Proceedings of 2013 IEEE
International Conference on Mechatronics and Automation
August 4 - 7, Takamatsu, Japan

SEMG-based Continuous Posture Recognition of Elbow Flexion and Extension in Sagittal Plane

Zhibin Song[*1*2], Zhenyu Wang[*1] and Shuxiang Guo[*1,*2,*3]

*1Beijing Institute of Technology, China
5 South Zhongguancun Street, Haidian District, Beijing,100081,China

[*2]Dept. of Intelligent Mechanical Systems Eng'g, Kagawa University, Japan
[*3]School of Electrical Engineering, TianJin University of Technology, TianJin, China

songbin02717@ hotmail.com guo@eng.kagawa-u.ac.jp

***Abstract* – Surface electromyographic signal (sEMG) is used in some fields such as human machine interaction and measurement of human motor function, because it can reflect the activation of human muscle. Though the recognition of motion pattern of human limbs has been researched for many years, continuous recognition for human elbow motion without load is still difficult because of low signal noise ratio (SNR). In this paper, we proposed an improved weighted peaks method to process the filtered sEMG signals from the biceps muscle and adapted linear fitting method to obtain the elbow motion in sagittal plane. The experiments showed the proposed method can effectively process the sEMG signals and obtain the activation of biceps muscle. The experimental results show the similar data of elbow motion compared to the data derived from an inertia sensor.**

Index Terms* – *SEMG; Recognition for motion pattern; Improved Weighted Peaks.

I. INTRODUCTION

Surface electromyographic signal (sEMG) has been applied in many fields such as human machine interaction, rehabilitation [1], measurement of human motor function [2] and prethesis control [3] and so on, because it can provide the information regarding the neural activation of muscles [4]. SEMG signal is a complex and non-stationary signal which is influenced by many factors such as physiological and anatomical properties and recoding tool. Most of research in this filed focus on the human motion pattern recognition such as the multi gestures in hand which is difficult to be assessed with physical sensors [5]-[8].

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 [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.

Early research on motion recognition is discrete 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. Continuous recognition is basically constructed using hierarchical control recently. Most of commercial prosthetic hands implement the prosthetic-driven control using either amplitude or level coding of the EMG signal generated from an active muscle [18].

In this paper, we combined these two parts to implement the continuous recognition which is useful in human machine interaction and bilateral rehabilitation based on sEMG signal [19], [20]. It is different from other researches in motion pattern recognition that we focus on only one channel signal processing that means only one active muscle is recruited in our search. Some searchers proposed an EMG-driven state space model to estimate continuous joint angular displacement and velocity, demonstrated by elbow flexion/ extension [21]. This research was done when the subject held some load in his hand and it increased the SNR. We did the experiment to recognize the elbow flexion and extension motion in sagittal plane when subjects wore no load and the motion was performed in a low speed in order to decrease the influence of the acceleration to activation of muscle.

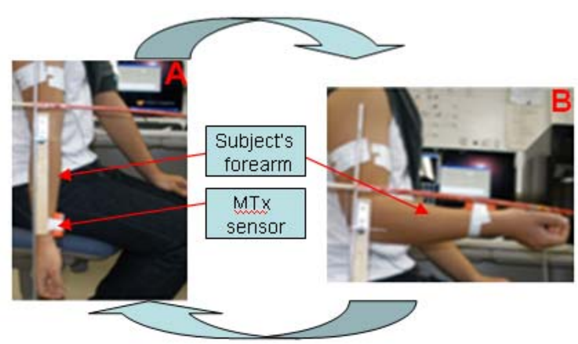

Fig1. Elbow extension and flexion in experiment

There are two main parts in our research. One part is to process the sEMG signal to get the feature during the whole motion. We proposed a weighted peaks method in previous research [22] and in this paper, we improved it to make the feature more effective. The second part is to map the feature vector to the motion in sagittal plane that is detected by using an inertia sensor. The first section 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

Though the elbow flexion and extension performed in the sagittal plane involved biceps muscle, triceps and other muscles, it is simpler to analyze this motion on the sagittal plane with upper arm relaxed, because the main active muscle is biceps muscle. Therefore, it is easier to obtain the relationship between muscle activation and human body motion. The motion was performed from status A (Fig. 1) to status B and range of motion is about 90 degree. The motion is required to be done three times in one experiment.

A. 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 2). 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. In order to have a good skin contact with the electrodes, the subject's skin was shaved and cleaned with an alcohol swab. Fig. 3 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.

Four 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.1. The angle of forearm is detected via an inertia sensor. SEMG recorded is processed through Matlab software.

Fig2. Experimental setup of sEMG acquisition

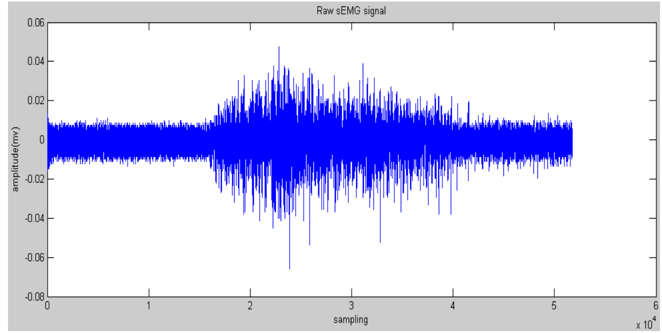

Fig.3 Example of raw sEMG signal recorded from biceps muscle

B. Wavelet Transform Packet (WPT)

Though the filter box is used to filter the noise in signals, it is inevitable to interlard some noise during sampling. Therefore, Wavelet Packet Transform (WPT) is used to process the original signal firstly. 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).

$$U^{n}_{j-1} = U^{2n}_{j} \oplus U^{2n+1}_{j}, j \in Z; n \in Z_{+} \tag{1}$$

where j is the resolution level and $\oplus$ stands for orthogonal decomposition. U^{n}_{j-1}, U^{2n}_{j} 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].

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

where the function $u_0(t)$ can be identified with the scaling function φ and $u_1(t)$ with the mother wavelet ψ. $h(k)$ and $g(k)$ are the coefficients of the low-pass and the high-pass filters respectively. The sub-signal at U^{n}_{j-1}, the nth subspace on the jth level, can be reconstructed by (3).

$$s_j^n(t) = \sum_k D_k^{j,n} \psi_{j,k}(t),\ k \in Z \tag{3}$$

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

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

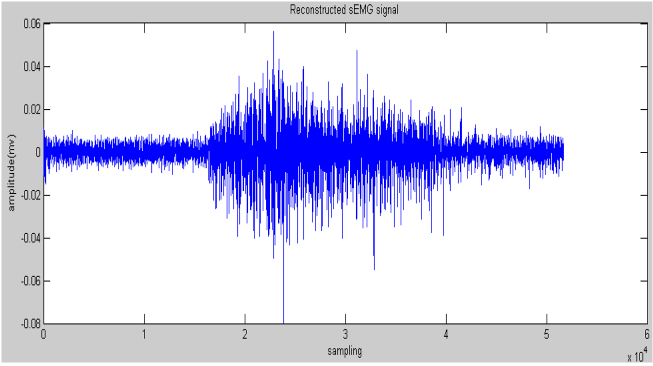

Fig.4 Reconstructed sEMG signal processed by WPT in node 4.0

In this research, we chose Daubechies 2 and decomposition raw sEMG signal to the forth level. The reconstructed wavelet signals obtained by (4) are analyzed. The figure 4 shows the reconstructed sEMG signal processed by WPT in node 4.0. WPT generates a high-dimension feature vector. Some researches proposed lots of methods to reduce the dimension to save the calculation cost such as principle component analysis (PCA) and a self-organizing feature map (SOFM) [23]. In this paper, the most effective feature vectors are selected rather than all of vectors, namely the node 4.0, because the effective component of sEMG signals distribute in low frequency domain.

C. Weighted peaks method

The reconstructed sEMG signals processed by WPT have the different frequency in different nodes; therefore, the amount of peaks obtained in different nodes is different. First, zero crossing is used to find where the peak exists.

- Zero crossing (ZC)

$$ZC = \sum_{n=1}^{N-1}[\mathrm{sgn}(s_n \times s_{n+1}) \cap |s_n - s_{n+1}| \geqslant threshold] \qquad (7)$$

where $\mathrm{sgn}(x)=\begin{cases} 1, & \text{if } x<0 \\ 0, & \text{otherwise} \end{cases}$; 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 $\max(s_{zc(i)} : s_{zc(i+1)}) + \min(s_{zc(i)} : s_{zc(i+1)}) \geqslant 0$

$$P(i) = \max(s_{zc(i)} : s_{zc(i+1)}) \qquad (8)$$

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

$$P(i) = (-1) \times \min(s_{zc(i)} : s_{zc(i+1)}) \qquad (9)$$

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.

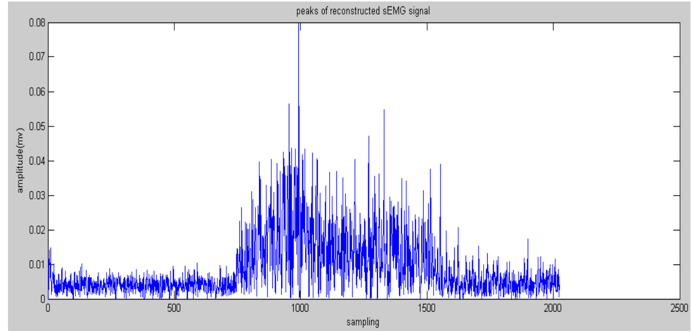

Fig.5 Peaks of the reconstructed sEMG in node 4.0

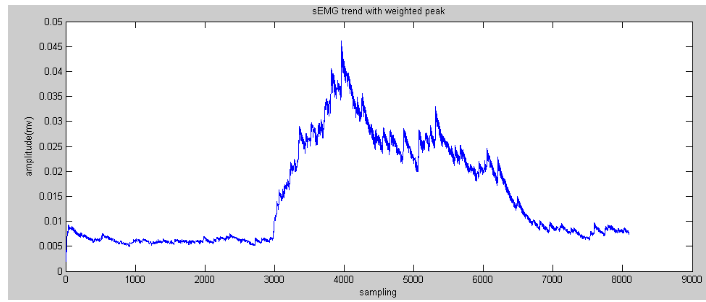

Fig.6 Trend acquisition from the reconstructed sEMG in node 4.0

According to the signals in Fig.5, 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. In (10), the parameter of weighted peaks is set as 3 according to many times experiments. The figure 6 shows the results of weighted peaks using the values of figure 5.

$$P(i+1) = \frac{1-n}{n}P(i) + \frac{1}{n}P(i+1) \qquad (10)$$

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

C. Improved Weighted peaks method

The weighted peaks methods aimed to extract feature of peaks of EMG signals based on increasing the component of the higher amplitude and decreasing the component of the lower amplitude. The weight bias to the high peaks can obtain the main features; however, the fixed weight can not smooth the feature trajectory because of the instability of sEMG signals. Therefore, the variable weight will be useful to process the instable peaks. The main method to improve the weighted peaks is controlling the variation of current data to the previous data. If the value obtained by the weighted peaks method is certain value (B) higher or lower than the previous value, the method will be carried out once more, until the variation is under the certain value (B). The effect of carrying out the weighted peaks method changed the weighted values in fact.

If $|P(i+1) - P(i)| > B$

$$P(i+1) = \frac{1-n}{n} P(i) + \frac{1}{n} P(i+1) \quad (11)$$

If $|P(i+1) - P(i)| \leqslant B$

$$P(i+1) = P(i+1) \quad (12)$$

D. linear 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. The activation of biceps muscle is considered to be proportional to the motion of subject's forearm. Therefore, we adapted a simple proportional fitting line to map the weighted peaks of sEMG signals to the motion.

$$M(i) = aP(i) + b \quad (13)$$

The least square method was used to obtain the parameter a and b. Based on ten times experiments, average of a is 710 and value of b is -43.

III. EXPERIMENTS AND RESULTS

In this paper, four subjects were required to perform the elbow flexion and extension in sagittal plane with their upper arms relaxed. The rational angle of forearm is about 90 degree in the sagittal plane from posture that forearm is vertical to the ground to the posture that forearm is parallel to horizontal plane. Figure 7 shows one subject was grasping an inertial sensor and one electrode was attaching on his biceps muscle and other subject wore the exoskeleton device. All of subjects were acquired the sEMG signals for their biceps muscles and only two subjects wore the exoskeleton device to evaluate the efficacy of the proposed methods. The experiment includes two levels. In the first level, the posture of subject's forearm was predicted through the weighted peaks method. In this level, elbow flexion and extension was required to be done three times in one experiment. Each subject was required to perform ten times experiments. After once experiment, the subject was allowed to rest for one minute. In the second level, the subjects' forearm posture was obtained by using the improved weighted peaks and the elbow flexion and extension was required to be done once in one experiment. It is the same with that in the first level the experiments were required to be performed ten times.

One example of the first level experiment was shown in figure 8.In this figure, the vertical axis stands for the angle of forearm and it is easy to understand subject A performed elbow flexion and extension three times during the status A and status B (shown in Fig.1). The blue curve means the rational angle of forearm detected by using the inertia sensor. The red curve stands for the rational angle obtained by using the proposed method. Because the subjects perform the elbow flexion and extension from 0 degree to 90 degree, we did the simple processing that limits the minimum values of predicted results.

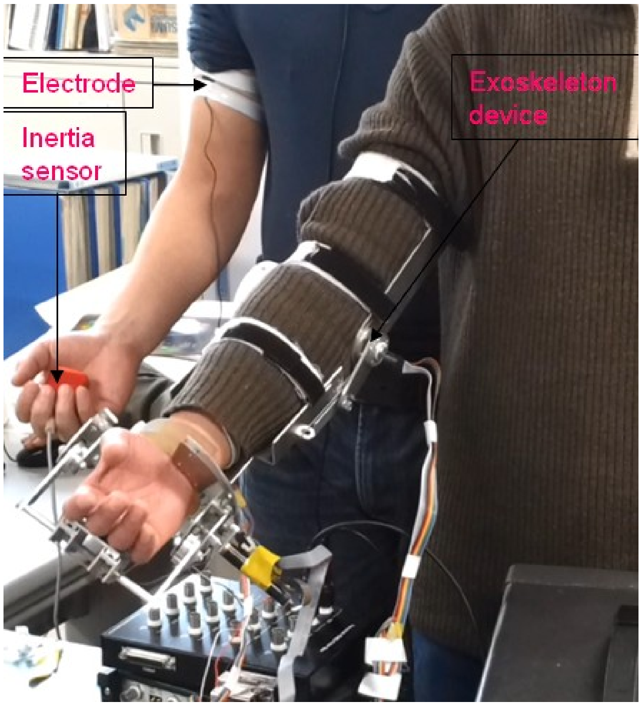

Fig.7. Two subjects were performing elbow flexion and extension, where one subject was attaching one electrode on the surface of biceps muscle and the other subject wore the exoskeleton device.

Fig.9 shows another typical experimental results from subject B . Subject B obtained better prediction for continuous posture of elbow flexion and extension in the first time. The other two times performance did not obtain good prediction due to the unstable sEMG signals. It is also indicated that it is difficult to predict the continuous posture for upper limb with weak sEMG signals.

Table I shows the average errors between detected angles and predicted angles for four subjects for ten times experiments, which indicated that the proposed method can predict the elbow flexion and extension in the sagittal plane at a certain degree. Subject A got the best prediction efficacy among all of subjects

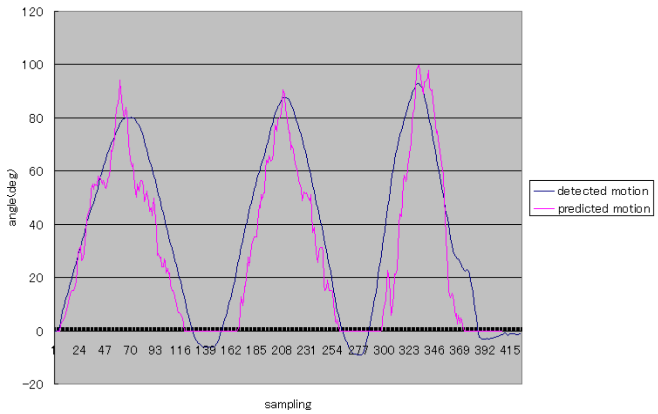

Fig.8 The typical experimental result for subject A

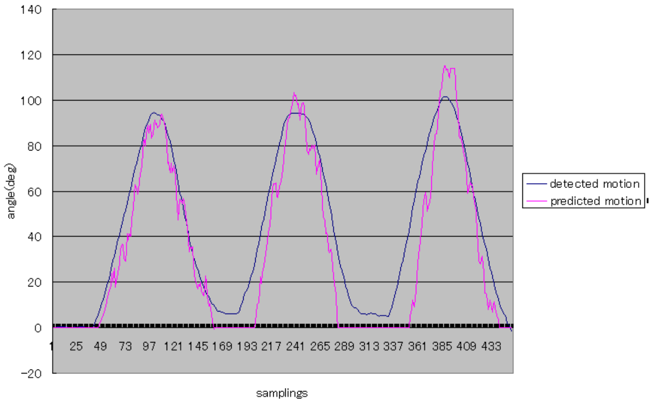

Fig.9 The typical experimental result for subject B

Table.I Average errors between detected motion and predicted motion in the first level experiment

Subject	Average errors(deg)
A	7.4(±1.4)
B	9.1(±2.1)
C	8.2(±1.9)
D	9.4(±2.6.)

One example of the second level experimental results was shown in figure 10. In this figure, the trajectories of prediction and detection for elbow flexion and extension in the sagittal plane are almost the same. The predicted trajectory is smoother than that in the first level experiment, which indicated the improved weighted peaks method is more effective in reducing the instability of sEMG signals. Though the trajectory is smoother than that obtained by the weighted peaks method, there is still some instability where the variation of data is low, because the certain value B was not set low enough. However, if the B was set too low, the variation of sEMG peaks will be reduced and the posture of subjects' forearm can not be predicted accurately. The figure 11 shows the subject B's elbow flexion and extension which are obtained through prediction and detection in the second level experiment. This result also indicated that the predicted trajectory is almost the same with the detected trajectory.

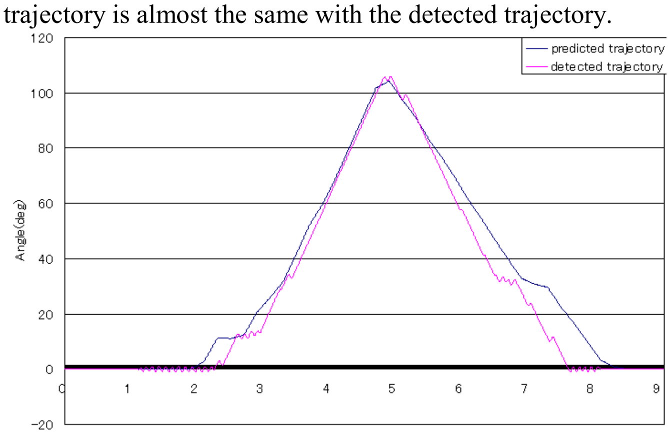

Fig.10 The typical experimental result for subject A

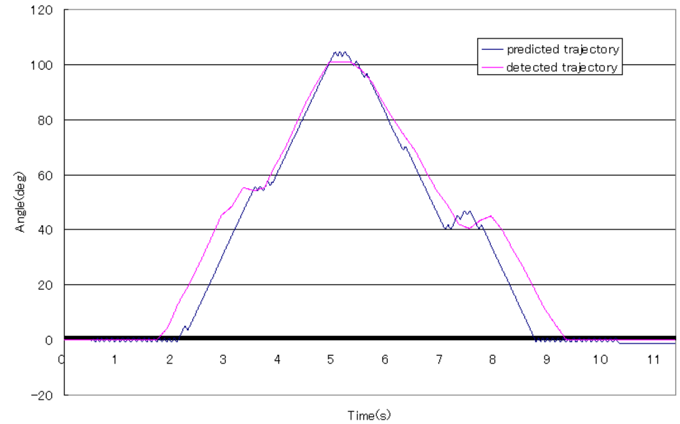

Fig.11 The typical experimental result for subject B

Table.II Average errors between detected motion and predicted motion in the second level experiment

Subject	Average errors(deg)
A	4.3(±0.8)
B	4.8(±1.1)
C	4.1(±0.7)
D	4.6(±1.6.)

Table II shows the average errors between detection and prediction motion for all subjects in the second level experiments. The average errors in the second level experiments are lower than those in the first level experiments. Different from the results in the first level experiments, the subject C got the smallest errors.

IV. Conclusions

In this paper, we focused on the relationship between surface EMG from the biceps 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. WPT was used to process the raw sEMG signals for its good filter efficacy. The proposed weighted peaks method was used to obtain the signals where the higher amplitude signals got higher weight and lower amplitude signals got lower weight, so that the obtained signals reflect the activation of muscle smoothly. Last, linear equation was used 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 higher errors for prediction existed, which indicated it was difficult to predict the continuous posture of forearm on sagittal plane accurately because the weak sEMG signals are unstable. The second level experimental results show the lower errors between the predicted trajectories and the detected trajectories. In the future, we will focus on the rehabilitation application based on this work.

ACKNOWLEDGEMENT

This research was supported by the Kagawa University Characteristic Prior Research Fund 2013.

REFERENCES

[1] Zhibin Song, Shuxiang Guo and Yili Fu, "Development of an upper extremity motor function rehabilitation system and an assessment system," *International Journal of Mechatronics and Automation*, Vol. 1, No. 1, pp. 19-28. 2011.

[2] M Hallett, B T Shahani and R R Young "EMG analysis of stereotyped voluntary movements in man," *Journal of Neurology, Neurosurgery, and Psychiatry*, , 38, pp. 1154-962. 1975.

[3] Pradeep Shenoy_, Kai J. Miller, Beau Crawford, and Rajesh P. N. Rao. "Online Electromyographic Control of a Robotic Prosthesis." *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, VOL. 55, NO. 3, pp.1128-1135. 2008.

[4] Mahdi Khezri and Mehran Jahed, "Real-time intelligent pattern recognition algorithm for surface EMG signals," *BioMedical Engineering Online*, 2007.6:45.

[5] Kevin R. Wheeler, Mindy H. Chang, and Kevin H. Knuth. "Gesture Based Control and EMG Decomposition". *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS*, VOL. 1, NO. 11, pp. 1-12. 2005

[6] Siddharth S. Rautaray. "Real Time Multiple Hand Gesture Recognition System for Human Computer Interaction." *I.J. Intelligent Systems and Applications*, pp.56-64, 5, 2012.

[7] Ganesh R. Naik1,2, Hans Weghorn Dinesh K. Kumar, Vijay P. Singh Marimuthu Palaniswami. "Real-time Hand Gesture Identification for Human Computer Interaction based on ICA of Surface Electromyogram." *International Conference Interfaces and Human Computer Interaction* pp.83-90. 2007.

[8] Xiang Chen, Xu Zhang, Zhang-Yan Zhao, Ji-Hai Yang, Lantz, V., Kong-Qiao Wang, 2007. "Hand Gesture Recognition Research Based on Surface EMG Sensors and 2D-accelerometers," *11th IEEE International Symposium on Wearable Computers*, pp. 11 – 14. 2007

[9] M. Zecca, S. Micera, MC Carrozza, and P. Dario. "Control of multifunctional prosthetic hands by processing the electromyographic signal." *Critical Reviews in Biomedical Engineering*, Vol. 30(4), pp.459-468, 2002.

[10] A. Phinyomark, C. Limsakul, and P. Phukpattaranont. "A novel feature extraction for robust EMG pattern recognition." *Journal of Computing*, Vol. 1(1), pp.71–80, 2009.

[11] M. W. Jiang, R.C. Wang, J.Z. Wang, D.W. Jin, "A Method of Recognizing Finger Motion Using Wavelet Transform of Surface EMG Signal." *Proceeding of the 2005 IEEE Engineering in Medicine and Biology* , pp.2672-2674, 2005.

[12] Saevarsson Gdmundur, Sveinsson Johannes R, Benediktsson Jon Atli. "Wavelet-packet Transformation as a preprocessor of EEG waveforms for classification." *Proceeding of 19th International Conference IEEE/EMBS*. pp. 1305–1308, 1997.

[13] Hyeon-Jae Yu and Youngjin Choi, "Real time tracking algorithm of sEMG-based human arm motion," *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*. pp. 3416-3421. 2007.

[14] Jiaxin Jiang, Zhen Zhang, Zhen Wang and Jinwu Qian, "Study on real-time control of exoskeleton knee using exlectromyographic signal," *Life system modeling and intelligent computing*, Vol. 63, No.30. pp. 75-83. 2010.

[15] D. Moshou and Herman Ramon, "Wavelets and Self-Organizing Maps in Financial Time-Series Analysis. Neural Network World." *International Journal on Neural and Mass-Parallel Computing and Information Systems*, Vol. 10, No.1, pp.231-238, 2000.

[16] Ajiboye AB, ff. Weir RF: "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control." *IEEE Trans Neural sys and Rehabil Eng*, 13(3):280-291. 2005.

[17] Subasi A: "Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using feature extraction." *Computers in Biology and Medicine*, vol. 37, pp.227-244. 2007.

[18] Roberto Merletti,. "Electromyography Physiology, Engineering and oninvasive Applications." IEEE Press, John Wiley & Sons Inc. 2004

[19] Muye Pang, Shuxiang Guo, and Zhibin Song. "Study on the sEMG driven Upper Limb Exoskeleton Rehabilitation Device in Bilateral Rehabilitation." *Journal of Robotics and Mechatronics*, Vol. 24, No. 4, pp. 585-594, 2012.

[20] Zhibin Song, Shuxiang Guo, Muye Pang and Songyuan Zhang "Recognition of Motion of Human Upper Limb using SEMG in Real Time: Towards Bilateral Rehabilitation" *Proceedings of 2012 IEEE International Conference on Robotics and Biomimetics*, pp.1404-1408, 2012.

[21] Qichuan Ding, Anbin Xiong, Xingang Zhao, Jianda Han. "A novel EMG-driven state space model for the estimation of continuous joint movements." *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, pp. 2891-2897, 2011.

[22] Zhibin Song, Shuxiang Guo, Muye Pang, and Songyuan Zhang. "Study on Recognition of Upper Limb Motion Pattern Using surface EMG signals for Bilateral Rehabilitation," *Proceedings of 23rd 2012 International Symposium on Micro-NanoMechatronics and Human Science*, pp.425-430, Nov. 4-Nov. 7, , 2012.

[23] Matsumura, Y., Mitsukura, Y., Fukumi, M., Akamatsu, N., Yamamoto, Y. and Nakaura, K. "Recognition of EMG signal patterns by neural networks." *International Conference on Neural Information Processing*, Vol.2 , pp.750-754, 2002.