Proceedings of 2012 IEEE
International Conference on Mechatronics and Automation
August 5 - 8, Chengdu, China

A Surface EMG Signals-based Real-time Continuous Recognition for the Upper Limb Multi-motion

Muye Pang[*2] Shuxiang Guo[*1,*3] Zhibin Song[*1] and Songyuan Zhang[*2]

*[*1] Department of Intelligent Mechanical Systems Engineering*
*[*2] Graduate School of Engineering*
Kagawa University
Hayashi-cho, Takamatsu, 761-0396, Japan
{s12d505,s11g528}@stmail.eng.kagawa-u.ac.jp

*[*3] College of Automation*
Harbin Engineering University
145 Nantong Street, Harbin, Heilongjiang, China
{guo,song}@eng.kagawa-u.ac.jp

***Abstract* - This paper was aimed at the continuous recognition of the upper limb multi-motion during the upper limb movement for rehabilitation training. The amplitude of the surface electromyographic (sEMG) signals change during movement of the upper limb and the features of sEMG signals are different with the changes. These variances in the features represent the different statuses of the upper limb. Recognizing the variances will lead to recognition of the upper limb motion. In this study, sEMG signals were recorded through five non-invasive electrodes attached on the anatomy points of the upper limb and an autoregressive model was used to extract the features of the detected sEMG signals. After that the Back-propagation Neural Networks was applied to recognize the patterns of the upper arm motion using the variant features as the training and input data. Three volunteers participated in the real-time experiment and the results stated that this method is effective for a real-time continuous recognition of the upper limb multi-motions.**

Index Terms – Electromyography, Continuous recognition, Multi-motion, Rehabilitation.

I. INTRODUCTION

Aimed at solving the problems of increasing requirements for the therapy of rehabilitation because of the increasing number of hemiplegic patients, a robotic rehabilitation strategy, with the characteristic of more intensive, longer duration and higher-level training, was applied to therapy processes to help with conquering this situation. Many studies demonstrated that the robotic rehabilitation has a great potential for better therapeutic rehabilitation, such as the MIT-MANUS, which is one of the most famous and earliest upper-limb rehabilitation robot and has the ability to guide the movement of a subject's or patient's upper limb with impedance control[1]; and the MIME, which can perform bimanual robot-assisted recovery training at any impairment level and complete stereotyped movement patterns[2]. And also, there are many rehabilitation robots for hand and lower-limb movement function restoration, such as the EMG-driven exoskeleton hand robotic training device, which is mounted on patient's impaired hand and detects the sEMG signals as the driven signals[3]; the EMG-driven musculoskeletal model of the ankle, which combines the Hill-model and sEMG signals to estimate the forces of the triceps surae muscle and Achilles tendon[4]; and a real-time upper limb's motion tracking exoskeleton device for active rehabilitation[5].

Among these rehabilitation robots, the recognition of the limbs or hands movement patterns is one of the most important issues. Generally, position sensors are attached on subjects' or patients' limbs[6-8], or a predefined trajectory was designed before a rehabilitation progress[9-10]. With the development of electromyography technology, the EMG signals have been applied to limbs movement pattern recognition. The EMG signals, which represent for the nature activation potentials of skeleton muscle, can provide a direct index to the status of whether the muscle is activated or not. There are mainly two kinds of EMG signals measurement: the surface EMG signals detection method using non-invasive surface electrodes and the invasive EMG signals detection method using fine wire electrodes. They have been applied on the control for prosthesis[11]. In many cases, a certain threshold is set for the value of the amplitude of the EMG signals to estimate the activation of the muscle, such as in the exoskeleton hand robotic training device, a 20% of the maximum voluntary contraction threshold was set[11]. This method is simple and useful but has its own disadvantage. The value of the threshold can only be set experientially, and with the different individual conditions, it is hard to find a proper value for all the subjects.

In this study, a real-time continuous recognition of the upper limb multi-motion was realized with the implementation of autoregressive (AR) model and Back-propagation (BP) Neural Networks, without threshold set. As mentioned above, the amplitude of the sEMG signals change with the movement of upper limb and the features of the amplitude are different with the changes. Thus these variances in the features represent the different statuses of the upper limb. With the characteristic of the AR model, the coefficients of this model have potential to stand for the changes in the amplitude and the BP Neural Networks was used to train and recognize the movement patterns with these coefficients.

II. DESIGN OF THE MULTI-MOTION RECOGNITION METHOD

In this study, the upper limb multi-motion includes the upper arm flexion and extension, forearm pronation and supination and palmar flexion and dorsiflexion. As these three movements involve three pairs of muscles, which are biceps brachii and triceps brachii, pronator quadratus and pronator teres, extensor digitorum and flexor digitorum superficialis respectively, three pairs of surface electrodes were attached above the skin of these muscles to detect the three movements individually. And the multi-motion recognition is based on the combination of these individual movements recognition.

A. Recognition of Individual Movements

The amplitude of sEMG signals changes during upper limb movement, given rise to the changes of the motor unit action potentials (MUAP), which reflect the magnitude of the muscle activation essentially. Fig.1 shows a normalization result of the detected raw sEMG signals from the biceps brachii during the upper arm flexion and extension, compared with the value of the elbow angle collected from a position sensor. It indicates that the trend change of the sEMG signals amplitude has a high correlation with the movement of the upper arm.

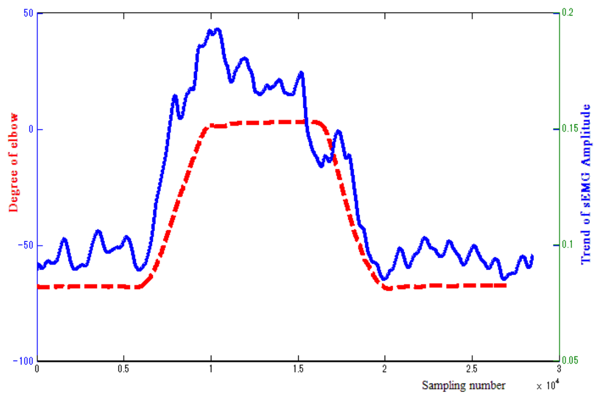


Fig. 1 The angle degree of the elbow to the trend of sEMG amplitude

And the general flow chart for single movement recognition is presented in the following figure(fig.2), which includes four parts: the sEMG signal filtering, recording, feature extraction and BPNN recognition.

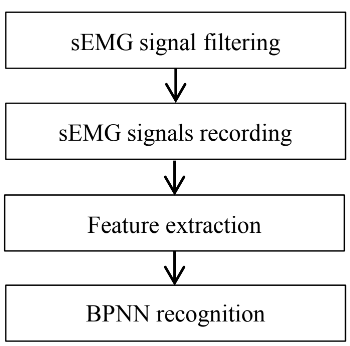


Fig.2 A general flow chart for single movement recognition

The autoregressive (AR) model was used to extract the feature of the filtered raw sEMG signals. In statistics and signal processing, an AR model is a type of random process which is often used to model and predict various types of natural phenomena. And AR model was first introduced to represent the muscle activation electrical behavior since 1975[12]. The AR model is defined as following

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (1)$$

where p is the order of the AR model; X_t is the value of the data; φ_i is the coefficients; c is a constant and ε_t is a white noise.

According to the function of the AR model, which is to predict a future output of a system based on the previous detected input, it is reasonable to consider the coefficients have some representativeness for the sequence of the input data. Fig.3 , in which the red line represents the second order of the AR model, provides some calculation results using the Burg method to fit a 4 order AR model to the raw sEMG signals. The changes of the coefficient follow the changes of the amplitude of the original signals.

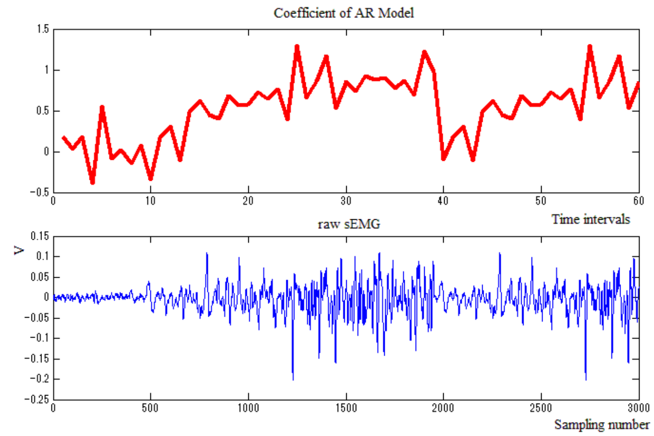


Fig.3 The change of AR model coefficients compared to the amplitude trend of sEMG signals

As Fig.2 showed, after feature extraction, the Back-propagation Neural Networks (BPNN) was applied to realize the recognition of the upper limb movement. The activation function of the BPNN is described as following:

$$f(s) = \frac{1}{1 + e^{-\mu s}}$$

where μ is a constant coefficient and s is the summation of the input defined as following:

$$s = \sum w_i x_i$$

where w_i is weighted parameter to each input to the neural node. The learning method is the back propagation algorithm:

$$\begin{cases} w_i^q(k+1) = w_i^q(k) + \alpha D_i^q(k+1) \\ D_i^q(k+1) = \sum \delta^q f^{q-1} \\ \delta^q = (\sum \delta^{q-1} w^{q-1}) \mu f^q (1 - f^q) \\ f^q = \dfrac{1}{1 + e^{-\mu s^q}} \\ s^q = \sum w^q x^q \end{cases}$$

where w_i^q is the ith node weight coefficient of the qth hidden layer and x^q is the input of the qth hidden layer. The input matrix to the BP neural network is the combination of the coefficients vector of the AR model, which forms as follows:

$$\begin{pmatrix} a_{11} & \cdots & a_{1p} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{np} \end{pmatrix}$$

where n is the number of the input vectors and p is the AR model order. The output matrix is the combination of the quantification of the upper limb movement classification and different classifications have unique combinations of zeros and one. As the following matrix shows:

$$\begin{pmatrix} 1\,0\,0 \\ 1\,0\,0 \\ \vdots \\ 0\,1\,0 \\ 0\,0\,1 \end{pmatrix} \tag{4}$$

where the row one and two belong to the same classification and row three and four belong to the different ones. The rank of the output matrix is the classification number of the upper limb movement.

After the raw sEMG signals recorded from upper limb, they are fitted using the AR model with the Burg algorithm. Then the coefficients of the model are combined with the expected output column to be as the training data of the BPNN. And this well-trained BPNN is applied to the signal movement recognition.

B. *Recognition of Multi-motion*

The multi-motion recognition is based on the single-motion recognition. There are three individual BPNN to the three upper limb movements after single-motion recognition. Although the three pairs of muscles have coupling relationship during multi-motion, such as when doing the upper arm flexion while forearm pronating or supinating, the value of the sEMG signals amplitude is higher than the one in the single upper arm flexion movement, this coupling relationship just amplified the single movement function and the generalization ability of the BPNN makes it possible to classify them correctly in this range of amplification.

Fig.4 shows a sketch of the multi-motion recognition:

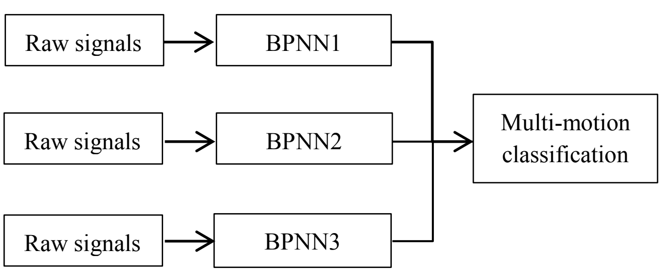


Fig.4 Multi-motion recognition

where the BPNN1, BPNN2 and BPNN3 represent for the individual neural networks.

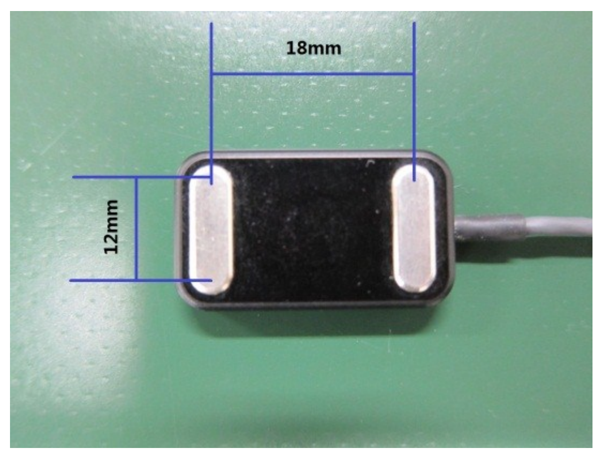
The raw sEMG signals recorded from the different pairs of muscles are calculated using the AR model and send to the coordinate well-trained BPNN to finish the motion pattern recognition. Each recognition result is sent to the multi-motion classifier which combines the three recognition information to make out the final result.

III. Experiments and Results

A. *Experimental System*

The sEMG signals were collected using the bipolar surface electrodes with 12mm in length, located 18mm apart, and the sampling rate is 3000Hz with differentially amplified (gain 1000) and common mode rejection (104dB). The sampling data were pre-processed with a commercial filter box (Oisaka Electronic Device Ltd. Japan.) before recorded to the control program with the sampling rate of 1500Hz (as the most frequency power of EMG signals are between 20 to 150Hz) through an AD board (PCI3165, Interface Co. Japan). The surface electromyographic activities were monitored from the biceps brachii and triceps brachii.

(a). The personal EMG filter box



(b). The surface electrode

Fig.5 The sEMG signals recording devices.

The user interface was programmed using Visual C++ 2010 (Microsoft Co. USA) which can collect A/D data from the AD board through the application programming interface and process the data with MATLAB (MathWorks Co. USA) via a communication from the custom interface to the commercial software running on a person computer with a 2.8GHz quad-core processor (Intel Core i7 860) and 4GB RAM. The general sketch of the custom GUI is showed in Fig.6

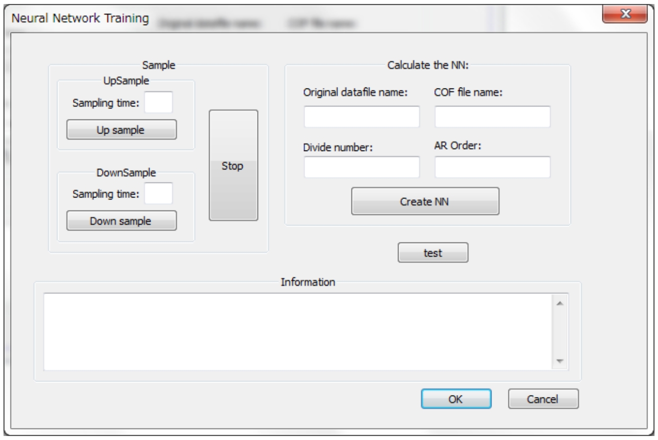


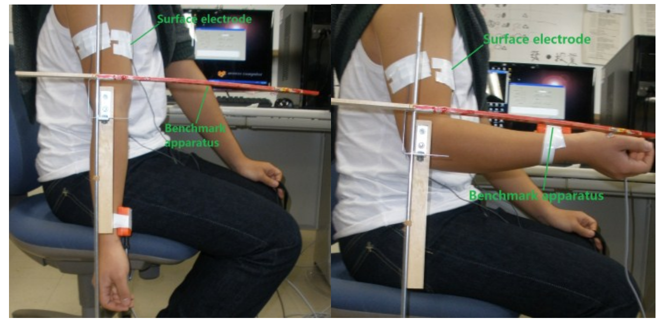
Fig.6 The Custom GUI for application

B. *Experimental Protocol*

Three healthy volunteers (age from 22-26, all male, one left handed and two right handed) participated in the experiment. Before placing the electrodes which were aligned parallel to the muscle fibres over the belly of the muscle and positioned following the recommendations, the skin was shaved, abraded and cleaned with alcohol in order to reduce the skin impedance. In order to generalization the upper limb movement of the volunteers, their motions were restricted as requirement directing by a video. In the experiment of upper arm flexion and extension, the volunteer were asked to sit on a chair started with upper limbs relaxed vertically fitting to the vertical pillar of the benchmark apparatus (as shown in Fig.7 a) and then contracted their experimental upper forearm to the horizontal beam (as shown in Fig.7 b). After a short stop keeping the forearm to the horizontal position, the volunteer was asked to extend the forearm to the initial vertical position. In the experiment of forearm pronation and supination, the upper arm kept vertical and volunteer only pronated with his forearm, keeping the upper arm still. There is a cross mark on the ground to be the benchmark for pronation and supination(as shown in Fig.8). In the experiment of palmar flexion and dorsiflexion, volunteer kept his forearm horizontal and flexed or dorsiflexed to the contracted bounds(as shown in Fig.9).

Each volunteer repeated these three experiments fifteen times with a relaxation of one minute in every five tests. The raw sEMG signals were recorded separately from the three experiments and a special BP neural network coordinate to one experimenter would be trained using the collected data from the ten times repeated tests. After all the three volunteers finished their experiments, there were three independent neural networks belong to the different experimenters. The movement of each volunteer had been recognized with their own neural networks and the results were applied to the multi-motion recognition.

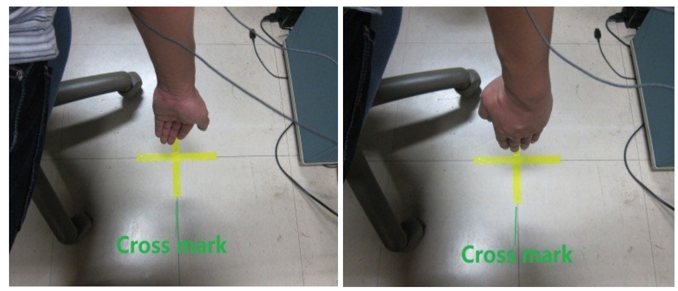
In the multi-motion experiments, there were three combination motions: the upper arm flexion while forearm pronation or supination, the forearm pronation while palmar flexion or dorsiflexion, and the upper arm flexion while palmar flexion or dorsiflexion. There is no strict restriction in the multi-motions but each part of the movement was followed the direct in the single motion experiment. Each volunteer repeated each experiment ten times.



(a). The start position of the experiment

(b). The vertical position as the keeping position in the experiment, from which forearm moves downward

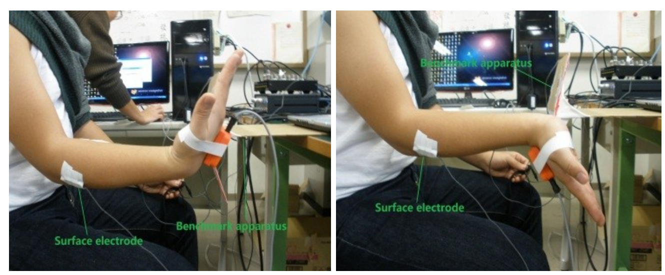
Fig.7 Experimental procedure A.



(a). The forearm pronation

(b). The forearm supination

Fig.8 Experimental procedure B.



(a). The palmar flexion

(b). The palmar dorsiflexion

Fig.9 Experimental procedure C.

C. *Experimental Results*

There is a constraint that the AR model requires the predicted data to be wide-sense stationary. It has been indicated that the raw sEMG signals are non-stationary[13]. But with sufficient short time intervals, this nature electrical behavior could be considered stationary. In this study, the time interval was set as 33ms (every 50 samples at 1500Hz sampling rate). And the Akaike Information Criterion (AIC), which is described as followed, was used to optimize the order of the AR model:

$$AIC(p) = \ln(E_p) + 2(p+1)/N \tag{2}$$

where E_p is the estimated linear prediction error variance for the model with order p and N is the number of input sEMG signal. The order which minimizes the AIC function results will be selected as the optimal one. The value of AIC method was represented in table 1 with the AR model order p from 1 to 40 and Fig.10 describes a general trend of the changes and table 1 shows the detail value.

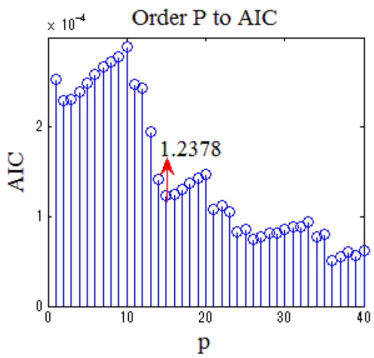


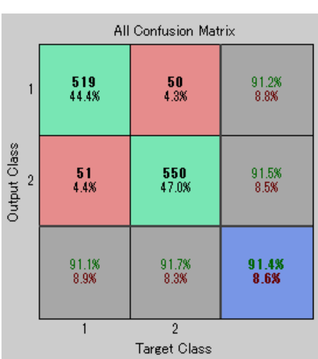
Fig.10 The value of AIC algorithm to the increasing of order p

Fig.10 provides that the trend of the AIC value decreases gradually with small increasing during order 2 to 10. From order 10 to 15, there is a distinct decrease (from 2.899×10^{-4} to 1.237×10^{-4}) and from 16 to 40 the decrease is not very overt ignoring little increasing during some ranges. Considering the calculation time cost, 15 was selected as the optimal order for the AR model.

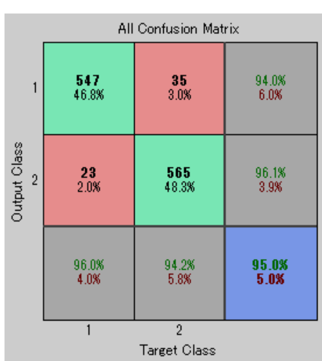
In the single movement recognition experiment, every volunteer repeated each movement 15 times, and each movement took about 4 to 5 seconds at the sampling rate of 1500Hz in two channels. And about 225000 samples were recorded in each experiment for one volunteer. 10 in the 15 groups samples were divided as the training data and the other 5 as the test data for ANN. All the data was calculated with the time interval of 33ms. Table 2 lists the recognition accruace result, where the Group A, Group B and Group C mean the upper arm flexion and extension, palmar flexion and dorsiflexion and forearm pronation and supination respectively, and Fig.11 is the performances of these individual BPNNs.

Table II. Accuracy of the BP artifical neural network

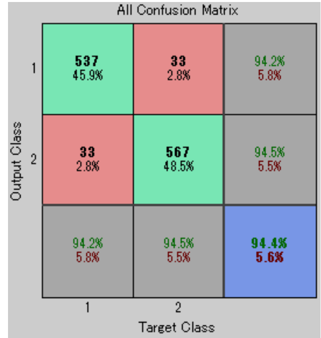
Volunteer	Group A (%)	Group B (%)	Group C (%)
A	91.4	86.7	78.4
B	95.0	85.9	78.8
C	97.1	85.6	80.5



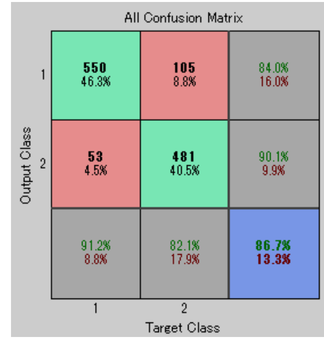
(a)Group A of Volunteer A



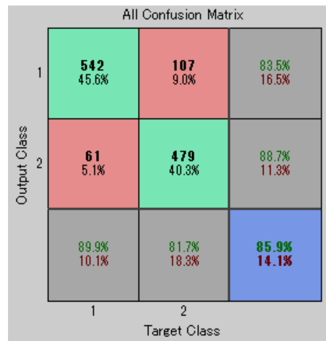
(b) Group A of Volunteer B



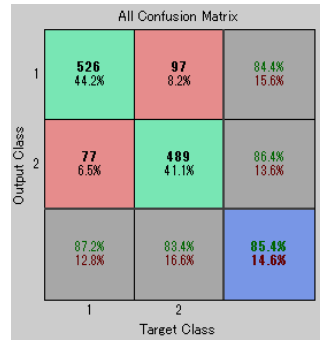
(c) Group A of Volunteer C



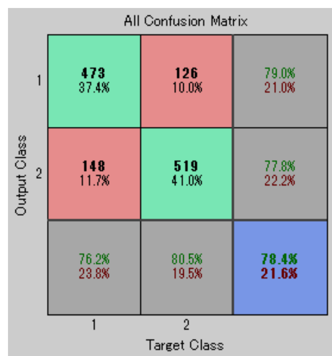
(d) Group B of Volunteer A



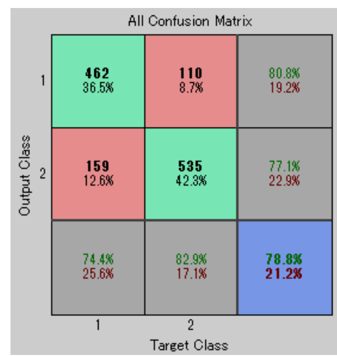
(e) Group B of Volunteer B



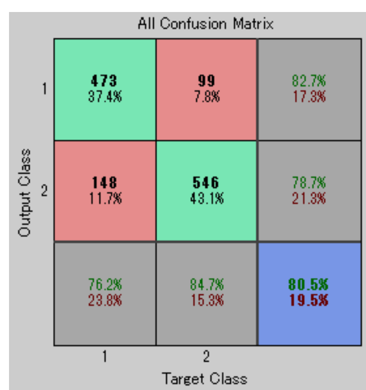
(f) Group B of Volunteer B



(g) Group C of Volunteer A



(h) Group C of Volunteer B



(i) Group C of Volunteer C

Fig.11 The confusion matrix of the performance, Group A, Group B and Group C mean the upper arm flexion and extension, palmar flexion and dorsiflexion and forearm pronation and supination respectively.

Table II. The value of AIC algorithm to the increasing of order p

P	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
AIC	**2.53**	**2.29**	**2.31**	**2.39**	**2.48**	**2.59**	**2.67**	**2.73**	**2.87**	**2.90**	**2.47**	**2.43**	**1.94**	**1.42**	**1.24**	**1.25**	**1.31**	**1.37**	**1.43**	**1.48**
P	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
AIC	**1.08**	**1.12**	**1.06**	**0.83**	**0.86**	**0.75**	**0.77**	**0.82**	**0.80**	**0.86**	**0.88**	**0.88**	**0.94**	**0.78**	**0.80**	**0.56**	**0.55**	**0.61**	**0.57**	**0.63**

In the multi-motion recognition experiments, three combination of movments were performed by volunteers. They were the upper arm flexion while forearm pronation or supination, the forearm pronation while palmar flexion or dorsiflexion, and the upper arm flexion while palmar flexion or dorsiflexion. Total six electrodes were attached on volunteer's upper limb and the sEMG signals of the six channels were recoded separately. Each pair of the signals was calculated simultaneously and sent to the correlative BPNN for recognition. Table 3 lists the recognition accruace result, where the Group A, Group B and Group C mean the upper arm flexion while palmar flexion or dorsiflexion, the palmar flexion while forearm pronation or supination, and the upper arm flexion while forearm pronation or supination respectively.

Table III. Accuracy of the multi-motion recognition

Volunteer	Group A (%)	Group B (%)	Group C (%)
A	89.4/84.4	83.7/80.0	90.2/72.4
B	88.0/83.1	81.9/73.5	90.3/74.8
C	90.1/80.0	81.6/77.3	89.5/73.5

IV. Discussion

In this paper, a sEMG based continuous pattern recognition for upper limb multi-motion has been presented. In many cases, a certain threshold is set for the value of the amplitude of the EMG signals to estimate the activation of the muscle. In this study, no threshold is set and all the volunteers did the experiment in the natural and relaxed conditions and the motions are recognized without a threshold value. A BPNN was applied into the recognition of the motions. Considering the individual conditions between persons, different BPNNs are trained to estimate the movement patterns. The generalization ability of the BPNN can achieve a high recognition accuracy rate.

During the three single movement recognitions, the recognition of forearm pronation and supination is the lowest. In the experiment, the pronator quadratus which involves the forearm pronator is not very easy to be detected and the raw signals recoded during the forearm pronation were not clearly to be discriminated. There was no overt difference of the recognition accuracy between different volunteers in the same movement. But the personal inherent conditions, such as different tissue characteristics, are different individually, so the recognition accuracy of the same movement is not the same during volunteers.

The multi-motion recognition results are some like the ones in the single movement recognition. But in most the cases, the accuracy declines which may be given rise to the coordination of the muscle during multi-motion. Such as in the motion of upper arm flexion while forearm pronation, the biceps are activated during extension because of forearm pronation, which made it like the raw signals in the flexion movement.

Acknowledgment

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

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