Posture Recognition of Elbow Flexion and Extension Using sEMG Signal Based on Multi-Scale Entropy

Zhenyu Wang\textsuperscript{1}, Shuxiang Guo\textsuperscript{1,2}, Baofeng Gao\textsuperscript{1}, Xuan Song\textsuperscript{1}
\textsuperscript{1}School of Life Science, Key Laboratory of Biomimetic Robots and Systems, Ministry of Education, Beijing Institute of Technology, Haidian District, Beijing, China
\textsuperscript{2}Faculty of Engineering, Kagawa University, 2217-20 Hayashi-cho, Takamatsu, Kagawa, Japan
920668665@qq.com, guoshuxiang@bit.edu.cn, gaobaofeng@bit.edu.cn, 295473653@qq.com

Abstract – Recognition for human elbow motion with surface electromyographic signal (sEMG) research receives more and more attention, especially in some fields like human machine interaction and measurement of human motor function due to the reason the EMG can reflect the activation of human muscle. However, continuous recognition for human elbow motion without load is still difficult due to the low signal noise ratio (SNR). In this paper, we utilized the multi-scale entropy and moving-window method to reveal the elbow motion information hidden in the filtered sEMG signals from the biceps muscle with good performance compared to the angle record derived from an inertia sensor.

Index Terms—Rehabilitation, Surface EMG, Multi-Scale Entropy

I. INTRODUCTION

Surface electromyographic signal (sEMG) has been applied in many fields like human machine interaction, rehabilitation [1], measurement of human motor function [2], prothesis control [3] and so on, for the reason that it can reveal the information regarding the neural activation of muscles [4]. As the complex and non-stationary properties it may be easily influenced by physiological and recording tool which would increase the difficulties when realizing human motion pattern recognition using sEMG signal such as the multi gestures in hand which is difficult to be assessed with physical sensors [5]-[8].

Usually the pattern recognition can be divided into two important processes: feature extraction and feature classification. In general, the method of feature extraction can be separated into three types: time domain, frequency domain and time-frequency domain according to analysis method [9]. The methods of time domain mainly include Integrated EMG (IEMG), Mean Absolute Value (MAV) and so on [9]. The methods of frequency domain mainly include Auto-Regressive coefficients (AR), frequency Median (FMD) and so on [10]. The methods of time-frequency domain were developed based on that in frequency domain and include Wavelet Transform (WT) and Wavelet Packet Transform (WPT) [11]. To the process of feature classification, the typical method is Artificial Neural Network (ANN) which is good at dealing with nonlinear problems. Besides it, there are Bayesian classifier (BC), Fuzzy Logic Classifier (FLC) and Support Vector Machines (SVM) [12]. In this paper, WPT is used to process the raw sEMG signals while ANN is used to implement the classification.

Early research can realize the discrete motion recognition is which only including several gestures of human body [13]-[17]. Recently, some researches focus on the continuous recognition which means some relationship between sEMG and human motion should be indicated [18].

In this paper, continuous motion recognition in human machine interaction and bilateral rehabilitation was implemented based on sEMG signal [19], [20] in which only one channel signal processing was concentrated on, that is only one active muscle is recruited in our search. [21]showed EMG-driven state space model could perform well to estimate continuous joint angular displacement and velocity in elbow flexion/extension. However it was done when the subject held some load in his hand in order to increase the SNR. In our research, subjects were asked to perform the elbow flexion and extension in sagittal plane with no load at hand and the motion was performed in a low speed in order to decrease the influence of the acceleration to activation of muscle.

![Fig.1 Elbow extension and flexion in experiment](image)

For the EMG signal processing, we had proposed a weighted peaks method in previous research [22], as an improvement in this paper, we utilized multi-scale entropy to make the feature more effective, then BP network was used to construct an effective model to recognize the motion information hidden in the EMG signal.

The first section of the paper introduces the research background about the sEMG signals; the second section shows the research methodology including the experimental approaches and experimental procedure. The third part shows the experimental results and last part shows the conclusions.

II. METHODOLOGY

The continuous elbow motion was shown as fig.1. The subjects were asked to perform the elbow flexion and
extension in the sagittal plane. Though it may involve biceps muscle, triceps and other muscles, the biceps muscle dominate with upper arm relaxed. So it is suitable to complete the motion recognition with one channel EMG signal from the biceps muscle. Fig.2 shows the flowchart of our whole system which involves nearly five parts: data acquisition, data preprocessing, feature extraction, motion recognition and bilateral rehabilitation.

WPT was used to get the filtered EMG signal, multi-scale entropy combined with moving-window method was used to extract the effective feature. A three-layer BP network was constructed as the classifier to complete the motion recognition. Then the output from the BP network was used as a command to drive the upper limb exoskeleton rehabilitation device which is called ULERD for short to implement the bilateral rehabilitation. This paper will give a detailed introduction just in these three parts: data preprocessing, feature extraction and motion recognition.

![Fig.2 Flow chart of the whole system](image)

**A. SEMG signal acquisition and experiments**

In the first part we need to get the raw sEMG signal. Fig.3 shows the raw sEMG signal from a subject’s biceps muscle and the motion record from the MTx sensor.

![Fig3. Raw sEMG signal and motion record](image)

The process of elbow flexion and extension can be easily divided into four states for convenience: s0 is the initial state that the forearm vertical to the ground; s1 is the motion state during flexion while s3 is the motion state during extension; Therefore s2 is the hold state that the forearm horizontal to the ground.

The raw sEMG signals were acquired using the bipolar surface electrodes with 12mm in diameter, located 18mm apart, and the sampling rate is 1000Hz [22]. The electrodes are reusable and adhered to biceps muscles while a reference electrode is adhered to body where no muscles exist as ground signal. The sampling data were pre-processed with a commercial sEMG acquisition and filter device (Oisaka Electronic Device Ltd. Japan.) with 8 channels. In order to have a good skin contact with the electrodes, the subject’s skin was shaved and cleaned with an alcohol swab.

**B. Wavelet Packet Transform (WPT)**

Then we need to apply a novel filter to extract the clean EMG signal containing the motion information. Wavelet Packet Transform (WPT) is used by generating a full wavelet basis decomposition tree. In each scale, not only the approximation signal as in DWT, but also the detail signals can be obtained.

Given an EMG signal $s(t)$, whose scaling space is assumed as $U_0^n$, wavelet packet transform can decompose $U_0^n$ into small subspaces in dichotomous way, which can be calculated according to (1).

$$U_{j+1}^n = U_{j+1}^{2n} \oplus U_{j+1}^{2n+1}, j \in \mathbb{Z}; n \in \mathbb{Z}$$  \hspace{1cm} (1)

where $j$ is the resolution level and $\oplus$ stands for orthogonal decomposition. $U_0^n$, $U_{j}^{2n}$ and $U_{j}^{2n+1}$ are three close spaces corresponding to $u_n(t)$, $u_{2n}(t)$ and $u_{2n+1}(t)$ . $u_n(t)$ satisfies the following (2) [20].

$$\begin{align*}
    u_{2n}(t) &= \sqrt{2} \sum_{k \in \mathbb{Z}} h(k) u_n(2t - k) \\
    u_{2n+1}(t) &= \sqrt{2} \sum_{k \in \mathbb{Z}} g(k) u_n(2t - k)
\end{align*}$$  \hspace{1cm} (2)

where the function $u_n(t)$ can be identified with the scaling function $\phi$ and $u_1(t)$ with the mother wavelet $\psi$. $h(k)$ and $g(k)$ are the coefficients of the low-pass and the high-pass filters respectively. The sub-signal at $U_{j+1}^n$, the nth subspace on the jth level, can be reconstructed by (3).

$$s_j^n(t) = \sum_{k \in \mathbb{Z}} D_{j}^{k^n} \psi_{j,k} (t)$$  \hspace{1cm} (3)

where $\psi_{j,k}(t)$ is the wavelet function, $D_{j}^{k^n}$ was the wavelet packet coefficients at $U_{j+1}^n$, which can be calculated by (4).

$$D_{j}^{k^n} = \int_{-\infty}^{\infty} s(t) \psi_{j,k}^*(t) dt$$  \hspace{1cm} (4)

In this paper, we chose Daubechies 2 to do the decomposition of raw sEMG signal to eight levels. The reconstructed wavelet signals obtained by (4) are analysed.

The fig.4 below shows the reconstructed sEMG signal processed by WPT in several low-frequency nodes. To reveal the elbow motion in the sEMG signal, it’s essential to extract the appropriate scale of coefficients. As analysed before, the subjects were asked to perform the elbow flexion and
extension very slowly, so the motion information must have been in the low-frequency scale coefficients. To be easily understood, we chose the symbol c1, c2…c8 to represent the low-frequency node 1.0, 2.0 … 8.0 located at frequency band 0-250Hz, 0-125Hz…0-1.95Hz respectively due to the sampling rate 1000Hz. By comparison of all the eight scale coefficients, we found that the energy of c4 and c5 coefficients was stronger and more effective to be chosen to represent the motion information by calculating the energy distribution during the whole motion process for the reason that energy was more concentrated in the motion states S1, S2 and S3 while less distributed in state S0.

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C. Multi-Scale Entropy

As discussed above, the reconstructed sEMG signals processed by WPT have the different frequency in different nodes. To enhance the motion information hidden in EMG, we utilized the entropy calculated in each node or each scale coefficients to reveal the motion information of the elbow flexion and extension, which was called multi-scale entropy.

Entropy was used conventionally to be the symbol of the complexity of the system. Therefore the combination with moving window method would represent the information varies or complexity changes during the time series. In our research the motion changes from state to state would arise the complexity of nervous system that was shown in the EMG signal. Many researchers used energy to measure the increased information during the motion process. However it usually ignored the point-to-point connection or the interrelationship of EMG time series. So it would be suitable to utilize the entropy in the feature extraction of nonlinear EMG time series.

Traditionally the entropy $H_j$ was calculated at scale $j$ like:

$$H_j = -\sum_{k=1}^{n} p_{jk} \log p_{jk}$$  

In which $p_{jk}$ is calculated as follows:

$$p_j = D_j / \sum_{i=1}^{n} D_j$$  \(6\)

Where $n$ is the window length in the $j$ scale coefficients. However, it is so sensitive that it may be influenced by the weak but rapid oscillatory noise. Therefore the generalized entropy [24]was introduced to be the solution.

$$H_j = \sum_{i=1}^{n} \frac{(p_{jk})^\alpha - p_{jk}}{\alpha - 1}$$  \(7\)

Where $\alpha$ is a real number bigger than zero. When $\alpha$ equals one in which way the generalized entropy just becomes the traditional entropy as formula (5). The generalized entropy can be able to reveal the variable oscillations in EMG signal with different $\alpha$ values which will be discussed later in experimental section.

D. Nonlinear map from the sEMG to motion

In this experiment, the subject was required to perform the elbow flexion and extension with his upper arm relaxed in the sagittal plane in a low and constant speed. As the complexity, non-stationary and nonlinear characteristic of EMG signal, we adapted a three-layer BP Artificial Neural Network (ANN) method to implement the classification of several motion states in EMG signal. Moving window entropy of the specific scale of EMG was used as the feature vector in the input layer. To get a better modelling of the complex activities of nervous system during elbow motion, we utilized 10 hidden neuron nodes in the hidden layer. In the output layer we simplified the continuous motion to be discrete four state defined in the second section. Fig.5 shows the flow chart of the motion recognition using BP network.

III. EXPERIMENTS AND RESULTS

To verify the robustness and efficiency of multi-scale entropy applied in the motion recognition, four healthy subjects were invited into the experiment. They were asked to perform elbow flexion and extension slowly on the sagittal plane with upper arm relaxed as fig.1 shows. Ten times for each person and between two motions they have 20 seconds for the rest. Then we got the raw EMG signals from the data acquisition device and motion angle record from the MTx inertial sensor in Fig.3.

As there existed much noise in the raw sEMG signal especially the high-frequency white noises, WPT method was used to do the filtering. Taking into account that subject were
asked to perform the elbow motion very slowly so we chose the average of the c4 and c5 scale coefficients to be the filtered sEMG signal.

The combination of moving window method and entropy could be the effective way. Besides we also introduced the generalized entropy to replace the traditional entropy to improve the robustness and fitness to represent the complexity changes during the motion process. The width of the moving-window was set 200ms to get a better performance. Fig.6 shows the moving-window entropy with different $\alpha$ values of filtered EMG signal. Entropy with $\alpha$ equals 10 can fit the trend of the EMG signal well, it is sensitive enough to catch the amplitude changes of the signal. While entropy with $\alpha$ equals 0.1 arises its specificity to the low-amplitude but high-frequency oscillation in the signal by ignoring the sensitive to the high amplitude changes that would increase the stability of the motion recognition. Traditional entropy that $\alpha$ equals 1 just has the mean effect of the two discussed above. So in our experiment we chose the entropy with $\alpha$ equals 0.1 to implement the motion recognition.

To model the complex motion process we constructed and trained a three-layer BP network to implement the classification. Fig.7 shows a predicted motion sample in comparison with original motion record from the inertial sensor. The both are normalized just for easily comparison. The performance was good though there existed a little time delay and slow oscillation during the initial and stop state. However, some results were not as good as fig.7 shows while it improved a lot compared with our previous research in [22].

To make it convincible, we analysed 40 predicted samples for four subjects, errors were calculated in motion states S1, S2, S3 by setting a threshold to measure the displacement of the predicted motion and the motion record. Then we got the average errors to evaluate the performance of the motion recognition.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Error Rate</th>
</tr>
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<tbody>
<tr>
<td>A</td>
<td>0.0363 ± 0.0106</td>
</tr>
<tr>
<td>B</td>
<td>0.1104 ± 0.0222</td>
</tr>
<tr>
<td>C</td>
<td>0.0467 ± 0.0065</td>
</tr>
<tr>
<td>D</td>
<td>0.0788 ± 0.0154</td>
</tr>
</tbody>
</table>

Table 1 shows the average errors between detected motion and predicted motion with four healthy subjects. For subject A and C the model we constructed had good performance in the motion recognition, while for B and D it still existed big errors. It might have something about the personality we didn’t consider, which would be our future work to improve the robustness and stability of our proposed method.

The results from fig.7 and Table 1 showed that the proposed multi-scale entropy can be applied into the motion recognition during our bilateral rehabilitation research. The unhealthy subjects were not invited just to minimize the unpredicted individual variances during the motion process. The error rates in Table.1 implied our method could also implement the muscle strength evaluation effectively for the reason that the motion intension has strong relationship with the muscle constraction. It could help come up with effective strategies for the upper-limb rehabilition in our future research.

IV. CONCLUSIONS

In this paper, we concentrated on the recognition of continuous elbow flexion and extension motion on sagittal plane with one channel surface EMG from the biceps muscle. WPT and moving-window multi-scale entropy method were used to process the raw sEMG signals and to reveal the motion information hidden in the sEMG signal respectively. However it was different from the traditional entropy research that we introduced the generalized entropy with parameter $\alpha$ to improve the fitness of the signal. Fig.6 shows us entropy with different $\alpha$ has variable sensitivity and specificity and we chose entropy with $\alpha$ equals 0.1 to construct the input vector of the three-layer BP network to map the processed sEMG to human motion. Four subjects participated in experiments and the results show the proposed method can
obtain the effective mapping relationship between sEMG and the flexion and extension on sagittal plane. Some bigger average errors occurs for subject B and D which would be the future work for us to improve the performance of recognition by decreasing the effect caused by individual conditions. And we will focus on the real-time rehabilitation application based on this work.

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REFERENCES


