension cord of AB is defined as $\theta_3$. Take the angle indicated in the figure as the positive direction and increase counter clockwise.

$$\begin{align*} \theta_1, \theta_2, \theta_3 \text{ and } \theta_4 \text{ belongs to the DOFs (degrees of freedom) of shoulder flexion/extension, abduction/adduction.} \\
\text{The masses of rod AB and BC are } m_1 \text{ and } m_2 \text{ respectively. The coordinates of the three points A, B and C are written as } (x_A, y_A, z_A), (x_B, y_B, z_B) \text{ and } (x_C, y_C, z_C). \text{ Hence the vectors } \vec{l_1} = (x_B - x_A, x_B - x_A, x_B - x_A), \vec{l_2} = (x_C - x_B, x_C - x_B, x_C - x_B). \text{ The four joint angles are calculated by the vectors as } \\
\theta_1 = \arccos \frac{y_B - y_A}{|\vec{l_1}|}, \theta_2 = \arccos \frac{x_B - x_A}{|\vec{l_1}|}, \\
\theta_3 = \arccos \frac{l_1 \cdot l_2}{|l_1| \cdot |l_2|}, \theta_4 = \arccos \frac{z_B - z_A}{|l_1|}. \end{align*}$$

3.2. Channel correlation analysis and dimension reduction

$\mathbf{v}(k) = [v_0(k), v_1(k), \ldots, v_T(k)]^T$ is the MYO signals (the sample time $k$ is omitted below), where $v_i (i = 0, 1, \ldots, 7)$ represents the sample signals of channel $i$. The correlation coefficient between channels is calculated as...
\[ \sigma_i = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (v_{i,k} - \overline{v})^2} \]  
\[ \text{cov}(i,j) = \frac{1}{N} \sum_{k=1}^{N} (v_{i,k} - \overline{v})(v_{j,k} - \overline{v}) \]  
\[ r_{i,j} = \frac{\text{cov}(i,j)}{\sigma_i \sigma_j} \]

where \( N \) is the number of sample points, \( v_{i,k} \) is the muscle activity of channel \( i \) at sampling time \( k \). \( \sigma_i \) is the standard deviation of channel \( i \) and \( \text{cov}(i,j) \) represents the correlation coefficient between channel \( i \) and \( j \).

Considering the large degree of signal correlation, we hope to verify whether the data can be reduced by PCA method so that the data has the largest variance. Effective simplification cannot be achieved when the number of dimensions is too large after reduction. However, data information may be lost and the information contained may not be comprehensive when the number of dimensions is too small.

3.3. Joint angles estimation by neural network
The joint angles are estimated by the basic BPNN. The input vector is muscle activity signals after passing PCA method, and the output vector is composed of four joint angles. The hidden layer contains 1 layer. The number of nodes is calculated according to the empirical formula by

\[ S = \sqrt{m(n + 2)} + 1 \]

where \( S \) represents the number of hidden layer nodes. \( m \) and \( n \) represent the numbers of input nodes and output nodes respectively.

4. Experiment design
Motion analysis motion capture system is a system developed by American motion company that can capture, process, measure and report motion data. Motion analysis is based on optical principles and provides users with professional 3D optical motion capture, 6 DOFs measurement and micro-motion measurement.

![Pre-defined upper limb motion trajectory](image)

**Figure 4.** Pre-defined upper limb motion trajectory

The motion information of the subject is collected by the myoelectric sensor of MYO armband; at the same time, the infrared cameras captures the position information of the marker points attached to the human body, and the standard joint motion during exercise is obtained through Cortex-Getac test analysis system. In the neural network training phase, sEMG is used as the input of the network and the standard motion state values of the joints obtained by the motion capture system are used as the network output for training. The obtained model is applied for the intent recognition algorithm above; the optimal state estimation value during the test phase is synchronized with the motion capture. The state values captured by the system are compared to judge the performance of the algorithm. Among
them, the sampling frequency of MYO armband and the motion capture system are 200Hz and 60Hz respectively. Therefore, the sEMG signals need to be down-sampled to 60Hz.

Define a set of pre-set motion trajectory as shown in figure 4. The natural drooping state of the arm is the initial state of movement. The trajectory covers the movement of 3 DOFs of 2 joints through movements such as forward extension, uplift, and side extension, covering a wide range of angle changes. The conclusions drawn from this are relatively comprehensive and have a wide range of training data, which is helpful to the accuracy of recognition.

The subject wore the MYO armband in the middle of the forearm with indicator electrode (channel 0) pointed to the middle finger direction. 3 marked points for infrared recognition were located at the shoulder, elbow and wrist joints. Keep the angle of the wrist joint unchanged and ensure that the relative positions of the three marked points fix during the experiment.

A total of 7 groups of experiments were performed with 20s of every group during which a set of pre-set trajectories were completed. A 1-minute rest time is given among each group of movement. Other variables are kept unchanged such as the speed of the arm movement, the temperature of the room, the state of the surface skin, the hand action and the load. The movements information is collected in real time using Motion Analysis. The first five group are used as the training group of the neural network. Due to the small number, data needs to be manually expanded 50 times. The latter 2 groups are used as validation groups to verify the accuracy of the neural network estimation.

5. Results
Correlation analysis was performed on the muscle activity after down decimation. The correlation results between the muscle activity of each channel are shown in table 1. Only the correlation in the upper triangle of the table is displayed. Each solid line indicates the change in the correlation coefficient between the electrode path and other path signals currently being analysed and the abscissa indicates the distance from the front path in the anticlockwise direction. The result of correlation analysis shows the necessity of PCA. Due to the large degree of signal correlation between the data, the PCA data is used to reduce the dimension to make the data have the largest variance.

| Channel | 0 | 1  | 2  | 3  | 4  | 5  | 6  | 7  |
|---------|---|----|----|----|----|----|----|----|
| 0       | 1.000 | 0.739 | 0.454 | 0.336 | 0.308 | -0.050 | 0.834 | 0.894 |
| 1       | 1.000 | 0.714 | 0.597 | 0.492 | 0.047 | 0.494 | 0.559 |
| 2       | 1.000 | 0.715 | 0.788 | 0.405 | 0.456 | 0.432 |
| 3       | 1.000 | 0.893 | 0.351 | 0.347 | 0.292 |
| 4       | 1.000 | 0.535 | 0.437 | 0.316 |
| 5       | 1.000 | 0.319 | 0.098 |
| 6       | 1.000 | 0.938 |
| 7       | 1.000 |

Table 1. Channel correlation efficient among 8 channels

| RMSE   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|
| $\theta_1$ | 37.46 | 26.74 | 15.43 | 16.33 | 11.43 | 12.78 | 11.41 | 10.30 |
| $\theta_2$ | 17.76 | 16.38 | 13.15 | 13.41 | 10.10 | 12.16 | 11.18 | 10.19 |
| $\theta_3$ | 20.44 | 17.81 | 15.19 | 16.85 | 12.23 | 13.26 | 10.05 | 10.55 |
| $\theta_4$ | 28.94 | 25.68 | 17.56 | 17.35 | 16.34 | 13.45 | 12.26 | 9.19 |
| Average | 26.15 | 21.65 | 15.33 | 15.99 | 12.53 | 12.91 | 11.23 | 10.05 |

Table 2. RMSE of choosing different channel number.
The number of principal components after PCA is used as input of network training and joint angles estimation from 0-7. Table 2 shows the accuracy of each joint angle estimation accuracy in terms of RMSE (Root Mean Square Error) in each dimension. Table 2 shows that the estimation algorithm has the most accurate results when the number of MYO channels are chose as 8.

6. Conclusion
In the context of enhanced exoskeleton research, this article analyses the data dimensions when using MYO armband. In order to ensure a suitable input dimension of the neural network, the PCA method is used to reduce the dimensions so that the data has the largest variance. BP neural network was used to estimate the four joint angles of the elbow and shoulder joints in upper limb movements. To verify the accuracy of the estimation results, a standard angle information was collected using motion capture system for comparison. The experiment results show that the network has the best estimation results when the 8-dimensional input is selected.

This article explores the dimensions of the input data and lays the foundation for future work. The RMSE is still in large scale so it is unrealistic to expect it to be applied in practice. Subsequent considerations include the use of time series neural network instead of BPNN to further optimize. In addition, it is considered to add subjects of the experiment to obtain a general conclusion.

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