Motion Recognition of the Bilateral Upper-limb Rehabilitation using sEMG Based on Ensemble EMD

Xuan Song 1, Shuxiang Guo 1, K. Baofeng Gao 1, Zhenyu Wang 1
1School of Life Science, Key Laboratory of Biomimetic Robots and Systems, Ministry of Education, Beijing Institute of Technology, Haidian District, Beijing, China
2Faculty of Engineering, Kagawa University, 2217-20 Hayashi-cho, Takamatsu, Kagawa, Japan

Abstract – Surface electromyography signal (sEMG) is deeply related with the activation of motor muscle and motion of human body, which can be used to estimate the intention of the human movement. So it is advantaged in the application of bilateral rehabilitation, where hemiplegic patients can perform rehabilitation training to their impaired limbs following the motion of intact limbs by using a certain training tool. Therefore, a novel framework based primarily on empirical mode decomposition (EMD) was developed to reduce all the three noise contaminations from surface EMG. In addition to regular EMD, the ensemble EMD (EEMD) was also examined for surface EMG denoising. The advantages of the EMD based methods were demonstrated by comparing them with the traditional digital filters, using signals derived from our routine electrode array surface EMG recordings. The experiments showed good performance of motion recognition with EEMD compared to the angel record derived from an inertia sensor.

Index Terms – Surface electromyography; Ensemble empirical mode decomposition; Recognition for motion.

I. INTRODUCTION

Stroke is one of the most significant leading causes of hemiplegia which leads to different levels of limbs disability. According to official statistics, there are approximately 800,000 people suffering a stroke every year in the United States [1]. A lot of rehabilitation robotic systems rose rapidly in response to the time and conditions that more and more people are confronting the dyskinesia caused by stroke which affects people’s normal life seriously.

In recent years, bioelectric signals like electroencephalogram (EEG), electrocardio (ECG) and electromyography (EMG) have attracted a great deal of attention owing to their particular capacities in medical rehabilitation engineering. Comparing with the information detected by other normal sensors, surface electromyography (sEMG) reveals numerous advantages in practical use. sEMG is a complex biological signal generated by the electric waves of skeleton muscle contractions, not only directly reflecting the tissue physiological characteristics of muscles but also the neuromuscular control system [2]. sEMG provides a significant and immediate information source of discovering what does the patient suppose doing at the stage of physiology. Therefore, (sEMG) is frequently applied in motion recognition, the process to explore the movement intention of patients [3]-[4]. The motion recognition process is mainly consisted of four sections which are pre-processing of the raw sEMG signals, feature extraction, classification and post-processing all together in order to realize a valid and accurate motion recognition process, thus efficient processing methods should be necessarily put into use for preferable motion recognition. The mainly influenced factors-noises, such as power line interference, white Gaussian noise, and baseline wandering make sEMG signal much more complex and non-stationary. In consequence, it is necessary to utilize effective feature extraction methods - one of the critical parts in motion recognition to accomplish the process integrally and obtain a separate feature set. Precise feature extraction aiming at acquiring more valuable information from the input raw sEMG signals with the purpose of accomplishing the motion we want.

According to the researches in the past years, a lot of classical algorithms based on the parameters obtained in the time-domain, frequency-domain and time-frequency domain are proposed to extract features from sEMG signals. The representative feature extraction method in the frequency domain-Fourier Transform requires that the raw signal data must be stationary enough and the experiment system must be linear, so it does not meet the processing requirement for sEMG to obtain useful motion information. Some methods based on joint time-frequency recently were proposed to the application for signal feature extraction, such as the Short-Time Fourier Transform, Wavelet Transform, Wavelet Packet Transform [5]-[6].

Among all the methods for extracting features, method based on time-frequency is relatively better than the method based on time-domain or frequency-domain for receiving more specific and detailed information from raw bioelectric signals. Based on these considerations above, a novel technique named Huang-Hilbert Transform (HHT) was presented for analysis of typically nonlinear and non-stationary signals [7]-[8]. The Empirical Mode Decomposition (EMD) was proposed as the fundamental part of the HHT. The HHT is carried out in two stages. First, using the EMD algorithm, it is obtained intrinsic mode functions (IMF). Then, at the second stage, the instantaneous frequency spectrum of the initial sequence is obtained by applying the Hilbert transform to the results of the above step [7]. The EMD algorithm is a potential technique to be applied with sEMG. Given a signal, the method adaptively decomposes it into a number of modes (IMFs) that are topologically equivalent to amplitude and frequency modulated, sinusoidal signals, [9]. EMD has proven to be...
useful in detecting motor units and removal of background noise in the extraction of relevant features of SEMG signals [10]-[11].

In addition to EMD, the ensemble EMD (EEMD) was used to overcome the limitation of the mode mixing routinely induced by the regular EMD [12], thus further improving the surface EMG denoising performance. The advantages of the EMD or EEMD based methods were demonstrated by comparing them with the traditional digital filters, using signals derived from our routine electrode array sEMG recordings.

In this paper, our research group has developed a lighter and more suitable upper limb exoskeleton rehabilitation device (ULERD) based on sEMG. We analyzed the most important motion recognition of the articulation cubit, flexion and extension, and we applied the EEMD algorithm to process sEMG signal which is used to control the rehabilitation device through motion recognition instead of other assessment based on position sensors. This paper is organized in four sections as follows: 1.Introduction. 2. Methodology. 3. Experiment and results. 4. Conclusion.

II. METHODOLOGY

Motion recognition process based on sEMG are consisted of several sections, they are obtaining the raw sEMG signals, pre-processing the sEMG signals, division of the signal, extracting effective features, classifying and post-processing. EEMD is the pretreatment part of the HHT process and actually used for signal analysis during pre-processing.

To ensure that the time frequency spectra yields meaningful frequency estimates (e.g. no negative frequencies), IMFs \( x_i(t) \) are defined so as to have symmetric upper and lower envelopes, with the number of zero crossings and the number of extremes differing at most by one. An IMF resulting from the EMD shall satisfy only the following requirements:

1. The number of IMF extremes (the sum of the maxima and minima) and the number of zero-crossings must either be equal or differ at most by one;
2. At any point of an IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima shall be zero.

To extract IMFs using EMD, an iterative method known as sifting process is used and is composed by the following steps:

1. Identify all the extremes of \( f(t) \).
2. Interpolate between successive maxima and minima (say cubic splines), respectively, to obtain upper and lower envelopes, \( IMF^u(t) \) and \( IMF^l(t) \) respectively.
3. Calculate the local mean \( p(t) \) between the envelopes.

\[
p(t) = \frac{IMF^l(t) + IMF^u(t)}{2}
\]

4. Subtraction of the average from the original to yield \( m(t) = f(t) - p(t) \)

5. Repeat steps (1-3) until \( m(t) \) satisfies the two conditions for being an IMF. Once an IMF is generated, the residual \( r(t) = f(t) - IMF(t) \) is regarded as the original signal, and steps (1-4) are repeated to yield the second IMF, and so on.

Decomposition results in a family of frequency ordered IMF components. Each successive IMF contains lower frequency oscillations than the preceding one. And although the term “frequency” is not quite correct when used in relation to IMFs, it is probably best suited to define their nature.
Taking into account that IMFs provide valuable “frequency” information, HHT have been applied to detect fatigue from EMG signals [13].

B. EEMD

The EEMD is a noise-assisted approach developed to improve the standard EMD [14]. For EEMD, the sifting process is performed on an ensemble of noise-added signals \( u(t) \), each derived from a summation of the original signal \( f(t) \) and a different white noise \( w(t) \) of finite amplitude, i.e. \( u(t) = f(t) + w(t) \). Each \( u(t) \) can be decomposed by the EMD algorithm. The resultant IMFs, namely \( x_i(t) \), are averaged across trials to obtain the final IMFs:

\[
x_i(t) = \frac{1}{N_T} \sum_{j=1}^{N_T} x_j(t)
\]

Where \( i \) is the the order of IMF, \( j \) denotes the trial index, and \( N_T \) is the total number of trials.

By such an average, it is assumed that the added noise in each trial can be cancelled. The rationale for addition of the white noise is to facilitate the final IMFs in comparable scales that are relatively independent of the local time-domain characteristics of the signal, thus reducing the mode mixing induced by the regular EMD [15].

C. Weighted peaks method

The reconstructed sEMG signals processed by EEMD have the different frequency in different scales; therefore, we utilized the weighted peaks method to get the trend of signal as the feature vector, however, the amount of peaks obtained in different scales is different. First, zero crossing is used to find where the peak exists.

- **Zero crossing (ZC)**
  \[
  ZC = \sum_{n=1}^{N_c} \text{sgn}(s_n \times s_{n+1}) \cap |s_n - s_{n+1}| > \text{threshold}
  \]
  where \( \text{sgn}(x) = \begin{cases} 
  1, & \text{if } x < 0 \\
  0, & \text{otherwise}
  \end{cases} \); threshold equals zero.

All the reconstructed sEMG signals of zero crossing are saved to obtain peaks and valleys among them.

- **Trend acquisition with weighted peaks**

  If \( \max(s_{zc}(i) : s_{zc(i+1)}) + \min(s_{zc}(i) : s_{zc(i+1)}) > 0 \)
  \[
  P(i) = \max(s_{zc}(i) : s_{zc(i+1)})
  \]
  else if \( \max(s_{zc}(i) : s_{zc(i+1)}) + \min(s_{zc}(i) : s_{zc(i+1)}) < 0 \)
  \[
  P(i) = (-1) \times \min(s_{zc}(i) : s_{zc(i+1)})
  \]
  where \( s_{zc}(i) \) is the reconstructed sEMG signal of zero crossing.

\( P(i) \) is the peaks or valleys between the data of zero crossing and valleys is transformed into positive number.

\[
P(i+1) = \begin{cases} 
  \frac{1-n}{n} P(i) + \frac{1}{n} P(i+1) & \text{if } 3, P(i+1) < P(i) \\
  1 & \text{if } P(i+1) = P(i) \\
  \frac{1}{3} & \text{if } P(i+1) > P(i)
  \end{cases}
\]

III. EXPERIMENTS AND RESULTS

The upper limb exoskeleton rehabilitation device we used in our research is shown in Fig.2 shows the upper and lower view of the ULERD in detail.

**Fig. 2** The upper view of the ULERD (b) The lower view of the ULERD.

A. Acquisition of sEMG.

The sEMG signals were recorded by using the bipolar surface electrodes with 12mm in diameter, located 18mm apart, and the sampling rate is 1000Hz (Fig.3). The electrodes are reusable and they are adhered to relative muscles and 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 (Osaka Electronic Device Ltd. Japan.) with 8 channels before read to the processing program with the sampling rate of 1000Hz (as the most frequency power of EMG signals are between 20 to
150Hz) through an AD sampling board (PCI3165, Interface Co. Japan). In order to have a good skin contact with the electrodes, the subject’s skin was shaved and cleaned with an alcohol swab.

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**Fig. 3** Experimental setup of sEMG acquisition

![Personal-EMG](image)

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In Fig.4, there is the raw sEMG signal obtained from a subject’s biceps muscle (blue curve) and the motion record from the MTx sensor (red curve). The process of elbow flexion and extension can be easily divided into four states: s0 is the initial state that the forearm vertical to the ground; s1 is the flexion state while s3 is the extension state; Therefore s2 is the hold state that the forearm horizontal to the ground.

**Fig. 4** Raw sEMG signal and the motion record

![Raw sEMG and its motion record](image)

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**Fig. 5** Flow chart of EEMD

![Flow chart of EEMD](image)

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B. Signal pre-processing

Though the filter box is used to filter the noise in signals, it is inevitable to interlard some noise during sampling. Therefore, EEMD is used to process the original signal firstly.

**Fig.5** shows the flow chart of EEMD in our research, Hilbert–Huang transform (HHT) [17]-[18] is an adaptive signal processing technique based on the local characteristic time scale of the data. The key part of the HHT is the EMD process, which uses the sifting process to break down a complicated signal without a basis function, such as sine or wavelet functions, into several IMFs that are embedded in the complicated signal [19]. Each IMF, linear or nonlinear, represents a simple oscillation, which has the same number of extremes and zero-crossings.

**Fig.6** Raw sEMG and its fifteen IMFs.

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**Fig.6** Raw sEMG and its fifteen IMFs.

Fig. 6 shows that decomposing with EEMD method is just depending on the intrinsic characteristic of the signal itself which means we can’t be able to know what is the exact distribution of oscillation in the IMFs extracted. However, the motion information must have been in the low-frequency scales for the reason that the subjects were asked to perform the elbow flexion and extension very slowly.

To reveal the elbow motion in the sEMG signal, it’s essential to extract the appropriate scale of coefficients. Energy density distribution method was utilized to do the evaluating of all the scale coefficients.

Here we introduce $\mathcal{E}$ to represent the energy density distribution of state1, 2, 3 during the whole motion process. It
would be our choice only when the $\varepsilon$ value of this scale coefficients exceed the threshold we set.

$$\varepsilon = \frac{E(S1,S2,S3)}{E(S0,S1,S2,S3)}$$ (9)

Fig.6 shows the raw sEMG and its fifteen IMFs, comparing with the curve of motion angle in the state S1, S2 and S3. By comparison of all the 15 scale coefficients decomposed by EEMD, IMF6 and IMF7 scale were chosen according to the energy density distribution to represent the motion information.

C. Feature extraction

After the successful denoising process by EEMD in section B, we got the cleaner EMG signals which could be beneficial in feature extraction part.

In this part we utilized the weighted peaks method to obtain the trend of the filtered sEMG signal. Fig.7 shows the trend acquisition result. It is not difficult to find that, the higher peaks reflect the trend of motion more than the lower peaks, therefore, the method of weighted peaks is proposed to increase the component of higher peak and decrease the component of lower peak to obtain the feature near to the motion of subject’s forearm.

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. The trend of the specific scale of EMG filtered by the EEMD decomposing with weighted peaks method 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 states defined in the second section.

**E. Experimental result and discussion**

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. Ten times for each person and each motion lasts for about 18 seconds. Then we got the raw EMG signals from the data acquisition device and motion angle record from the MTx inertial sensor. Fig.8 and Fig.9 show predicted motion in comparison with original motion record from the inertial sensor. The performance was good though there is a little time delay and slow oscillation during the initial and stop state.

**IV. CONCLUSIONS**

In this paper, we focused on the relationship between surface EMG from the bicep muscle to the motion of elbow flexion and extension on sagittal plane. This work can recognize the continuous posture of forearm on sagittal plane with subject’s upper arm relaxed. A novel method EEMD was used to process the raw sEMG signals for its good and adaptive filter efficacy. The proposed weighted peaks method
was used to reveal the motion information hidden in the sEMG signal and the trend of the filtered sEMG signal was used to construct the input vector of the three-layer BP network to map the processed sEMG to human motion. Seven subjects were involved 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. We got the good performance for most subjects while some bigger average errors occurs in some subject 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 rehabilitation application based on this work.

REFERENCES


