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Identification Method of Human Movement Intention based on the Fusion Feature of EEG and EMG

Ping Xie, Xiaoling Chen, Peipei Ma, Xiaoli Li, Yuping Su

Abstract*—To resolve the problem of low identification merely relying on the EEG or EMG from the patients with perceptual-motor dysfunction, this paper proposes a quantitative description method to extract instantaneous feature of the EEG and EMG based on local mean decomposition and multiscale entropy. In the method, EEG and EMG are adaptively decomposed into product functions (PFs), and the PFs in different characteristic frequency bands are quantitatively described by the multiscale entropy to consist a multiple features information space (MFIS). Then, a fusion model based on Extreme Learning Machine (ELM) is established to realize the mapping from the EEG-EMG IMFS to human movement intention (HMI) by analyzing the MFIS. The HMI can be identified by the proposed model. 20 patients with perceptual-motor dysfunction of lower limbs (including 10 stroke patients in chronic phase (stroke) and 10 patients with peripheral nerve injury (PNI)) and 10 healthy people (HP) are enrolled. All subjects performed a knee extension and flexion task in which EEG and EMG of the quadriceps femoris and gastrocnemius muscle are synchronously recorded. Applying the above method, the feature of EEG-EMG are extracted and training in three groups (group 1: only EEG as input; group 2: only EMG as input; group 3: EEG-EMG as input) are performed. The results illustrate that the identification accuracy for group 1 can arrive 69.2% (stroke), 75.4% (PNI), 85.3% (HP); the identification accuracy for group 2 can arrive 80.5% (stroke), 79.6% (PNI), 93.4% (HP); the identification accuracy for group 3 can arrive 84.4% (stroke), 85.3% (PNI), 98.9% (HP). Conclusion is obtained that the human movement intention is reflected complementarily by EEG and EMG features. Especially for the perceptual-motor dysfunction patients, the algorithm can improve the identification accuracy on the human movement intention, and can be helpful in rehabilitation training process based on biological feedback control.

***Index Terms*—perceptual-motor dysfunction, EEG-EMG, feature fusion, human movement intention**

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I. INTRODUCTION

Neuromuscular pathways injury results in nerve damage or movement dysfunction for the patients with stroke hemiplegia, traumatic disability and poisoning, which draws the high attention in recent years [1]. The generation and development of brain-computer interface (BCI) [2], [3] technology makes it possible that electrophysiological brain signals recorded by the electroencephalogram (EEG) can directly control the machine to complete a set of tasks without depending on the normal output channel of peripheral nervous and muscles, which affords auxiliary function for the patients with movement dysfunction but with intake ideation. BCI is an international, cutting-edge, interdisciplinary technology that bridges the gap between human-computer interaction, rehabilitation science, physical and mathematical sciences and humanities However, for the nerve damage in patients, relying solely on BCI, the acquisition of brain signals are still more limited, and the feature extraction of highly efficient signal is also difficult, so the identification accuracy is relatively lower; in addition, multiple source coupling of the generating mechanism of the brain signals as well as the complexity of the signal itself also increases the difficulty to realize BCI technology. Moreover, in considering of the inherent function and contact among all sorts of bioelectric signals, a hybrid brain-computer interface technology [4], [5] is established based on a combination and parallel usage of at least one BCI and at least one additional communication. The hybrid BCI uses the patients all remaining functionalities as control possibilities and to use the currently best available ones. Especially for neuromuscular pathways injury in patients, brain and muscle activities are changing over the day. The fusing of EEG and EMG activity reflecting "subjective motion intention" and "musculoskeletal kinematic state" can achieve a good control command.

The paper proposes a quantitative description method to extract instantaneous feature of the EEG and EMG based on local experience decomposition [6] and multiscale entropy [7]. In the method, EEG and EMG are adaptively decomposed into a set of product functions (PFs), and the PFs in different characteristic frequency bands are quantitatively described by the multiscale entropy to consist a multiple features information space (MFIS). Then, a fusion model based on ELM [8], [9] is established to realize the mapping from the EEG-EMG MFIS to human movement intention (HMI) by clustering and analyzing the MFIS. The HMI can be identified by the proposed model.

II. Materials And Experiments

A. Subjects and EEG/EMG Recording

a. Subjects

10 stroke patients in flaccid paralysis period (prunnstrom I), 10 patients with peripheral nerve injury (PNI), and 10 healthy subjects between 20 and 58 years of age (mean: 36.2) are enrolled in the study. The experiment was performed in accordance with the protocol that all subjects need clean their scalps with 70% ethanol and lower limbs, keep in good mood and promise to eat nothing for least two or three hours. Furthermore, the patients need wear loose clothes. All those can guarantee that the signals in measurement not be affected and before in the experiment.

b. Experimental Tasks and Design for Subjects

Each subject was asked to lie on the bed, and an angle sensor was fixed on the inside of each knee joint, in order to control the magnitude of the force in the experiment. The subjects are allowed to perform isometric contraction tasks, and perform two tasks including a flexion task with 80-100 degree and an extension task with 0-20 degree. After attaching EMG electrodes to the subjects' quadriceps femoris and gastrocnemius muscle, and wearing the EEG cap in the head, subjects were asked to contract their muscles so as to reach pre-determined target levels according to the angle sensor signals during both the EEG and EMG experiments. Target levels were determined in practice sessions immediately before the experiments. During these practice sessions, muscle activities were calculated using EMG signals recorded through electrodes on the quadriceps muscles and calf muscle. To avoid cognitive load effects associated with trying to hit the target levels precisely, the indicators were disabled during the actual experiments. Therefore, before the sessions, subjects practiced each experimental sequence until they were able to control their movement.

This study was comprised of three experiments, one only using EEG, one only using EMG and another using EEG+EMG. The experiment was conducted in two types of task. As shown in Fig.1, a trial started with eyes “blink” period before executing an instructed task for 4s. Then the next trial started.

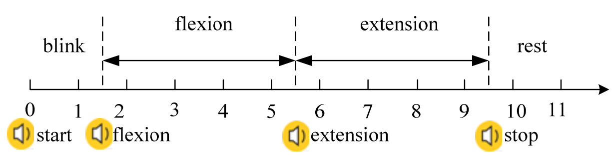

Fig.1 Flow chart of the experiment

c. Data Acquisition

The subjects were studied while seated in an electrically shielded, soundproof, light-controlled recording room. Standard scalp electrodes were placed in accordance with the International 10–20 System [10]. The EEG and EMG signals were recorded for a total of 1 minute, and EEG was recorded with 128 channels at 14 electrodes sites: FC_3, C_1, C_3, C_5, CP_1, CP_3, CP_5, FC_4, C_2, C_4, C_6, CP_1, CP_4, and CP_6, referenced to physically-linked ear lobe electrodes. The EEG signals were acquired at a sampling rate of 1000Hz and band-pass filtered from 0.5 to 75Hz. The amplifier was set to a resolution of 0.5μV and a range of ±16mV. Surface EMG signals were recorded using a BrainAmp ExG amplifier. Two pairs of 2cm-spaced Ag/AgCl electrodes were placed over the quadriceps femoris and gastrocnemius muscles, which are the major muscles for knee flexion and extension. EMG signals were rectified to extract the timing information of muscle action potentials. For both recordings, the skin was cleaned with 70% ethanol and subjected to a mild abrasion before filling the electrodes with conducting gel and attaching them. An angle sensor was fixed on the interior of each knee joint. Signals were acquired at a sampling rate of 1000Hz and band-pass filtered from 0.016 to 1000Hz using BrainVision Recorder. The amplifier was set to a resolution of 0.5μV and a range of ±16mV.

B. EEG and EMG Data Preprocessing

The artifacts in raw EEG recordings, such as EOG, EMG ECG and power signal of 50Hz, are bound to obscure information of EEG representation and lower the accuracy and precision during the subsequent analysis, because of the low frequency (0.5-30Hz) and small amplitude (2-200uV) of EEG [11]. To reduce these artifacts, a combined filter is designed. First, mean and standard deviation methods are used to reject the outlier points. Then, a notch filter is used to remove the power signal of 50Hz and an adaptive high-pass filter is used to remove baseline drift. Finally, Informax-based independent component analysis (ICA) is used to remove ECG, ECG, and EMG, which is a useful method for constructing spatial filters for preprocessing raw, multichannel EEG data based on the theory of blind source separation (BSS).

Comparing to the brain electrical signals, the interferences of EMG signals are easily removed, because the amplitude ranges 0-6mV and main frequency band is 50-500Hz, the main interference source is also power signal of 50Hz and electromagnetic radiation and the internal electronic noise interference of instruments (primarily including close DC low frequency and above 500Hz high frequency) [12]. According to these, this paper mainly designs an adaptive notch filter to removes power signal of 50Hz, and to remove DC high frequency interference with a bandpass of 10-500Hz filter.

III. Method

A. Feature Extraction Based on LMD-MSE

Given a time series $x(t)=\{x_1,x_2,\cdots,x_N\}$ of length N, which is preprocessed. Based on the combination of LMD and MSE, the method of extracting features is following as:

a. The decomposition of LMD

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For the signal $x(t)$, n PFs and a residue can be produced by means of LMD, whose detailed procedure can be seen in reference [7], [8]. Thus, the original signal $x(t)$ can be expressed as

$$x(t)=\sum_{i=1}^{n} pf_i(t)+\mu_n(t) \tag{1}$$

b. Selecting the effective PFs

In order to select the effective PFs, this paper defines the concept of correlation coefficient ρ_{X,C_i} in frequency domain between the original signal $x(t)$ and the PF components:

$$\rho_{X,C_i}=\left|\frac{E\left[\left(C_i(f)-\mu_{C_i}\right)\left(X(f)-\mu_X\right)\right]}{\sigma_{C_i}\sigma_X}\right| \tag{2}$$

Where $C_i(f)$ and $X(f)$ denote the frequency form of $c_i(t)$ and $x(t)$ respectively; μ_{C_i} and μ_X denote the mean values of $C_i(f)$ and $X(f)$ respectively; σ_{c_i} and σ_x denote the mean values of $C_i(f)$ and $X(f)$ respectively. The correlation coefficient ρ_{X,C_i} represents the correlation between the original signal $x(t)$ and the PF components.

c. Calculating the multiscale entropy of effective PFs

The multiscale entropy is based on the application of approximate entropy or sample entropy. First, a 'coarse-graining' process is applied, constructing a consecutive coarse-grained time series by averaging the data points in non-overlapping windows of lengths. Each element of the coarse-grained time series is calculated according to the calculation of sample entropy [13]. Under certain scale factor τ, the LMD-MSE feature vectors of signal $x(t)$ can be described as

$$s=\left\{PE_{pf_1},PE_{pf_2},\cdots,PE_{pf_k}\right\}^T \tag{3}$$

Where PE_{pf_k} is the MSE of the k th effective PFs.

The fig.2 is the flow chart of the above description.

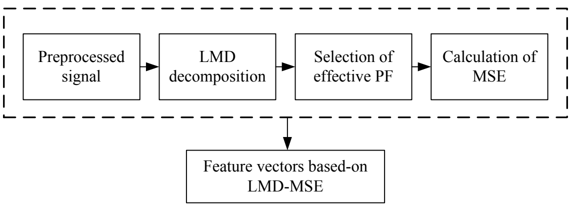

Fig.2 Flow chart of extracting features based on LMD-MSE

B. *Pattern Recognition Based on ELM*

Extreme learning machine (ELM) is a new feed-forward neural network learning algorithm. In this method, when the activation function of the hidden layer in the single-hidden layer feed-forward network is infinitely differentiable, the input weights and hidden layer biases can be assessed at random, and then the output weights can be achieved fast. The ELM not only avoids the risk of getting into the local optimum, but also improves learning speed and better generalization ability.

The idea behind ELM algorithm is presented as follows. Suppose learning N arbitrary different instances (s_i,t_i), where $s_i=\left[PE^i_{PF_1},PE^i_{PF_2},\cdots,PE^i_{PF_k}\right]^T\in R^k$ are the feature vectors calculated by above and $t_i=\left[t_{i1},t_{i2},\cdots,t_{in}\right]^T\in R^m$ is the identifier of categories. The standard single-hidden layer feed-forward networks with L hidden neurons and activation function $g(x)$ are mathematically modeled as a linear system

$$\sum_{i=1}^{L}\beta_i g\left(\omega_i\cdot s_j+b_i\right)=o_j\ ,\ j=1,2,\cdots,N \tag{4}$$

Where $\omega_i=\left[\omega_{i1},\omega_{i2},\cdots,\omega_{in}\right]^T$ denotes the weight vector connecting the i th hidden neuron and the input neuron; $\beta_i=\left[\beta_{i1},\beta_{i2},\cdots,\beta_{im}\right]^T$ denotes the weight vector connecting the i th hidden neuron and output neurons; b_i denotes the biases of the i th hidden layer and the $g(x)$ denotes the activation function of hidden layer. If the single-hidden layer neural network is able to approximate N distinct instances (s_i,t_i) with zero error means that $\sum_{i=1}^{N}\left\|o_i-t_i\right\|=0$, there exists three parameters β_i、b_i and ω_i:

$$\sum_{i=1}^{L}\beta_i g\left(\omega_i\cdot s_j+b_i\right)=t_j\ ,\ j=1,2,\cdots,N \tag{5}$$

That is to say:

$$H\beta=T \tag{6}$$

Where

$$\begin{aligned}&H\left(\omega_1,\cdots,\omega_L,b_1,\cdots,b_L,x_1,\cdots,x_N\right)\\&=\begin{bmatrix} g\left(\omega_1\cdot x_1+b_1\right) & \cdots & \\ \vdots & \vdots & \vdots \\ g\left(\omega_1\cdot x_N+b_1\right) & \cdots & g\left(\omega_L\cdot x_N+b_L\right)\end{bmatrix}_{N\times M}\end{aligned} \tag{7}$$

$$\omega=\begin{bmatrix}\omega_1^T\\ \vdots\\ \omega_L^T\end{bmatrix}_{L\times m},\ T=\begin{bmatrix}t_1^T\\ \vdots\\ t_N^T\end{bmatrix}_{N\times m}$$

H is the hidden layer output matrix of the SLFN.

The ELM algorithm is outlined as follows:

(1) Choose arbitrary value for input weights ω_i and biases b_i of hidden neurons.

(2) Calculate hidden layer output matrix H.

(3) Obtain the optimal $\hat{\beta}$ in the light of equation

$$\hat{\beta}=H^{+}T \tag{8}$$

Where H^{+} is the Moore-Penrose generalized inverse of H.

After above training, the output vectors can be calculated. Furthermore, the human movement patterns can be recognized.

C. *Feature Extraction, Fusion and Classification*

Here gives an example based on the above step of the experiment. First, preprocess the original data; hereafter apply the method of LMD to separately decompose the EEG and EMG signals, after this operation, the EEG or EMG

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signals are broken into a series of PF components. It can be seen that the frequency band of each PF still have large span based on the spectrum analysis, so it is necessary to give a multiscale processing for the effective PFs, aiming to analyze the signals in detail. After then, in order to quantitatively describe the inherent characteristic and complexity of the time sequence, the multiscale entropy (MSE) is introduced. Calculate the MSE of the selected PFs, and take the values as classifier input (see figure 3).

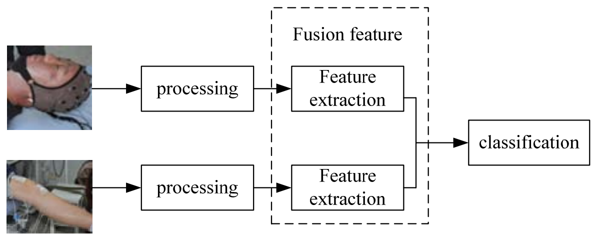

Fig.3 The fusion principle of EEG and EMG

IV. Results

In our experiment, the movement pattern identification can depend on a single modality (EEG or EMG) or the fusing activity of both. In total there are three group experiments: group 1: only EEG as input; group 2: only EMG as input; group 3: EEG-EMG as input. There thirty participants all perform two motions: knee flexion and extension. According to the detailed description of the experimental designs in the above section and the data analyzed, we adopt the 3-5s (knee flexion movement) and 7-9s (knee extension movement) epochs.

Applying the above method, the results illustrate that the identification accuracy for group 1 can arrive 69.2% (stroke), 75.4% (PNI), 85.3% (HP); the identification accuracy for group 2 can arrive 80.5% (stroke), 79.6% (PNI), 93.4% (HP); the identification accuracy for group 3 can arrive 84.4% (stroke), 85.3% (PNI), 98.9% (HP) (see figure 4). Conclusion is obtained that the human movement intention is reflected

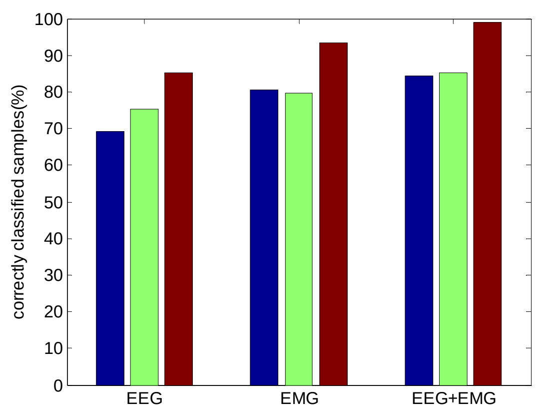

Fig.4 correctly classified samples of Pattern recognition at different input features: the blue lines present the stroke patients; the green lines present the traumatic disability patients; the red lines present the healthy people

complementarily by EEG and EMG features. From the results,

We can know that the stroke patients have a higher recognition rate than traumatic disability patients when the input is EMG, and a lower rate when EEG is the input. But for healthy subjects, the rate is the highest no matter what the input is. Furthermore, for all subjects, the rate based on the fusion of EEG and EMG is highest under the three conditions, which indicates that the fusion of multi-signals can perform a good performance for the recognition of human movement intention.

V. Discussion

This experiment demonstrates a new fusion method of muscular and brain activity. Thereby, the recognition rate of human movement intention can be improved comparing to the single based on EEG or EMG for the subjects, especially for the neuromuscular pathways injury patients, such as stroke patients and traumatic disability patients. Furthermore, for all subjects, although EMG or EEG alone yielded good performance, its combination with EEG or EMG improved it very well. Therefore such a fusion can achieve a very reliable recognition and a complementary for the patients with bad brain or muscle activities.

The paper proposes a quantitative description method to extract instantaneous feature of the EEG and EMG based on local experience decomposition and multiscale entropy. In the method, EEG and EMG are adaptively decomposed into a set of PFs, and the PFs in different characteristic frequency bands are quantitatively described by the multiscale entropy to consist MFIS. Then, a fusion model based on ELM is established to realize the mapping from the EEG-EMG MFIS to HMI by analyzing the MFIS. Therefore we adapt the way of consisting a MFIS, which includes the features of EEG and EMG, but without describing the inherent essences.

VI. Conclusions And Future Work

This experiment mainly researches the recognition of multimodal movement intention based on biological signals. The paper proposes a method of quantitatively describing inherent features based on the combination LMD and multiscale entropy, and designs a movement pattern recognition model based on ELM. The experiment verifies the validity of the proposed method. Furthermore, The result demonstrates that Multimodal fusion of EMG and EEG yielded better and more stable performance compared to single condition (EMG or EEG), no matter for healthy subjects, peripheral nerve injury patients or stroke patients.

The fusion of multimodal biosignal can promote the improvement of BCI technique and development of biofeedback, especially for the neuromuscular pathways injury patients. In the following work, we will carry out some new studies about the fusion of EMG and EEG in the view of physiological mechanism, and explore a new method to assess it.

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