Proceedings of the 2012 IEEE
International Conference on Robotics and Biomimetics
December 11-14, 2012, Guangzhou, China

Recognition of Motion of Human Upper Limb using SEMG in Real Time: Towards Bilateral Rehabilitation*

Zhibin Song, Shuxiang Guo, Muye Pang and Songyuan Zhang

Abstract— **The surface electromyographic (sEMG) signal has been researched in many fields, such as medical diagnoses and prostheses control. In this paper, recognition of motion of human upper limb by processing sEMG signal in real time was proposed for application in bilateral rehabilitation, in which hemiplegia patients trained their impaired limbs by rehabilitation device based on motion of the intact limbs. In the processing of feature exaction of sEMG, Wavelet packet transform (WPT) and autoregressive (AR) model were used. The effect of feature exaction with both methods was discussed through the processing of classification where Back-propagation Neural Networks were trained. The experimental results show both methods can obtain reliable accuracy of motion pattern recognition. Moreover, on the experimental condition, the recognized accuracy of WPT is higher than that of AR model.**

I. Introduction

Bilateral rehabilitation for hemiplegia patients is an idea that involvement of the unaffected upper limb facilitates learning the spatial and temporal parameters required for motor recovery of the affected limb [1]. Many strong evidences existed indicate that bilateral training is effective in functional recovery of the upper limb for hemiplegia patients [2]-[4]. It has some advantages besides the active effect on neuro-rehabilitation. First, the rehabilitation strategy derives from individual so that more reasonable training approach can be provided to rehabilitation for affected limb. Second, this kind of rehabilitation decreases the therapist's labor intensity so that it saves medical treatment. Last, it can enhance the patient's interest to rehabilitation and avoid the problem that the patient unconsciously compensates for the affected limb to complete the tasks with unaffected limb [5].

According to systematic reviews, few rehabilitation robots have been adapted for bilateral training [6]. The MIME is one such robot [7], [8]. However, the MIME is an adapted PUMA robot as rehabilitation device in affected side; and in the unaffected side, the upper limb is constrained by a forearm splint which could decrease the patient's enthusiasm. As biological signals, electromyography (EMG) is more benefit to reflect the activation of skeletal muscle than other sensors.

*Resrach supported by the Kagawa University Characteristic Prior Research Fund 2011.

Zhibin Song, Hayashi-cho, Takamatsu, 761-0396, Japan. Graduate School of Engineering, Kagawa University, Japan (e-mail: s09d505@stmail.eng.kagawa-u.ac.jp).

Shuxiang Guo , Hayashi-cho, Takamatsu, 761-0396, Japan. Dept. of Intelligent Mechanical Systems Eng'g, Kagawa University, Japan 081-87-864-2333; fax: 081-087-864-2369; e-mail: guo@eng.kagawa-u.ac.jp..

Muye Pang and Songyuan Zhang, Hayashi-cho, Takamatsu, 761-0396, Japan. Graduate School of Engineering, Kagawa University, Japan .

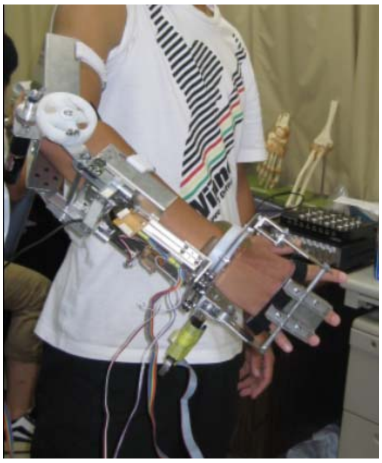


Figure 1. the Upper Limb Exoskeleton Rehabilitation Device (ULERD)

In this paper, surface electromyography (sEMG) signals derived from the unaffected upper limb were employed and then drove the rehabilitation device mounted on the affected upper limb as control signal. Therefore, the processing of sEMG signals is important and dominant in this paper which means the motion pattern recognition of the upper limb based on sEMG signals. The achievement of this research will be applied in an exoskeleton device (Figure 1) which we have developed in previous work [9]-[11]. It can provide assistance or resistance in three kinds of motion of human's upper limb.

The real time processing of EMG mainly includes four phases: signal acquisition, signal segmentation, feature extraction and classification. In the first phase (signal acquisition), there are two methods: invasively and non-invasively. During the second phase of signal segmentation, there are also two methods: disjoint and overlapped. Disjoint segmentation means that segments are divided in a certain length; overlapped segmentation means next segment slides over the current segment with a certain length which is shorter than that of segmentation. Oskoei and Hu assessed these two kinds of methods by comparing classification performance [12]. They indicated that the classification performance of overlapped segmentation is higher than that of disjoint segmentation. In the third phase of feature extraction, there are many methods proposed many years ago. In general, they can be separated into three types: time domain, frequency domain and time-frequency domain according to analysis method [13]. The methods of time domain mainly include Integrated EMG (IEMG), Mean Absolute Value (MAV), Modified Mean Absolute Value (MMAV) and so on [13]-[17]. The methods of frequency domain mainly include Auto-Regressive coefficients (AR), frequency Median (FMD), Modified Frequency Median

(MFMD) and so on [16] [17]. The methods of time-frequency domain were developed based on that in frequency domain and include Short Time Fourier Transform (STFT), Wavelet Transform (WT) and Wavelet Packet Transform (WPT) [18]-[20]. In the forth phase, there are many methods which are suitable for classification and attract many researcher to work on. The typical method is Artificial Neural Network (ANN) which is good at dealing with nonlinear problems [21]. Besides it, there are Bayesian classifier (BC), Fuzzy Logic Classifier (FLC) and Support Vector Machines (SVM) [22]-[24].

The EMG signal can be used widely, like multifunction prosthesis, wheelchairs, grasping control and gesture-based interfaces and so on [25]. In the application of rehabilitation, Krebs et al. [26] proposed a kind of rehabilitation system for upper limb motion for stroke survivors using EMG signals. In this filed, one problem is important and almost of researcher should be faced, which is how to process, analyze signal and identify the motion in real-time. Panagiotis K. Artemiadis et al. [27] proposed a methodology for the control of robots, in position and force using EMG signals from muscles of the shoulder and elbow and a switching model is used for decoding muscular activity to both joint angles and force exerted from the human upper limb to the environment. Hyeon-Jae Yu et al. [28] also proposed another real time tracking algorithm for human arm motion using EMG signals from upper arm and shoulder. Jiaxin Jiang et al. [29] used a four-layer feed-forward neural network which is processed by the wavelet transform to control exoskeleton knee using EMG signals in real time.

In this chapter, as the preliminary research of bilateral rehabilitation, three motions of unaffected upper limb are performed without any constraint and the sEMG signals related to these motions were recorded and analyzed by using AR model and WPT. Motion classification tool based Artificial Neural Network (ANN) was trained. Many facts can affect the quality of sEMG acquisition. Therefore, in this paper, there are two main phases to implement the motion pattern recognition in real time. One is batch processing, in this phase, ANN which can recognize the motion in current is trained automatically with an inertia sensor. In real time processing, the trained ANN previously is used to recognize the motion in real time without changing the current experimental condition. The first part of this paper presents the research target and relative researches. In the second part, the methodology of sEMG signals processing was presented. The third part shows the experimental setup and processing. The forth part shows the proposed exoskeleton device for upper limb rehabilitation. The last part is the conclusions.

II. METHODOLOGY OF SEMG SIGNALS PROCESSING

A. *Wavelet packet transform and feature extraction*

Wavelet was proposed based on the Short Time Fourier Transform (STFT) and it can be expressed as an infinite series of wavelets. The principle of wavelet transform is shifting and dilating one signal function which is called mother wavelet (1).

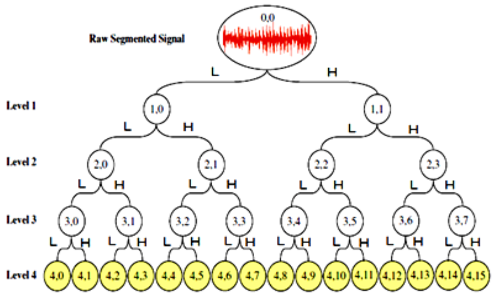


Figure 2. Decomposition tree and the four level of decompositions[33]

The wavelet can deal with the de-noising problem optimally with principle that it attempts to remove whatever noise is present and retain whatever signal is present without regarding the frequency content of the signal [30]. There are several kinds of mother wavelet proposed by some researchers [31], [32].

$$W_x(a,b) = \int x(t)\left(\frac{1}{\sqrt{a}}\right)\Psi^*\left(\frac{t-b}{a}\right)dt \tag{1}$$

where x(t) is the function representing the input signal, Ψ^* is the complex conjugate of the mother wavelet function, and $\Psi\ ((t-b)/a)$ is the shifted and scaled version of the wavelet at time b and scale a. The Discrete Wavelet Transform (DWT) is a transformation of the original temporal signal into a wavelet basis space. It decomposes a signal into an approximation signal and a detail signal and the approximation signal is divided again. 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 (Figure 2).

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 (2).

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

Where j is the resolution level and $\oplus$ stands for orthogonal decomposition. U_{-j-1}^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 (3) [20].

$$\begin{cases} u_{2n}(t) = \sqrt{2}\sum_{k\in Z} h(k)u_n(2t-k) \\ u_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} g(k)u_n(2t-k) \end{cases} \tag{3}$$

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_{-j}^{n-1}, the nth subspace on the jth level, can be reconstructed by (4).

$$s_j^n(t) = \sum_k D_k^{j,n} \psi_{j,k}(t), \ k \in Z \tag{4}$$

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 (5).

$$D_k^{j,n} = \int_{-\infty}^{\infty} s(t) \psi_{j,k}(t) dt \tag{5}$$

Most common approach of feature extraction of sEMG using WPT is entropy of wavelet packet coefficients. In this paper, we utilized MAV (6) and VAR (7) of wavelet packet coefficients with overlapped segmentation as feature vector to improve the response of real time recognition and effect of recognition.

$$M = \frac{1}{N} \sum_{i=1}^{N} \left| D_k^j \right| \tag{6}$$

$$V = \frac{1}{N} \sum_{i=1}^{N} (D_k^j - \overline{D}_k^j)^2 \tag{7}$$

B. AR model and feature extraction

Auto-Regressive model (AR) is known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter and it is an effective approach for decomposing the stochastic and non-stationary time sequences such as sEMG [34].

The definition that will be used here is as follows

$$y(n) = -\sum_{i=1}^{p} a_i y(n-i) + u(n) \tag{8}$$

Where a_i are the auto-regression coefficients, which is utilized as feature vector of sEMG signals. $y(n)$ is the series of sEMG signals, and p is the order of the filter which is generally very much less than the length of the series. $u(n)$ is white noise. There are many methods to obtain optimized p, such as Final Prediction Error Criterion (FPE) [35] and Akaike Information Criterion (AIC) [36. It is considered that four as order of the AR model can get a trade-off between effect and calculation cost.

C. Artificial Neural Networks and feature classification

An artificial neural network is a mathematical and computational model that is inspired by the structure of biological neural networks [37]. It is usually used to model nonlinear and complicated relationships between inputs and outputs and also widely utilized in pattern recognition. The most widely used neural network is the multi-layer perceptron. Through relative literature, the multi-layer feedforward network with Back Propagation seems the most widely used in pattern recognition. In this paper, an ANN of three-layers was designed: input layer, hidden layer and output layer. The input vectors derive from processed outcome of the feature extracted by WPT and AR model. Corresponding target vectors are generated automatically by using the data detected by an inertia sensor. Accordingly, the ANN can be trained until it approximates a function with specific output vector. There is no specific method to determine the optimized nodes number in hidden neurons, therefore, an optimized nodes number was obtained through many experiments of selecting different number. It was found that the ANN with 20 bidden neuros generates the most optimized train outcome. To avoid over fitting, all the input vectors are divided into three parts: 70% for training, 15% for evaluation and 15% for testing. The ANN is trained in the batch processing and it is used to classify the feature of sEMG in real time processing.

III. Experiments

A. SEMG acquisition

The sEMG signals were recoded by using the bipolar surface electrodes with 12mm in diameter, located 18mm apart, and the sampling rate is 1000Hz (Figure 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 (Oisaka 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.

Figure 3. Experimental setup of sEMG acquisition

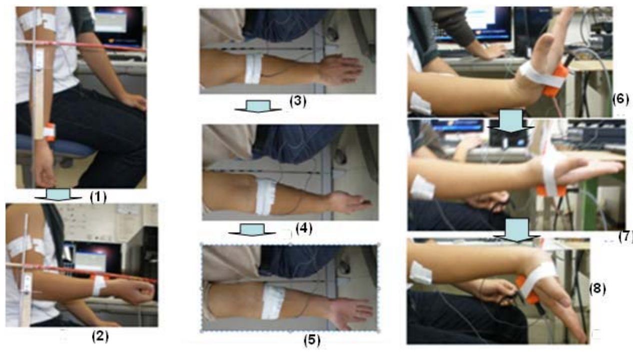


Figure 4. Three kinds of motion of the upper limb

TABLE I. AVERAGE RECOGNITION RATE FOR THREE MOTIONS

Motion	Muscles
EFE	Biceps brachii/triceps brachii
WFE	Extensor carpi ulnaris Extensor carpi radialis
WPS	Biceps brachii Extensor carpi radialis Anconeus muscle

B. Experimental process

The aim of this research is to do preparesion for bilateral rehabilitation for upper limb based on sEMG signals derived from the unaffected limb. According, we invited five healthy subjects to participate in the experiments which include three kinds motion recognition of the upper limb: Elbow Flexion and Extension (EFE), Wrist Flexion and Extension (WFE) and Wrist Pronation and Supination (WPS) (Figure 4). Detected muscles of three motions are shown in Table I.

All the subjects were required to perform the motions mentioned above without any constraint on their limbs. Each motion was performed 15 times. In elbow flexion and extension, every subject was required to lift his forearm from vertical plane to horizontal plane with upper arm stable and then extended it to original position (Figure 4 (1) and (2)). There are four motion patterns to be recognized: stop, flexion, stop on the horizontal plane and extension (S, F, SH and E). In forearm pronation and supination motion, every subject was required to perform motion from the status at (Figure 4 (4)) to (Figure 4 (3)) and return back and then from original pose to the pose at (Figure 4(5)) and last return back again. During this process, there are three motion patterns to be recognized: stop, pronation and supination (S, P and SP). In wrist flexion and extension, every subject was required to perform the motions like forearm pronation and supination and it also includes three motion patterns (S, F and E). During all of experiments, the motions of upper limbs were detected with an inertia sensor, which can be used to divide the motion and provide target vectors for ANN. Transfer function used in ANN is shown in (9).

$$Tan\sin(n) = 2/(1+\exp(-2*n))-1 \qquad (9)$$

Where n is the weighted sum of the inputs. Since situation of electrodes contact with a subject's skin can influence the qualities of sEMG, building the new ANN to each experimental condition will improve the outcome of recognition. It is not only suitable to each subject, but also suitable to each experiment. To implement it, there are two phases (Figure 5). The first phase is batch processing. During this phase, motion of upper limb can be detected and divided by using the inertia sensor automatically according to the desired patterns mentioned above. On the other hand, sEMG signals collected synchronously are processed with two methods: AR model and wavelet packet transform. After the motion finished, sEMG signals are processed with divided in a slide window. To compare the recognition rate of both methods, the same slide window (250 samplings) was set.

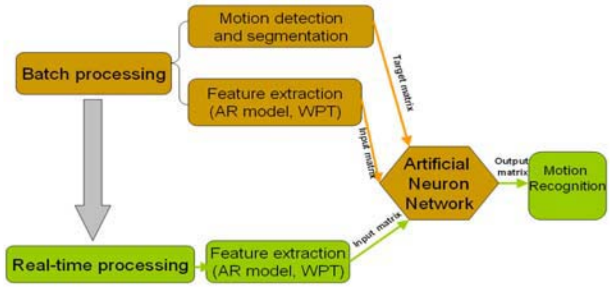


Figure 5. The flowchart of implementation of motion recognition

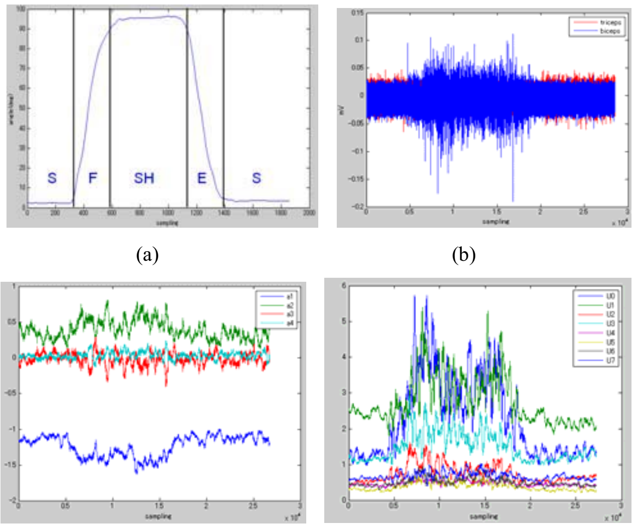
Therefore time delay was within 300ms and the structure of ANN and the transfer function are the same. The mother wavelet selected is Daubechies 2. According, the input matrix is the coefficients of AR model and MAV and VAR of coefficients of WPT respectively; the target matrix is the segmentation of motion which is group of binary data. After the ANN built, real time processing can be carried out. Once data of sEMG collected filled in the slide window, feature extraction and motion recognition are performed by using the trained ANN.

IV. EXPERIMENTAL RESULTS

Each subject was required three kinds of motion and ten motion patterns should be recognized in total. Each motion was performed 15 times by each subject and the subject can rest 30 seconds after finishing one motion so that he did not feel tired.

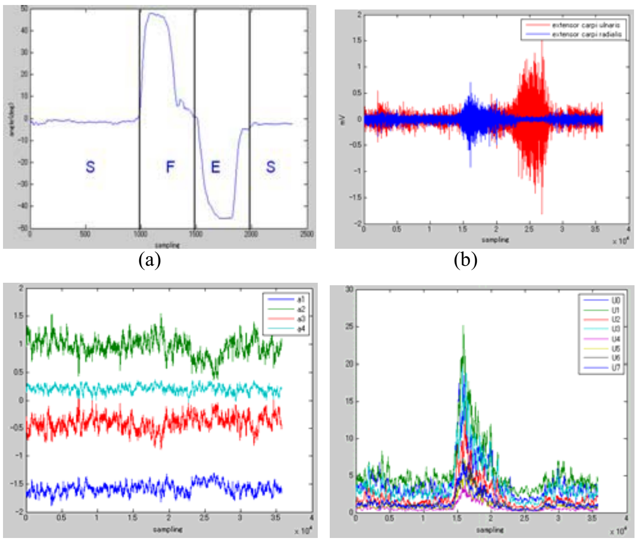
Following figures show the typical experimental results for subject A. Figure 6 (a) shows the angle of elbow flexion and extension. In this figure, there are four motion patterns: stop, flexion, stop on the horizontal plane and extension (S, F, SH and E), which can be divided automatically by using the inertia sensor. Figure 6 (b) shows the sEMG signal collected from triceps and biceps brachii during EFE. From this figure, the signal noise ratio (SNR) is low because this motion is performed at slow speed and no any additional load exerted to the subject's limb. It is difficult to recognize the motion under this condition but it is useful in activity of daily living (ADL). The response of biceps brachii is more active than triceps brachii. As the typical signal, coefficients of AR model which was as input vectors of ANN was shown in Figure 6 (c). There are four groups of coefficients because AR model was selected with order 4. Figure 6 (d) also presented the processed results of sEMG detected from biceps brachii. Because the effective sEMG signals focus on 20 to 150Hz, the components of low frequency were selected and its MAV data were shown in Figure 6 (d).

Figure 6 shows the typical experimental results of wrist flexion and extension. In the experiment of wrist flexion and extension, there are three motion patterns to be recognized. First is relaxing posture with palm in the horizontal plane (Figure 4 (7)), which is shown as "S" in Figure 7 (a). Second is flexion motion from status on Figure 4 (7) to status on Figure 4 (6) and then come back to Figure 4 (7) which is shown as "F" in Figure 7 (a). Third is extension motion from status on Figure 4 (7) to status on Figure 4 (8) and then come back to Figure 4 (7) which is shown as "E" in Figure 7 (a).



(a) (b) (c) (d)

Figure 6. One typical experimental results of elbow flexion and extension. (a) shows the angel of elbow flexion and extension; (b)shows the sEMG signal derived from triceps and biceps brachii during EFE; (c) shows coefficients of AR model derived from processing of sEMG signals of biceps brachii; (d) shows the MAV of coefficients of WPT of sEMG signals of biceps brachii.

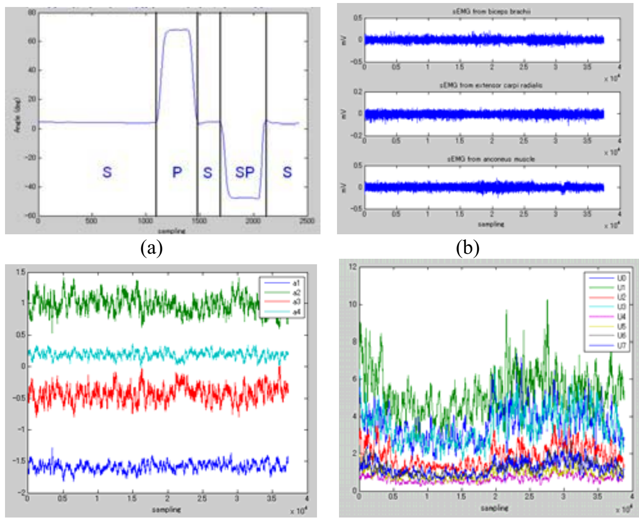


(a) (b) (c) (d)

Figure 7. One typical experimental results of wrist flexion and extension. (a) shows the angel of wrist flexion and extension; (b)shows the sEMG signal derived from extensor carpi ulnaris and extensor carpi radialis during WFE; (c) shows coefficients of AR model derived from processing of sEMG signals of extensor carpi radialis; (d) shows the MAV and VAR of coefficients of WPT of sEMG signals of extensor carpi radialis.

Figure 7 (a) shows the angle of wrist flexion and extension. Figure 7 (b) shows the sEMG signals from extensor carpi ulnaris and extensor carpi radialis during this motion. Figure 7 (c) and figure 7 (d) show the coefficients of AR model and MAV of coefficients of WPT of sEMG signals derived from extensor carpi radialis.

In the experiment of wrist pronation and supination, we found it is difficult to get effective sEMG signal from extensor carpi radialis and anconeus muscle under a free condition. According, we detected the sEMG from biceps brachii with the forearm of a subject on horizontal plane. Figure 8 shows the typical experimental results of WPS.



(a) (b) (c) (d)

Figure 8. One typical experimental results of wrist pronation and supination. (a) shows the angel of wrist pronation and supination; (b)shows the sEMG signal derived from biceps brachii, extensor carpi radialis and anconeus muscle during WPS; (c) shows coefficients of AR model derived from processing of sEMG signals of anconeus muscle; (d) shows the MAV of coefficients of WPT of sEMG signals of anconeus muscle.

TABLE II. VERAGE RECOGNITION RATE FOR THREE MOTIONS

Subjects	Motion	Elbow F/E	Forearm P/S	Wrist F/E
A	AR	74.5%	91.4%	90.7%
	WPT	78.2%	93.8%	95.4%
B	AR	73.1%	87.8%	86.6%
	WPT	79.4%	91.4%	93.2%
C	AR	77.4%	90.1%	89.9%
	WPT	81.0%	92.0%	94.4%
D	AR	74.0%	89.7%	91.2%
	WPT	84.9%	92.8%	94.5%
E	AR	82.1%	92.7%	91.8%
	WPT	87.7%	93.1%	96.7%

From the Table II, recognition of wrist flexion/extension gained the highest rate and the elbow flexion/extension was recognized in the lowest rate. Because the motion patterns in elbow flexion and extension recognized are more than the other two motions, the recognition rate of former is lower than the other two motions. Especially, we found it is difficult to recognize when the extension happened, which means the sEMG signals hardly changed from “SH” to “E”, so that it is time delay to recognize the elbow extension in real time processing. Another important result which can be found in Table II is that the recognition ratio with WPT is higher than that with AR model. Maybe because the WPT can not only exact the feature of motion but also filter the undesired signals according to its lower filter function. The recognition rate online is not stable and not as high as that in the case of off-line.

V. CONCLUSION

sEMG signals has a widespread application like muscle diagnosing, human machine interface. In this paper, we presented motion patterns recognition based on sEMG, which aims to implement the bilateral training. In special we focused on the feature exaction of three kinds of motion by using

Autoregress (AR) model and Wavelet Packet Transform (WPT). We used an inertia sensor to track and record all the motions and divide the motions into several segments to train the Artificial Neural Network (ANN) as target vectors. In order to improve the effect of the ANN, we designed experiments with two phases so that the effect of contact condition of electrodes with skin can be avoided. According to the experimental results, the recognition rate of wrist flexion and extension is the highest. The recognition rate of elbow flexion and extension is lower because the statuses to be recognized are more than the other. On the other hand, the recognition ratio using coefficients of wavelet packet transform as input of artificial neural network is higher than that of using parameters of AR model.

ACKNOWLEDGMENT

This research was supported by the Kagawa University Characteristic Prior Research Fund 2011.

REFERENCES

[1] G. O. Young, Latimer CP, Keeling J, Lin B, Henderson M, Hale LA. The impact of bilateral therapy on upper limb function after chronic stroke: A systematic review. *Disabil Rehabil*. Vol.32, No.15, pp.1221-1231, 2010.

[2] Summers JJ, Kagerer FA, Garry MI, Hiraga CY, Loftus A, Cauraugh JH. Bilateral and unilateral movement training on upper limb function in chronic stroke patients: A TMS study. *J Neurol Sci.* ; Vol.252, No.1, pp. 76-82, 2007.

[3] Cauraugh JH, Lodha N, Naik SK, Summers JJ. Bilateral movement training and stroke motor recovery progress: A structured review and meta-analysis. *Hum Mov Sci.* Vol. 29, No.5, pp.853-870, 2010.

[4] Cauraugh JH, Summers JJ. Neural plasticity and bilateral movements: a rehabilitation approach for chronic stroke. *Prog Neurobiol.* Vol.75, pp. 309–320, 2005.

[5] Taub E. Harnessing brain plasticity through behavioural techniques to produce new treatments in neurorehabilitation. *Am Psychol.* Vol.59, pp. 692–704, 2004.

[6] Z. Song, S. Guo, and Y. 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.

[7] P. Lum, D. Reinkensmeyer, R. Mahoney, W. Z. Rymer and C. Burgar, Robotic devices for movement therapy after stroke, *IEEE Trans. Neural Syst. Rehabil. Eng,* Vol. 10, pp.40-53, 2002.

[8] L. E. Kahn, W. Z. Rymer and D. J. Reinkensmeyer, Adaptive assistance for guided force training in chronic stroke, *Proc of 26th Ann Int. Conf. of the IEEE EMBS*, pp. 2722-2725, 2004.

[9] Z. Song and S. Guo, "Development of a Master-slave System for Upper Limb Rehabilitation", *The 5th International Conference on Advanced Mechatronics*, pp.768-773, 2010.

[10] Z. Song, S. Guo, "Implementation of Self-rehabilitation for Upper Limb based on a Haptic Device and an Exoskeleton Device", Proceeding of the 2011 IEEE International Conference on Mechatronics and Automation, pp.1911-1916, 2011.

[11] Zhibin Song and Shuxiang Guo, Design Process of a Novel Exoskeleton Rehabilitation Device and Implementation of Bilateral Upper Limb Motor Movement, J*ournal of Medical and Biological Engineering*, Vol.32. 3, 2011.

[12] M.A. Oskoei and H. Hu. Support vector machine-based classification scheme for myoelectric control applied to upper limb, *IEEE Transactions on Biomedical Engineering*, Vol.55, No.8, pp.1956–1965, 2008.

[13] M. Zecca, S. Micera, MC Carrozza, and P. Dario. Control of multifunctional prosthetic hands by processing the electromyographic signal. *Critical Reviews in Biomedical Engineering*, Citeseer, Vol. 30, No.4, pp.459-468, 2002.

[14] Naik, G.R., Kumar, D.K., Arjunan, S.P. Pattern classification of Myo-Electrical signal during different Maximum Voluntary Contractions: A Study using BSS Techniques. Meas. Sci. Rev., Vol.10, No.1, pp. 1-6, 2010.

[15] K. Englehart and B. Hudgins. A robust, real-time control scheme for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering*, Vol. 50, No.7, pp. 848–854, 2003.

[16] A. Phinyomark, C. Limsakul, and P. Phukpattaranont. A novel feature extraction for robust EMG pattern recognition. *Journal of Computing*, Vol. 1, No.1, pp.71–80, 2009.

[17] M.A. Oskoei and H. Hu. GA-based feature subset selection for myoelectric classification. *In Proc. Int. Conf. Robot. Biomimetics*, pp.1465–1470, 2006.

[18] 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. *Processings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai*, pp.2672-2674, 2005.

[19] M. Weeks. Digital signal processing using MATLAB and wavelets. Jones and Bartlett Publishers, LLC, second edition, 2011.

[20] Saevarsson Gdmundur, Sveinsson Johannes R, Benediktsson Jon Atli. Wavelet-packet Transformation as a preprocessor of EEG waveforms for classification. Proc. Of 19th Int. Conf. IEEE/EMBS. Chicago, USA, pp. 1305–1308, 1997.

[21] S.S. Haykin. Neural networks and learning machines, Vol. 10. Prentice Hall Upper Saddle River, NJ, 2009.

[22] T.M. Mitchell. Machine learning. Mac Graw Hill, 1997.

[23] SN Sivanandam, S. Sumathi, and SN Deepa. Introduction to fuzzy logic using MATLAB. Springer Verlag, 2007.

[24] E. Alpaydin. Introduction to machine learning. The MIT Press, 2004.

[25] Oskoei MA, Hu H: Myoelectric control systems-A survey. *Biomedical Signal Processing and Control*, Vol. 13, pp.275-294, 2007.

[26] L. Dipietro, M. Ferraro, J. J. Palazzolo, H. I. Krebs, B. T. Volpe, and N. Hogan, Customized interactive robotic treatment for stroke: Emg-triggered therapy, *IEEE Trans. Neural Syst. Rehab. Eng.*, Vol. 13, No.3, pp. 325-334, 2005.

[27] Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, EMG-based position and force estimates in coupled human-robot systems: towards EMG-Controlled exoskeletons, in experimental robots, *springer tracts in advanced robotics*, Vol.54, pp.241-250. 2009.

[28] 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.

[29] 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.

[30] 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.

[31] Daubechies. I., Orthonormal bases of compactly supported wavlets, Commun. *Pure Applied Mathematics*. Vol. 41, pp. 909-996. 1988.

[32] Meyer, Y., Orthonormal Wavelets, Wavelets, time-frequency methods and phase-space, *Springer-Verlag*, pp.21-37. 1989.

[33] Mohammad Karimi., A Novel Prosthetic Hand Control Approach Based on Genetic Algorithm and Wavelet Packet Transform Features, Proceedings of the World Conference on Engineering 2011.

[34] Zhen Gao and Dan Zhang. Surface Electromyographic Sensor for Human Motion Estimation Based on Arm Wrestling Robot. Sensors & Transducers. Vol. 117.6. pp.50-61.2010.

[35] Inan Guler, M. Kemal Kiymik and Nihal Fatma Guler. Order Determination in Autoregressive Modeling of Diastolic Heart Sounds. Journal of Medical Systems.Vol.20. pp.11-17. 1999.

[36] Silvestro Micera, Angelo M.Sabatini, Paolo Dario and Bruno Rossi. A Hybrid Approach to EMG Pattern Analysis for Classification of Arm Movements using Statistical and Fuzzy Techniques. Medical Engineering & Physics. Vol.21. pp.303-311.1999.

[37] 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.