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Detection of muscle fatigue by fusion of agonist and synergistic muscle sEMG signals

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***Abstract*—Muscle fatigue detection has a wide range of applications in the field of rehabilitation medicine. The existing methods only collect a single agonist signal for detection, whose accuracy and real-time detection are usually poor. To handle this issue, in this study collects a dataset containing both agonist and synergistic muscle surface electromyography (sEMG) signals, by analyzing the synergistic working principle of muscles. Through the fusion processing of different muscle group signals, the significance of detection of muscle state changes is improved. Moreover, the impact of signal non-stationarity and non-linearity on fatigue detection is reduced. Based on the collected dataset, a multichannel fusion recurrent attention network (MFRANet) is proposed. First, MFRANet enhances local anti-interference ability by fusing multi-channel EMG signals and reduces the impact of single channel signal noise on the overall detection performance. Second, MFRANet analyzes the signal from two dimensions, namely time domain and space domain. A gating mechanism is used to enhance the complex time correlation between channels, and an attention mechanism is employed to reconstruct the nonlinear relationship between channels, thus improving the generalization. Experiments show that the proposed signal fusion method of agonist and synergistic muscle sEMG signals significantly improves the accuracy of muscle fatigue detection, as well as reducing processing time compared to traditional machine learning methods.**

***Index Terms*—Attention mechanism, muscle fatigue detection, recurrent neural network, surface EMG signals, signal fusion**

I. Introduction

During the rehabilitation treatment of patients with injury to motor nerves, due to their own cognitive impairment, the ability to discriminate the degree of fatigue is poor, and a reasonable amount of training according to their own conditions is difficult to assess. Indeed, excessive exercise will cause muscle strain and joint damage, but insufficient training will weaken the effectiveness of the rehabilitation treatment. Nowdays sEMG is widely used in muscle fatigue detection to arrange the amount of exercise for rehabilitation training. However, the sEMG signal is highly non-linear and non-stationary, it is greatly affected by the acquisition method and environmental conditions[1-2]. Effectively extract surface fatigue related information from sEMG signals has always been a challenging issue in the field of clinical rehabilitation treatments. At present, the sEMG signals from agonist muscles are generally collected for fatigue detection through Ag/AgCl electrode pads. Karthick[3] performed muscle fatigue detection by collecting agonist muscle sEMG signals and extracting muscle fatigue-related features. Venugopal[4] collected muscle surface signals of biceps brachii, divided the signals according to the time window and extracted the window function for muscle fatigue detection. The above approaches extract sEMG signals from the agonist surface and use different signal processing methods for muscle fatigue detection. However, when using agonist muscle sEMG signals only, the noise caused by differences among individuals will affect the final accuracy of fatigue detection. Contrary to these methods, we collect the sEMG signals from both agonist and synergistic muscles, making it easier to detect muscle status during exercise. Moreover, the signal changes more significantly before and after exercise, reducing the interference of noise on fatigue detection effectively. More and more researchers use neural networks to fatigue detection[5]. Ulysse Cot[6] collected eight-channel sEMG signals and used convolutional neural networks to classify poses. When the neural network processes signals, features are usually automatically extracted by the network itself, thus avoiding the problem of inaccurate classification caused by excessively large differences in feature values. Qihang Yao and coworkers[7] proposed an attention-based time-incremental convolutional neural network (ATI-CNN) to detect automatic arrhythmias. Feiteng Li[8] proposed a whole attention-based convolutional neural network to detect abnormal heartbeats, and achieved higher classification performance and pathological heartbeat detection accuracy. But the study of muscle fatigue using such networks is still rare. When the neural network performs fatigue detection by extracting the relevant features from the input signal, the longer the input signal time sequence to the network, the more fatigue-related information is included. However, the fatigue detection accuracy of most neural network methods decreases with the increase in the amount of time sequence data[9].

In this study, we focus on the nonlinear relationship among the features of the fusion signal channel obtained through

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the attention mechanism. we also concentrate on locations where the sEMG signals change more significantly before and after fatigue, and the features which has high correlation with fatigue detection are screened to improve detection performance. The main contributions of this work are as follows: (1) An sEMG signal dataset containing contributions by both agonist and synergistic muscles is collected. For the first time, sEMG signals from agonist muscles and synergistic muscles are fused for fatigue detection. The accuracy in fatigue classification by means of both agonist muscles and synergistic muscles is proved to be significantly higher than only using agonist muscles. (2) We use the original signal to train a deep neural network. Deep feature extraction is performed through a gated recurrent unit (GRU) network, and the non-linear relationship between the channels is reconstructed using the attention mechanism to screen high correlation features of muscle fatigue. (3) Experimental results demonstrate that the three signal fusion methods proposed in this study can reduce the effects of noise and the differences among individuals, and can improve the overall accuracy of fatigue detection. We directly use the original signal for fatigue detection, with no need to perform any time-frequency domain transformation on the original signal. Therefore, the processing time required for fatigue detection is effectively shortened. A block diagram displaying the MFRANet framework used in this paper is reported in Fig.1.

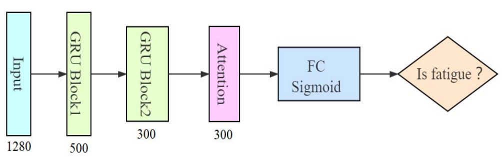

Fig. 1. MFRANet framework used in this study. Input through the GRU layer, attention mechanism, full connection and sigmoid. And finally according the output, we detected whether the muscle is fatigued. The numbers which belong the blocks represent the dimensions of each layer.

II. Materials and Methods

A. sEMG database

The sEMG instrument used in this study is by NCC Medical Co, model MyoMove. Disposable electrodes were Ag/AgCl ECG electrodes 3M, which pads were used with a sampling frequency of 2048Hz. In order to filter out some inherent interferences in the collected signals, MyoMove output frequency was adjusted to 10-300 Hz at the terminal based on the sEMG signal characteristics.

Subjects exposed both thighs and lay flat on a flat exercise therapy bed in a prone position with their legs relaxed and straightened. The wearable adjustable weight is fixed on the ankle. The weight of the male is 20 kg, and the weight of the female is 13 kg according to body mass index. The subject's upper body and thighs were kept fixed, and knee flexion was performed. The calf contracted from the horizontal state to the maximum flexed state. The subjects contracted the calf according to the prescribed period and frequency. when the subjects showed: 1.The calf could not be lifted again. 2. Compensating postures such as swinging the calf from side to side, upper body exertion, hip flexion were regarded as fatigues and stopped exercise. Compared with normal people, patients have fewer motor units recruited during rehabilitation, and their surface EMG signals are attenuated quickly. Our experimental selects normal people as experimental subjects. If the MFRANet proposed in the study could achieve a higher accuracy rate, then the patients will get a higher accuracy rate.

TABLE I
Subjects information

Gender	Age(year)	Height (cm)	Weight (kg)	BMI	Avg. fatigue time(s)	Avg. shrinkage(time)
Male	24±0.5	173±0.8	87±0.9	23±0.6	190.1±3.2	90±2
Female	22±0.2	166±0.7	53±0.8	19±0.23	194.6±2.4	77±4

The subjects were 15 healthy males and 15 healthy females, They had no history of muscle strain, and did not participate in any strenuous activities within 24 hours before the test. Subjects signed informed consent before the experiment and were approved by the local ethics committee. Information on the subjects is summarized in Table I. We used SPSS 22.0 data processing, the fatigue time and the number of contractions of all subjects were tested by *t* test, and there was no difference between genders.

B. Data preprocessing

In this study, We need to divide the fatigue and non-fatigue fragments on the original data. According to the intercept method[10], recently reported in the literature that we find Median Frequency and Average Power Frequency are decreased linearly. So we define the non-fatigue and the fatigue signals correspond to the first and the last exercise cycle, respectively. Based on the recorded duration of T and the number of contractions N, the cycle W of each exercise is calculated as follows:

$$W = \frac{T}{N} \tag{1}$$

The root mean square (RMS) is used to determine the peaks of the first and last periods, and 500 ms of data are extracted before and after the peak for analysis. In order to extract more timing information and deep features, we determined the length of the sliding window according to the action cycle W of each subject[3]. After a lot of experiments, we set the average window size and step size to 640, and 32, respectively. The sEMG signal fragment sent to MFRANet is shown in Fig.2.

C. MFRANet

1) GRU layer: GRU network can better extract the long-term and the short-term dependence and relationship of biological signals on time sequences. Moreover, the GRU can reduce the effects of non-linearity and non-stationarity of sEMG signals in muscle fatigue detection. A two-layer GRU network is used in our system to extract the deep features of the time sequence signals, as well as to explore the correlation

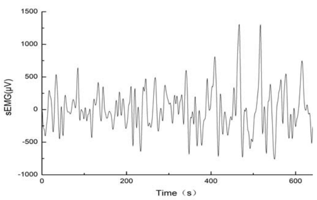

Fig. 2. The MFRANet input. When the window slides, an sEMG signal sequence is generated. Then it will be sent in to MFRANet. Because of the surface EMG signal are in a dynamic balance, the signal quality appears very poor. Experimental results show that MFRANet can effectively extract fatigue-related features

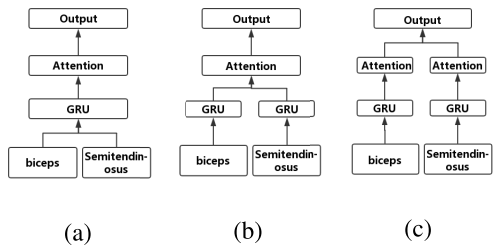

Fig. 3. Three different signal fusion methods: (a)signal source fusion (MFRANet-SF), (b)GRU layer fusion (MFRANet-GF), (c)attention mechanism layer fusion (MFRANet-AF).

between the agonist and the synergistic muscles. The GRU unit stores and filters the input signal by updating and resetting the gate, which reducing the dimension of the fusion signal and reducing the fatigue detection time, so that the time sequence information of the input signal can be stored for a longer time. The GRU unit also increases the time correlation between channels, and avoids the problem of gradient disappearance caused by too long time sequences. The extraction of the deep features from the input signal can be expressed by the following formula (2).

$$H_i = G\left(F_i\right)_{i=1}^{i=m}. \tag{2}$$

where F_i is the i_{th} sEMG time sequence of the input network, $G()$ represents the deep feature extraction operation of the GRU, and H_i indicates the deep features of the $i-th$ time sequence. After the extraction procedure, H_i is fed into the attention mechanism layer.

2) Attention Mechanism: The number of deep features extracted by the GRU layer increases with the length of the input time sequence signal, but the fatigue-irrelevant features caused by the differences among individuals increase as well. In order to overcome this problem, we use an attention mechanism learning of input time sequence signals. This procedure can be expressed by the following equation (3)

$$D_k = E\left\{H_j \otimes A_k\right\}_{k=1}^{k=h} \tag{3}$$

where $\bigotimes$ represents the point multiplication of corresponding elements, which transmits high-weight features accordingly, A_k is the k_{th} sEMG signal time sequence weight merge operation coefficient, and E is the fully connected layer and sigmoid operation. D_k indicates the MFRANet output.

D. Signal fusion method

We fuse the agonist and synergistic muscle signals at different levels into the MFRANet network, and compare the advantages and disadvantages of different fusion methods. Three signal fusion methods are investigated: signal source fusion (MFRANet-SF), GRU layer fusion (MFRANet-GF), and attention mechanism layer fusion (MFRANet-AF). The three fusion methods are schematically shown in Fig.3 and described in the following sections.

1) MFRANet-SF: First, the agonist and synergistic muscle signals are divided using sliding time windows, and combined according to the time sequence.Then, the fusion signal is sent to the MFRANet network for fatigue detection. The formula is as follows:

$$F_R = E\left\{G\left(\operatorname{cat}\left(MW\left(B_i, S_i\right)_{i=1}^{i=l}\right)\right)\right\} \tag{4}$$

where l is the number of samples, $cat()$ is the Concat operation, $MW()$ is the sliding window operation, S_i is the agonist surface of the i_{th} sample EMG signal, B_i indicates the coordinated EMG signal of the i_{th} sample, and F_R represents the result of signal source fusion output. The loss function is:

$$l_{\mathrm{R}} = \sum\left|R - F_R\right| \tag{5}$$

where$R$ represents true lable, F_R is the output result of MFRANet.

2) MFRANet-GF: First, the agonist and synergistic muscle signals are segmented using a sliding time window and sent to the GRU layer. Finally the deep features output by the GRU are merged according to the time sequence. The formula is as follows:

$$F_G = E\left\{\operatorname{cat}\left(G\left(MW\left(B_i\right)_{i=1}^{i=l}\right), G\left(MW\left(S_i\right)_{i=1}^{i=l}\right)\right)\right\} \tag{6}$$

where F_G represents the result of the GRU layer fusion output (the other terms are defined above). The loss function is:

$$l_G = \sum\left|R - E\left\{\operatorname{cat}\left(G_B, G_S\right)\right\}\right| \tag{7}$$

where G_B and G_S are the agonist and the synergistic muscle features after GRU layer.

3) MFRANet-AF: The MFRANet-AF method entails fusion of agonist and synergistic muscle signals respectively processed through the GRU layer, and the attention mechanism. The resulting features are finally combined according to the time sequence. The formula is as follows:

$$F_A = \operatorname{cat}\left(E\left\{G\left(MW\left(B_i\right)_{i=1}^{i=l}\right)\right\}, E\left\{G\left(MW\left(S_i\right)_{i=1}^{i=l}\right)\right\}\right) \tag{8}$$

where F_G represents the result of the fusion of the attention mechanism layer. The loss function is:

$$l_A = \sum cat\left(\left|R - E_B, R - E_S\right|\right) \tag{9}$$

where E_B and E_S represent the characteristics of agonist and synergistic muscles output by the attention mechanism layer, respectively.

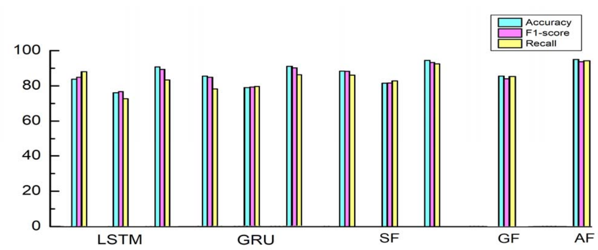

Fig. 4. Comparison of fatigue detection accuracy rates of different fusion methods: We introduce two comparative experiments-LSTM and GRU. The LSTM network consists of two layers of LSTM units and three layers of full connections.The GRU network consists of two layers of GRU units and three layers of full connections. LSTM, GRU, and MFRANet-SF include three results: agonist muscle, synergistic muscle ,and fusion signals. AF and GF only have fusion signal classification results because of the framework.

TABLE II
THE COMPARATIVE TEST OF ISOMETRIC CONTRACTION AND ISOTONIC CONTRACTION FATIGUE TESTING BASED ON OUR DATABASE(UNIT: %).

Reference	Contraction type	Methods	Acc. base Biceps	Acc. base Both	Time(s)
Venu [4]	Isometric	MTW features	75. 5	83	1. 6
Marri [11]	Dynamic	Mult-features	81. 3	86. 5	4. 3
Albe [12]	Isometric	cvxEDA	71	76. 6	2. 55
P. A [13]	Dynamic	S-transform	84. 4	88. 9	3. 8
Our method	Dynamic	MFRANet-SF	87. 84	94. 42	1. 35
Our method	Dynamic	MFRANet-AF	-	95. 04	2. 02

III. EXPERIMENT RESULT

In this study, we use evaluation metrics Accuracy, F1-score and Recall. The experimental results which used ten-fold cross-validation are shown in Fig.4. As shown in Fig.4, compared with the fatigue detection method use agonist alone, the accuracy of fatigue detection based on the fusion of agonist and synergistic muscle signals significantly improves over different models. MFRANet-GF has a lower accuracy if compared to MFRANet-SF and MFRANet-AF. MFRANet-AF accuracy is 0.61% higher than MFRANet-SF, and 9.47% higher than MFRANet-GF. This is because the attention mechanism to obtain features E_B and E_S, which are highly related to muscle fatigue. The fusion between E_B and E_S eliminates the redundancy between features to get a better representation of muscle fatigue characteristics F_A. Experimental results also show that the MFRANet-AF is optimal in all indicators, which accuracy achieved 95.03%, F1-score achieved 93.69%,and Recall achieved 94.18%. Table II provides the results that can be compared with other existing literature and the results in the table are all based on our database. As shown in Table II, Compared with the fatigue detection method using fusion signals, the accuracy of MFRANet-AF has been significantly improved. It is 12.34% higher than [4], 8.92%higher than [11], 18.44 %higher than [12], and 6.14% higher than [13]. The detection time of MFRANet-SF is 0.25s less than [4] and 2.95s less than [11]. The detection time is reduced by 1.2s compared to [12] and reduced 2.45s than [13].

IV. CONCLUSION

In this study, we have proposed an efficient fatigue detection network-MFRANet. First, the sEMG signals of the agonist and the synergistic muscle are fused to reduce the impact of noise caused by acquisition method and environment on fatigue detection, thus increasing the significance of changes in sEMG signals before and after muscle fatigue. Secondly, a GRU layer extracts the deep features of the time and space domains of the fusion signal to reduce the effects of non-linearity and non-stationarity of the sEMG signal. Finally, we have introduced an attention mechanism to fatigue detection for the first time, reconstructing the nonlinear relationship between the channels through the attention mechanism, and using the weighted method to select the deep features extracted from the GRU layer. The attention mechanism reduces the influence of differences among individuals and improves the generalization capability of the model. Experimental results show that MFRANet-AF improves the accuracy of fatigue detection to 95.04%, and MFRANet-SF reduces the time required for muscle fatigue detection to 1.35s. In the future, we will further optimize the MFRANet-AF and MFRANet-SF to achieve better fatigue detection capabilities.

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