Improving Wrist Angle Recognition Accuracy under Different Load Conditions

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***Abstract*-The wrist angle estimation based on surface electromyography (sEMG) signals plays an important role in the sEMG application. This paper confirms that the accuracy of the wrist angle recognition decreases with the increase of the wrist load by the changes of the sEMG features in different loads. To address the above problem, this paper proposes a combined feature, integrating frequency-domain and time-domain features, to improve the recognition accuracy, which has been demonstrated by comparative experimental results.**

Ⅰ. INTRODUCTION

The surface EMG signal is a bioelectrical signal generated by the biological muscle activity, and is very important for clinical muscle diagnosis and sports rehabilitation engineering. Each muscle movement produces a corresponding surface EMG signal. By collecting and analyzing signals from muscles in different parts of the body, the activity status of parts of the human body can be detected, such as the information of the shape, position and motion.

The surface EMG signal extraction method is convenient, accurate and non-invasive. At present, most studies about the recognition of human behavior through surface EMG signals focus on pattern recognition and few studies on the movement state of the limb such as the speed of movement, the range of motion. With the continuous development of information technology, the motion state of limbs predicted by surface EMG has become a key point in the research of electromyography signal control biomimetic prosthetic technology [1].

Muscle fatigue is a neuromuscular disease, surface EMG signals are an important way to assess muscle fatigue. In the experimental, once the process is too long, the muscles are prone to fatigue, which has a great influence on the recognition of joint angles [2]. So we need to quantify the muscle fatigue. In the time domain, the RMS eigenvalue and the MAV eigenvalue will gradually increase with the degree of fatigue. In the frequency domain, the MNF and MDF eigenvalues will gradually decrease with the degree of fatigue.

Ⅱ. RELATED WORKS

Joint angle recognition and prediction are the focus of myoelectric signal research. Yee Mon Aung et al [4]used BP neural network to predict the angle of the human shoulder, used the VR model to simulate the prediction results. Nikhil A Shrirao et al [3] predicted the bending angle of the index finger through a combination of six different neural networks. FengZhang [5] et made research on the joints of the human thigh and proposed an m-order nonlinear model to describe the relationship between sEMG signal and the angle of the human leg joint, the average angle of the leg extension was estimated to have an rms error of less than 9°. Yongsheng Gao et al [6]used TDF as the extracted signal feature and the least squares support vector machine (LSSVM) to estimate the continuous wrist flexion and extension angle.

The fatigue degree can be quantified by different characteristics. Jing C et al [7]verified that the RMS characteristics responded strongly to fatigue were able to characterize different muscle fatigue levels. Young Jin Na et al [8]proposed a muscle twitch model that used the MAV feature to estimate the flexion force of the elbow joint. Wenxiang Cui et al [9]applied the five characteristics of RMS, MNF, ARC1, SE and HFD to study the fatigue characteristics of skeletal muscle tendon units during static isometric contraction tasks. Soon Yew Guan et al [10]proposed a method to quantitatively estimate muscle fatigue by constructing a fatigue index, the average error is less than 10% MVC.

III. EXPERIMENTAL PROCESS

This paper mainly monitors the angle of the wrist under different loads. The whole experiment set nine test angles. Considering the degree of bending of the human wrist in reality, we choose the angle between 30 and 150 degrees, 60.00° and 120.00° are selected as the predicted angles. The surface EMG signals were collected for each set of angles. We also set three different loads (0N,10N,20N) and collect wrist angle signals under different load.

This paper collected signals from the left forearm of three healthy young people, each angle is collected for 10s, repeated 10 times. In order to reduce the fatigue of the muscles of the subjects, relax 10s when collect one group of the data. The original EMG signals need to be filtered before it can be analyzed. This paper used the combo filter to eliminate the 50Hz and its integral multiple, which does not eliminate the noise of other frequencies. The wavelet function was used to filter the EMG signal. We selected and adjusted the soft threshold according to the noise level of each layer of wavelet decomposition. The db3 wavelet was used to decompose the signal in three layers. The whole experiment process is shown in the Fig.1.

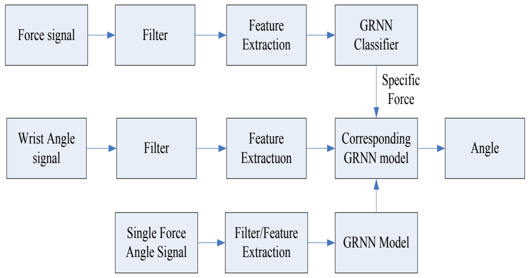

Fig.1 Experimental protocol flow

Ⅳ. ANALYSIS OF RESULTS

The RMS(Root Mean Square) value of the EMG signal actually represents the instantaneous electrical power, and its waveform is similar to the waveform of the linear envelope of the EMG signal. We initially chose the RMS value as the input to the neural network [11].

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}} \qquad (1)$$

Where, N is the total number of data.

Generalized Regression Neural Network is a kind of Radial Basis Neural Network. GRNN has strong nonlinear mapping ability and learning speed. The network finally converges on the optimal regression of sample size aggregation. When the data is small, the prediction effect is very good, and the network can also handle unstable data.

This experiment involves two variables of angle and load. In order to avoid the impact of load changes on the wrist angle prediction model, we designed two parallel GRNN network models. The first step is to load different loads (0N, 10N, 20N) for classification. The second step is to classify the corresponding seven different angles. Each load will have corresponding models, which are selected by the testing force data. The corresponding network model is used to predict the wrist angle.

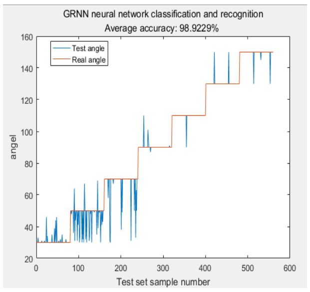

Fig.2 Wrist angle recognition under 0N weight

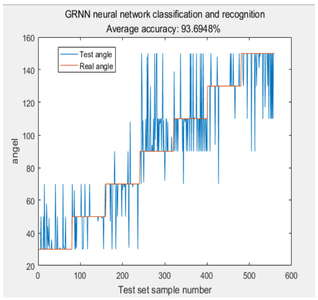

Fig.3 Wrist angle recognition under 10N weight

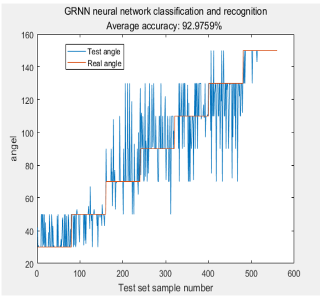

Fig.4 Wrist angle recognition under 20N weight

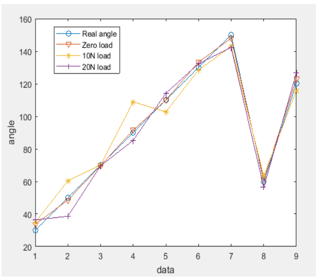

Fig.5 Wrist angle prediction under different loads

Table.1 Wrist angle prediction under different loads

	0	10	20
30.00	31.17	34.83	36.33
50.00	49.62	60.38	38.56
70.00	69.90	70.09	69.57
90.00	91.49	108.91	85.21
110.00	109.98	102.71	114.13
130.00	133.27	128.44	132.31
150.00	148.99	142.88	142.34
60.00	60.99	63.46	56.41
120.00	122.98	115.89	126.86

The above figure comforms that the recognition rate of the neural network is gradually decreasing with the increase of the weight of the load, the deviation of the wrist angle prediction is also increasing. When the load is 0, the wrist angle recognition rate has reached more than 98%, which indicate that the recognition effect is very good, when the load is increased, the recognition rate drops sharply. In the actual robot control, the zero load situation is very rare. so we need to analyze the cause of the decrease in the recognition rate caused by different loads, and try to improve the actual wrist angle recognition rate.

Ⅴ. FEATURE COMBINATION

Muscle fatigue is a very common phenomenon, which is defined as the failure to maintain the required or expected strength. In the experiment of the load wrist angle prediction, although the experimenter will take a rest for 10s every time when collect the next data, the experimenter still have a certain degree of muscle soreness. As mentioned above, as the weight of the load increases, the recognition rate of the wrist angle is gradually decreasing [12]. This may be the effect of muscle fatigue. When the weight of the load increases, the experimenter needs to spend more force to grab the object.

The sEMG signal can be used to characterize muscle fatigue. From the previous experimental results, we know that as the degree of muscle fatigue increases, the RMS characteristics of the EMG signal will gradually increase in the time domain. The degree of fatigue is higher [13] the trend of rising eigenvalues will be more obvious. We select the RMS eigenvalues under the same channel of different loads for analysis, and perform least squares fitting on RMS feature points. The results are shown in the Fig.6.

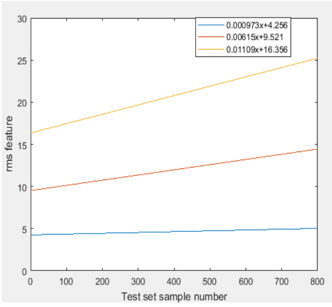

Fig.6 RMS value of the same channel under different loads

It can be seen from the above figure that as the weight of the load increases, the muscle begins to enter the fatigue state. It can be seen that the magnitude of the increase in the RMS characteristic increases significantly [14]. Therefore, in order to improve the recognition accuracy of the wrist angle, we need to slow down this trend and let it as same as the initial situation. From the previous experimental results, we can know that the MDF (Median frequency)characteristics and MNF (mean frequency)characteristics of the EMG signal gradually decrease with the muscle fatigue, and the average rectification value will also change.

$$\mathrm{MNF} = \frac{\int_0^{\infty} fP(f)df}{\int_0^{\infty} P(f)df} \qquad (2)$$

$$\mathrm{MDF} = \frac{1}{2}\int_0^{\infty} P(f)df \qquad (3)$$

$$\mathrm{MAV} = \frac{1}{N}\sum_0^N |x_i| \qquad (4)$$

Where f is the frequency, P(f) is the signal power spectral density function,N is total number of the data.

Although the median frequency and the mean frequency decrease with the increase of the fatigue program, they are not all related to the RMS characteristics. We need to select the features with strong correlation with the RMS features for feature combination. We can see that as the load increases, the correlation coefficient between each feature is gradually reduced, and the recognition rate is also decreasing [15]. Therefore, we should select the feature with the highest correlation coefficient between features as the new wrist angle recognition feature.

Comparing MDF and MNF with RMS correlation coefficient, it can be seen that the correlation between MDF and RMS is better, and the MAV feature is added, the correlation will be better, so we choose RMS-MAV-MDF as the first choice for feature fusion.

Table 2 Correlation coefficient between various features

	0	10	20
RMS-MDF	0.9941	0.9870	0.9820
RMS-MNF	0.0468	0.0347	0.0274
RMS-MDF-MAV	0.9973	0.9952	0.9948

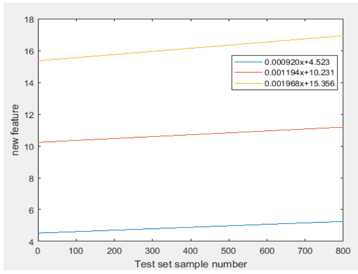

Fig.7 The same channel RMS value for different loads under the new feature

Comparing Fig. 6 and Fig. 7, under the new feature combination, the rising trend of new characteristic value under load is obviously slowed down, and the slope is gradually close to the slope under zero loads. This indicates new combination of features can greatly alleviate the impact of rising eigenvalues caused by muscle fatigue. We use new features to identify the wrist angle. The final recognition results are shown below:

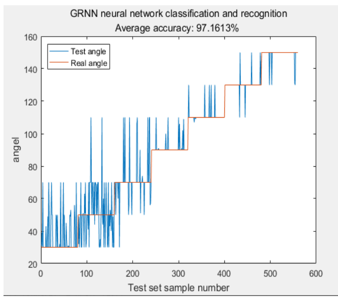

Fig.8 New feature angle recognition under 10N load

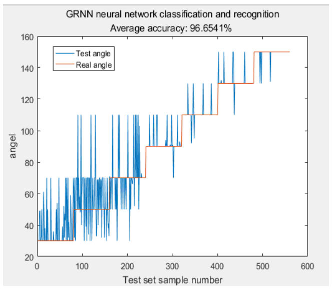

Fig.9 New feature angle recognition under 20N load

Table.3 Wrist angle prediction under different loads

	0	10	20
30.00	30.17	34.65	34.85
50.00	49.72	45.62	43.65
70.00	69.91	72.34	69.01
90.00	90.01	86.54	112.50
110.00	109.99	112.50	114.76
130.00	130.03	128.50	131.93
150.00	149.47	143.46	141.43
60.00	61.77	62.84	63.75
120.00	119.65	116.37	125.36

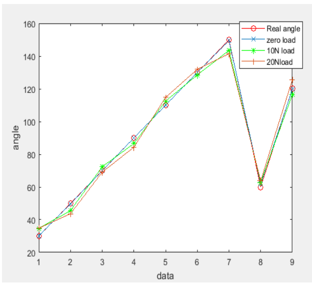

Fig.10 Wrist prediction angle for different loads

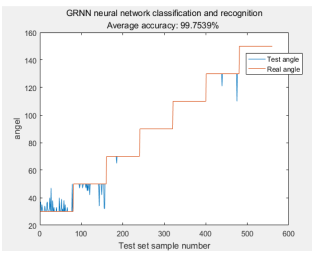

Fig.11 New feature angle recognition under 0N load under new features

Compare Figure 5 and Figure 10, we can find that the new combination of features can effectively alleviate the effects of muscle fatigue, and the recognition rate of the wrist angle under load is improved. Compare fig.2 and fig.11, we can see for the situation where there is no load or a small load, the recognition rate of the new features has been improved, but it doesn't change too much. For multiple feature combinations, the neural network will spend more time training data and take up more memory. Therefore, for the experiment of wrist angle estimation, we need to analysis the load condition. Multi-feature combination is not suitable for extremely small loads, because the selected features are more about the muscle fatigue. Only when the muscles are hard, the new features can improve the accuracy of recognition. At the same time, we should also pay attention to the fact that the combination of features is not arbitrary. We should choose the characteristics related to the angle of the wrist.

Ⅵ. CONCLUSIONS

In this paper, we use the characteristics of electromyography signals to design an effective wrist angle prediction system. The angle of the wrist is used to analyze the current intention of the human body. We collect the sEMG signal of the human forearm 16 channels in this experiment. Through the filtering and feature extraction of the original signal, we can obtain the EMG signal about the wrist angle. Since GRNN has strong nonlinear mapping ability and learning speed, GRNN is selected as the classification recognizer. The experimental results show that the recognition accuracy of the wrist angle will decrease when the load weight increase. Due to the change of the weight of the hand, the muscle will gradually appear fatigued. The muscle fatigue has great impact on the recognition accuracy. By comparing the RMS, MDF and MAV characteristics of the wrist angle, the three features are merged to obtain new features. Compared with the previous recognition results, the new features can deal with the fatigue state and obtain high recognition accuracy.

ACKNOWLEDGEMENT

This work was supported by Grants of the

National Natural Science Foundation of China (Grant Nos. 51575407, 51575338, 51575412, 51505349, 61733011) and Grants of the National Defense Pre-Research Foundation of Wuhan University of Science and Technology (GF201705). This paper is funded by Wuhan University of Science and Technology graduate students' short-term study abroad special funds.

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