Study on Recognition of Upper Limb Motion Pattern Using surface EMG signals for Bilateral Rehabilitation

1Zhibin Song, 1Shuxiang Guo, 2Muye Pang and 2Songyuan Zhang
1Department of Intelligent Mechanical Systems Engineering, Kagawa University
2Graduate School of Engineering, kagawa University
Hayashi-cho, Takamatsu, 761-0396 Japan
{song, guo}@eng.kagawa-u.ac.jp

Abstract:
Surface electromyographic signal (sEMG) is deep 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. In this paper, we discussed the motion pattern recognition of human upper limb based on the sEMG signals. The main features of motion patterns based on sEMG signals are extracted via wavelet packet transform. Because the sEMG signal is a kind of non-stationary signal and there are many factors which can affect it like inherent noise, cross talk and so on. Therefore, a simple new method to obtain the trend of sEMG with weighted peaks as features was proposed and support vector machine (SVM) is utilized as the classifier. The contrastive experimental results show that the proposed method improved the recognition rate.

1. INTRODUCTION

Stroke is one of the most serious diseases that make adults lose their ability of reading; speaking, understanding and movement even lose their lives. According to reports across seven countries (the US, France, Germany, Italy, Spain, the UK and Japan), stroke occurs in an average of 214 out of 100,000 people per year, with the incidence growing annually by 1.9% due to an aging population[1]. With the increase of the age population, it becomes more and more emergent to improve the technology of rehabilitation. Compared to traditional rehabilitation, robot-mediated rehabilitation has been identified as a possible method to improve patient access to therapy [2]. Bilateral rehabilitation based on robotic system appears recently aiming at the hemiparesis which is the most common outcome of stoke, resulting in movement deficits in the limbs contralateral to the side of the brain affected by the stroke [3]. One of the typical systems used in bilateral rehabilitation is named Mirror Image Movement Enabler (MIME), which incorporates a PUMA 560 robot that applies forces to the paretic limb [4]. In this system, affected limb was strapped to a forearm splint that attached to the manipulator of industrial robot and the unaffected limb was also strapped to a forearm splint and its motion was sensored by a position digitizer. In this case, patients’ enthusiasm could be decreased because of the constraint of their unaffected limb [5]. In this paper, we want to use surface electromyographic (sEMG) signal to recognize the motion of unaffected limb instead of the splint because electrodes that were used to detect the sEMG signal do not constrain the motion of unaffected limb. Moreover, the sEMG signal can be detected by wireless communication device [6]. On the other hand, sEMG reflect the activation of muscle and human motion not only including the movement of human limb but also including the trend of motion that can not be detected by other sensors directly.

There are two main and important processes during the recognition: 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 [7]. The methods of time domain mainly include Integrated EMG (IEMG), Mean Absolute Value (MAV) and so on [7]. The methods of frequency domain mainly include Auto-Regressive coefficients (AR), frequency Median (FMD) and so on [8]. The methods of time-frequency domain were developed based on that in frequency domain and include Wavelet Transform (WT) and Wavelet Packet Transform (WPT) [9]. 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) [10]. In this paper, WPT is chosen as basic method of feature extraction because of its predominant characteristic in filter and feature extraction of signals and SVM is chosen as classifier.

Until now, there are many researches on motion pattern recognition based on the sEMG signal, especially on hand’s motion. Most of motions on hand recognized can induce high activation of muscle and then induce strong sEMG signal. Therefore, most of them got high recognition ratio. In this research, we focused on the recognition of human elbow flexion and extension for bilateral rehabilitation with only one electrode attached on the biceps muscle. The subject was required to perform this motion in the sagittal plane without any load on this upper limb, which only can excite fewer muscle fibers and induce weak sEMG signals compared to other searches. It is more difficult to recognize
the motion pattern using such kind of sEMG signals due to low signal noise ration (SNR). Therefore, in this paper, some new methods of feature extraction are proposed to deal with the coefficient of WPT.

It is a preliminary search for bilateral rehabilitation in our project in which the affected limb of patient worn the exoskeleton device [11-13] to perform the synchronous motion recognized from the unaffected limb (Fig.1). The system requires the motion pattern is recognized in real time. In this paper, elbow flexion and extension on unaffected side is recognized which is divided into four kinds of motion patterns.

2. METHODOLOGY

To implement the bilateral rehabilitation using sEMG signals recorded from the unaffected side and driving the exoskeleton device to carry out the training of affected side, four motion patterns should be recognized in the sagittal plane: stop in the initial position (A), flexion to horizontal plane (B), stop in the horizontal plane (C) and extension to vertical plane (D) (Fig.2). WPT is used to decompose the sEMG signal and reconstructed signal is obtained as feature, and the basic classifier chosen is SVM which is proved effective in recently researches. During training the SVM classifier, an inertia sensor (MTx) is mounted on the wrist of unaffected side to detect the motion of the forearm as target of classification. A new and simple method of obtaining the trend of sEMG with weighted peaks is proposed to extract the feature of sEMG. In order to evaluate this method, constructive experiment is conducted between traditional WAV method and proposed method to extract feature (Fig.3).

2.1 SEMG signal acquisition and experiments

The sEMG signals were acquired by using the bipolar surface electrodes with 12mm in diameter, located 18mm apart, and the sampling rate is 1000Hz (Fig 4). The electrodes are reusable and they are adhered to biceps 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 (Oisaka Electronic Device Ltd. Japan.) with 8 channels before read to the processing program with the sampling rate of 1000Hz. In order to have a good skin contact with the electrodes, the subject’s skin was shaved and cleaned with an alcohol swab. Fig. shows the recorded raw sEMG signal from a subject’s biceps muscle. The window length of sEMG samples was set to 256 ms for the real-time requirement in engineering application.

Two subjects (healthy students in our lab) are invited to participate in this experiment. They are required to perform the elbow flexion and extension for ten times shown in Fig.2. The angle of forearm is detected via an inertia sensor. SEMG recorded is processed through Matlab software.

Fig.1 Bilateral rehabilitation system

Fig.2 Four motion pattern to be recognized

Fig.3 flow structure of recognition system

Fig.4 Experimental setup of sEMG acquisition
2.2 Wavelet Transform Packet (WPT)

Wavelet Packet Transform (WPT) is a generalized version of the Discrete Wavelet Transform (DWT). It generates a full wavelet basis decomposition tree. In each scale, not only the approximation signal as in DWT, but also the detail signals are filtered to obtain another two low and high frequency signals.

Given an EMG signal $s(t)$, whose scaling space is assumed as $U^0_0$, wavelet packet transform can decompose $U^0_0$ into small subspaces in dichotomous way, which can be calculated according to (1).

$$U^n_j = U^2_n \otimes U^{2n+1}_j, j \in \mathbb{Z}; n \in \mathbb{Z}. \quad (1)$$

where $j$ is the resolution level and $\otimes$ stands for orthogonal decomposition. $U^n_j$, $U^2_n$ and $U^{2n+1}_j$ 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].

$$\begin{cases} u_{2n}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k)u_n(2t - k) \\ u_{2n+1}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k)u_n(2t - k) \end{cases} \quad (2)$$

where the function $u_n(t)$ can be identified with the scaling function $\varphi$ and $u_n(t)$ 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 $U^n_j$, the $n$th subspace on the $j$th level, can be reconstructed by (3).

$$s^n_j(t) = \sum_k D^{j,n}_k \psi_{j,k}(t), k \in \mathbb{Z} \quad (3)$$

where $\psi_{j,k}(t)$ is the wavelet function, $D^{j,n}_k$ was the wavelet packet coefficients at $U^n_j$, which can be calculated by (4).

$$D^{j,n}_k = \int_{-\infty}^{\infty} s(t) \psi_{j,k}(t) dt \quad (4)$$

Some relative searches proved that Daubechies wavelet is effective to process the sEMG signals as mother wavelet. In this paper, we chose Daubechies 2 and decomposition raw sEMG signal to the forth level. The reconstructed wavelet obtained by (4) is analyzed as initial feature. According to Fig 2, WPT generates a high-dimension feature vector. Some researches proposed lots of method to reduce the dimension to save the calculation cost such as principle component analysis (PCA) and a self-organizing feature map (SOFM) [14]. In this paper, the most effective feature vectors are selected rather than all of vectors, namely the node 4.0 and node 4.1, because the effective component of sEMG signals distribute in low frequency domain.
2.3 Feature extraction methods
The aim of feature extraction is to obtain some typical data which can reflect the motion pattern of human limb in this field. Because most of researches in motion pattern recognition using sEMG signal focus on discrete motion pattern like hand open, grasp and so on, traditional feature extraction method can obtain the typical data to reflect the motion characteristic like MAV, AVR. In this research, motion patterns to be recognized are continuous in time domain. In order to decrease the fluctuation in processed sEMG signal, a simple method trend acquisition with weighted peak is proposed according to the motion of subject’s forearm detected by an inertia sensor.

- Integrated sEMG (IEMG)

\[
IEMG = \sum_{n=1}^{N} |x_n| \tag{5}
\]

where \(x_n\) is the raw sEMG signal recorded; \(N\) is set to 256. To obtain the smooth signal, overlapped window is utilized during this procedure.

- Mean Absolute Value (MAV)

\[
MAV = \frac{1}{N} \sum_{n=1}^{N} |s_n| \tag{6}
\]

where \(s_n\) is the reconstructed sEMG signal processed by WPT. The overlapped window is also used in this procedure. In generally, the entropy of reconstructed sEMG was commonly discussed, meanwhile, [15] proved the stastic method is also effective such as MAV.

- Zero crossing (ZC)

\[
ZC = \sum_{n=1}^{N} (\text{sgn}(x_n) \times |x_n|) [|x_n - s_{n+1}| \geq \text{threshold}] \tag{7}
\]

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 \(\max(s_{n(i)} : s_{n(i+1)}) + \min(s_{n(i)} : s_{n(i+1)}) \geq 0\)

\[
P(i) = \max(s_{n(i)} : s_{n(i+1)}) \tag{8}
\]

else if \(\max(s_{n(i)} : s_{n(i+1)}) + \min(s_{n(i)} : s_{n(i+1)}) < 0\)

\[
P(i) = (-1) \times \min(s_{n(i)} : s_{n(i+1)}) \tag{9}
\]

where \(s_{n(i)}\) 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.
Compared to the motion of subject’s forearm, 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.

\[
P(i+1) = \frac{1-n}{n} P(i) + \frac{1}{n} P(i+1) \quad (10)
\]

Where \( n = \begin{cases} 
3, & P(i+1) < P(i) \\
1, & P(i+1) = P(i) \\
1/3, & P(i+1) > P(i)
\end{cases} \)

Fig.14 Trend acquisition from the reconstructed sEMG in node 4.0

Fig.15 Trend acquisition from the reconstructed sEMG in node 4.1

2.4 Feature classification based on SVM

- Support Vector Machine(SVM)

Support Vector Machines is proposed by Cortes and Vapnik as a classification technique based on maximizing the margin between a data set and use optimal hyperplane to separate two data sets. In a mathematic view, SVM requires solving the following optimization problem: to find the minimum of Equ.(11) [16].

\[
\text{Min} \quad \varphi(\omega, \xi) = \frac{1}{2} \omega \cdot \omega + c(\sum_{i=1}^{l} \xi_i) \\
\text{subject to} \quad y_i[(x_i \cdot \omega) + b] \geq 1 - \xi_i, \quad i=1,2,\ldots,l 
\]

where \( x \) is an n-dimensional vector and \( b \) is a scalar. \( n \) is the independent variable; \( l \) is the number of data points; \( y \) is the learned model.

Classifier based on the current pattern

It is easiest to classify the pattern A from other pattern and the pattern C can be also recognized via several protrudent peaks, however it is difficult to recognize pattern B from pattern D by using one channel sEMG signal, because for single feature extracted from sEMG can not reflect the direction of the motion. Therefore, for training SVM model, the pattern B and D are same pattern, and we classified them based on the current pattern because of the continuous motion.

If pattern B or D is recognized
- If current pattern is A,
  Then current pattern is B
- If current pattern is C
  Then current pattern is D
- If current pattern is B,
  Then current pattern is B
- If current pattern is D
  Then current pattern is D

3. EXPERIMENTAL RESULTS

Constructive experiments are conducted for both subjects to compare the proposed method of feature extraction via weighted peaks to obtain the sEMG trend with traditional MAV method; on the other hand, as typical feature of sEMG, IEMG signals are used in both experiments. In this research LIBSVM software [17] is utilized to classify the different motion pattern. In each procedure of classification, target vector can be generated automatically via the inertia sensor, and feature vector is a 3*n matrix. Fig.16 shows the scatter graph of distribution of the MAV results of reconstructed sEMG signals and IEMG signals. From this figure, some features of pattern B and C overlapped in the connect area because of the strong fluctuation in MAV results, which can reduce the recognition rate. On the other hand, the pattern B and D almost overlap each other, because single feature can not reflect the direction of motion or the trend of sEMG signal, which can be solved via classifier based on the current pattern.
Fig. 17 Example of scatter figure on IEMG signals and sEMG trend with weighted peaks in node 4.0

Fig. 17 shows the scatter graph on the sEMG trend with weighted peak and the IEMG signal. From this figure, the superposition area between pattern B and pattern C obviously decrease because the trend of sEMG signal is smooth and reflect the motion of forearm. The results of whole contrastive experiments are shown in Table.1. From this table, the recognition rate of Weighted peak is higher than that in WAV for both subjects.

<table>
<thead>
<tr>
<th>Table.1 Average recognition rate of contrastive experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Subject A</td>
</tr>
<tr>
<td>Subject B</td>
</tr>
</tbody>
</table>

5. CONCLUSION AND FUTURE WORK

In this paper, a preliminary research for bilateral rehabilitation based sEMG signal is discussed, where human elbow flexion and extension is recognized using sEMG signal. Wavelet transform packet is used to process the raw sEMG signal and the WAV of the reconstructed signal is calculated as one of the feature. To get the trend of sEMG signal which is similar to the motion pattern, a simple method with weighted peaks of reconstructed sEMG signal is proposed. IEMG signal is also used as the feature vector. According to the contrastive experiment, the proposed method to get the trend of sEMG signal get higher recognition rate for both subjects. In the future, this result will be improved and used to drive the exoskeleton device to implement the bilateral rehabilitation.

ACKNOWLEDGEMENT

This research was supported by the Kagawa University Characteristic Prior Research Fund 2012.

REFERENCES


