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sEMG Based Movement Quantitative Estimation of Joins Using SVM Method

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Abstract: The sEMG based movement recognition developed rapidly in recent years, which focus on intention estimation that velocity and angle of movement joint are not concerned. This paper proposed a quantitative analysis method of sEMG, with ability to estimate motion of human joints, which can be used to control rehabilitation robot system control by patient's own intention. The quantitative model of the relationship between sEMG signals and movement joint was established utilizing error Back Propagation artificial Neural Network and support vector machine with a Gaussian kernel, where the features of sEMG were taken as input. Considering of the actual demands of rehabilitation, the 1-DOF, 2-DOFs and 3-DOFs movement experiments were supposed to collect the information of joint angle and sEMG signals for model training. The result shows the angle prediction curve outputted by model of SVM has more than 90% consistency with the actual movement, while the model of BPNN gets a more imprecise output with complexity of movement arising. Initial online experiments on rehabilitation robot controlled by a healthy subject demonstrate that sEMG based movement control using the proposed method is feasible.

Keywords: sEMG, movement estimation, quantitative estimation, SVM method, rehabilitation robot

1. INTRODUCTION

Surface electromyography (sEMG) signals are the potential variation when muscles contract controlled by central nervous system, which is control affected by muscle structure, contractility and chemical change. Under the control of the central nervous system, the impulse, carried down the motor neuron to the muscle via axons, fires an action potential in all of the innervated muscle fibers that accumulate to be motor unit action potential (MUAP). MUAP conducting to both sides of muscle fibers makes the fibers contract to generate muscle contractility (Tsai, 1999).

sEMG signal represents the nerve stimulation of the muscle fibers from central nervous system in a particular area. Hence, it is possible to research how central nervous system controls and coordinates movement via sEMG signal. Many EMG analysis methods have been proposed in previous works (JIA and LUO, 2007). Especially, the research of sEMG based body joint recognition is very important because not only could the result of recognition be taken as control input signal of humanoid robots and prosthetics, but also it could be the stimulation signal used for electrical stimulation treatment (Alizade and Bayram, 2004). At present sEMG features based movement pattern recognition is fully developed method in the field of sEMG control, which limited to recognizing only the predefined movement. To recognize the pattern, the mean of wavelet neural network based classifier can reach a high accuracy of 90% and achieve a satisfactory classification result (Subasi *et al*. 2006). However, since the musculoskeletal system is very complex and the relationship of the EMG signals and arm motion is highly nonlinear, in most cases, only discrete control can be realized. In robot control field, for example, most of researchers focused only on the directional control of robotic wrists (Fukuda *et al*. 2003) or on the control of multi-fingered robot hands within a limited number of discrete postures (Zecca *et al*. 2002; Dalley *et al*. 2012). Movement pattern recognition would have difficulties in smooth action switch and complex action realization. In order to address this problem, a switching regime model based robot arm control and ANN based control were proposed (Muceli and Farina, 2012). For example, when switching regime model was used to control an anthropomorphic robot arm, the user did not have to be acquainted with the interface mapping since natural arm motions sufficed to control the robot arm directly (Artemiad and Kyriakopoulos, 2010, 2011). Although the proposal of continuous movement recognition has a profound significance in sEMG based control, the accurate motion parameters such as joint velocity and angle for arbitrary of control have not been acquired yet. So the quantitative analysis method of sEMG signals was applied to the angle estimation of movement joint. Li Xingfei (2006) proposed the ANN based quantitative method to establish the relationship between sEMG signals and joint angles, which was just used in the simple 1-DOF situation however.

In this paper, the quantitative model of the relationship between sEMG signals and movement joints was established utilizing error back propagation artificial neural network (BPNN) and support vector machine (SVM) with radial basis function kernel. Performances of the two methods were compared by a large number of experimental data. Regarding the special requirements of rehabilitation for patients of stroke and upper limb damage, the experiments of 1-DOF, 2-DOFs and 3-DOFs movement were designed to collect the information of joint angles and sEMG signals for model training and testing. At the same time, the proposed method was implemented to control the rehabilitation robot by healthy subjects.

The rest of this paper is structured as follows: the proposed basic principles and methods are analyzed in Section 2, the experiments and results are reported in Section 3, while Section 4 discusses the result and concludes this paper.

2. METHODS

2.1 Subjects and Data Acquisition

Human upper limb can achieve a rather complex movement. In order to simplify the movement, the DOFs of the wrist joint and fingers will not be considered in the following works. The movements studied in this research include shoulder adduction/abduction, shoulder flexion/extension and elbow flexion/extension, so that the upper limb movement is regarded as simply two link models, where 2 DOFs in shoulder and 1 DOF in elbow are assumed. According to the muscle function and structure, 8 surface electrodes are attached to the surface of brachioradialis muscle, biceps, triceps, deltoid, pectoralis major, and trapezius to be suitable for monitoring the movements in experiments. The electrode placements are shown as Fig.2.1.

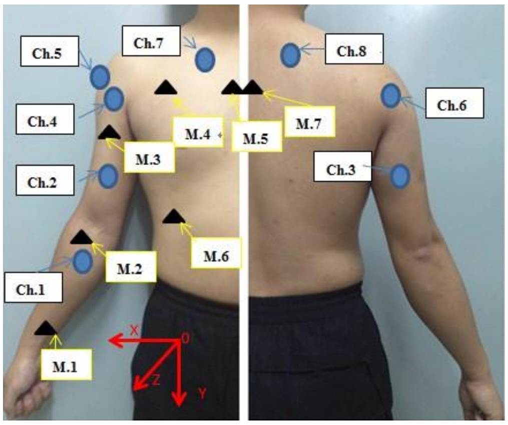

Fig.2.1 The circles represent the positions of the electrodes and the triangles represent the postions of Vicon markers

Vicon system starts to angle collecting at the same time as Delys system begins to make sEMG signals and angle simultaneously. The angles of the arm joints are measured by Vicon System. In this system, 3-D markers are stuck to the skin of human body to provide with the current position in Cartesian coordinate referring to the reference point. There are Marker1 and 2 attached to the forearm while Marker2 and 3 on the rear arm. Assuming the position of Marker1 to 3 as Point1 to Point3 as: $T_k = [x_k \quad y_k \quad z_k]$ (k=1~6), As each 2 points fixing the relevant axis, the vector representing forearm axis is $P_1 = T_2 - T_1$, the vector of rear arm axis is $P_2 = T_3 - T_2$, The angle between rear arm and forearm:

$$angle_{ellbow} = arc\cos\left(\frac{P_1 \cdot P_2}{|P_1||P_2|}\right) \tag{1}$$

The angles of shoulder-*x* and shoulder-*y* can be obtained calculated by the same way

2.2 Feature Extraction of sEMG

It is broadly reported in the biomechanics and physiology literature that sEMG signals are not stationary, in the sense that some signal features in accordance with respect to time. These changes can be observed by some statistical features of sEMG. The main work of this study is to establish a quantitative model using these features obtained by time domain analysis. Quantitative models actually establish the relationship between sEMG features and joint angles. Hence the feature extraction of sEMG is necessary. Time domain analysis is the common method applied to get sEMG features by regarding sEMG signals as the function related to time and getting its statistical features. The sEMG signals collected by the system are handled by amplification, notch frequency, high and low pass filtering. Aimed at movement five kinds of time domain features are extracted as below:

(1) *Mean absolute value:*

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{2}$$

Where N is the length of sEMG, k=1,2,3⋯, N, x_i is the signal amplitude of i sample.

(2) *Root mean square:*

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{3}$$

(3) *Slope sign changes*:

$$SSC = \frac{1}{N}\sum_{i=1}^{N-1}f_i, f_i = \begin{cases}1 & (x_i\text{-}x_{i-1})(x_i\text{-}x_{i+1}) > \sigma \\ 0 & else\end{cases} \tag{4}$$

Where σ is threshold value.

(4) *Waveform length*:

$$WL = \frac{1}{N}\sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{5}$$

Waveform length is the sum of length of N samples. The mutual effect of signal amplitude, frequency and action time of sEMG can be expressed by this parameter.

(5) *Zero crossing*:

$$ZC = \frac{1}{N}\sum_{i=1}^{N-1}f_i, f_i = \begin{cases}1 & x_i x_{i+1} < 0, |x_i - x_{i+1}| > \sigma \\ 0 & else\end{cases} \tag{6}$$

ZC is the frequency signal cross 0, which reflects signal fluctuation. *ZC* is an important feature of the signal for recognition.

2.3 Motion Estimation Based on sEMG

Vicon system is common equipment in estimation of the human joint angles. However, it is too expensive to be applied to daily life or robot control. Kincet is a simpler one, but the mutual interference is a disaster when the movement is complicated. Motion estimation based on sEMG is simple and practicable. An artificial neural network had been used in the quantitative estimation of joins based on sEMG, however, only one DOF was analyzed. In this paper, two methods, back propagation artificial neural network and support vector machine with a kernel of radial basis function were used to establish the model between the angle of the joint and sEMG.

2.3.1 Support Vector Machine

The Support Vector Machine (SVM) is a machine learning method based on the small sample statistics study theory. There are two cases for SVM regression approach that are linear case and nonlinear case. SVM approach to linear regression amounts to both the minimization of ε insensitive loss and the minimization of the norm of linear parameters ($\left\|\omega\right\|^2$). For nonlinear regression problem, SVM approach first performs a mapping from the input space onto a high-dimensional feature space, and then performs linear regression in the high-dimensional feature space using ε-insensitive loss. SVM is a novel learning method that has solid theoretical basis and requires only small amount of sample. It does not rely on probability measures and Law of Large Numbers. Hence is different from many other statistical methods. In essence, SVM smartly evades the traditional inference process from induction to deduction. Instead, it employs transductive inference from training sample to predicting sample, which greatly simplifies classification and regression problems. The decision function of SVM is only determined by a few support vectors. The complexity of computation concerns the number of support vectors rather than the dimension of the sample space.

2.3.2 SVM Model in Motion Estimation using sEMG Signals

The standard SVR learning algorithm (Du and Wu, 2003) used in the regression estimate. The purpose of learning is to construct a regression estimate function $f(x)$ making the distance of the target valueless than ε. The VC dimension of function minimizes at the same time, so the regression estimation problem can be converted into a quadratic programming problem with linear equality constraints and nonlinear inequality constraints, and then the only global optimal solution can be obtained. The generated samples (angles and sEMG) can be obtained according to some probability distribution $P(x,y)$ .The samples are written as (x_i, y_i) . The main work of support vector regression (SVR) is to find a real-valued function $f(x) = \omega \cdot \varphi(x_i) + b$ which can make the specific function $R(f) = \int c(x,y,f)dP(x,y)$ minimum, where c is loss coefficient. However, the $R(f)$ can't be minimized directly as the $P(x,y)$ is unknown, thus, the formula of (7) is minimized.

$$E(\omega) = \frac{1}{2}(\omega \cdot \omega) + C \cdot \frac{1}{l}\sum_{i=1}^{l}\left|y - f(x_i)\right|_{\varepsilon} \qquad (7)$$

Where $\left|y - f(x_i)\right|_{\varepsilon} = \max\{0, \left|y - f(x_i)\right| - \varepsilon\}$ is the insensitive loss function of ε. The formula shows that when the error between the observed value of y and function prediction $f(x)$ less than the given positive number ε, the fitting is considered error free. The loss on $(\overline{x}, \overline{y})$ is ξ: $\xi = \overline{y} - f(\overline{x}) - \varepsilon$ .The minimized formula of (7) is equivalent to the optimization problem as following.

$$\begin{cases} \min\limits_{\omega,\xi_i,\xi_i^*,b} \quad \Phi(\omega) = \frac{1}{2}(\omega \cdot \omega) + C\frac{1}{l}\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ s.t. \;\; (\omega \cdot \varphi(x_i) + b) - y_i \le \varepsilon + \xi_i, \\ \qquad y_i - (\omega \cdot \varphi(x_i) + b) \ge \varepsilon + \xi_i^* \\ \qquad \xi_i^*, \xi_i \ge 0 \end{cases} \qquad (8)$$

The dual form of (8) is

$$\begin{cases} \max\limits_{\alpha,\alpha^*} \quad \sum_{i=1}^{l}[\alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon)] \\ \qquad\qquad - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) \\ s.t. \;\; \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0, \quad 0 \le \alpha_i, \alpha_i^* \le C / l, \quad i = 1,2,\cdots,l \end{cases} \qquad (9)$$

Where $k(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_i)$ is kernel function, $(\overline{\alpha}, \overline{\alpha}^*)$ is the solution of (9), C is the penalty coefficient. In this paper, $K(x,y) = \exp\{-\gamma\left|x - y\right|^2\}$ (RBF kernel), the estimation function $f(x)$ can be described as follows.

$$f(x) = \omega \cdot \varphi(x) + b = \sum_{SV}(\overline{\alpha} - \overline{\alpha}^*)K(x_i, x) + \overline{b} \qquad (10)$$

The optimal regression function $f(x)$ could be obtained by dividing the sEMG signal futures as input and joint angles as output to train the initial model and then the quantitative relation model was established. SVR is based on structural risk minimization rather than the traditional empirical risk minimization that can guarantee reliable prediction ability.

2.3.3 Cross validation and Measuring error

Cross validation (Basheer and Hajmeer, 2000; Haselsteiner and Pfurtscheller, 2000) is often used to obtain the optimal parameters for SVM models. In this paper, there are two parameters C and γ of RBF kernel in SVM model that will be determined by K-fold cross validation. The K-fold cross validation is one way to improve the holdout method when the data set is larger. The data set is divided into k subsets, and the holdout method is repeated for k times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set. Then the mean square error across all k trials is computed which can assess generalization error. A group of optimal parameters can be obtained by comparing the k times MSE. According to the characteristics of data, k=10 is applicable in this study.

Due to the nonlinearity relationship between sEMG signals and joint angles, accurate mathematical model can't be put in place to carry on the regression. So there is absolutely an error existing in models. As the model is trained, the weights of the system are continually adjusted to reduce the difference between the output of the system and the desired response. The difference is referred to as the error and can be measured in several ways. The most common measurement is SSE and MSE. SSE is the average of the squares of the difference between each output and the desired output (Fausett, 1994). In this study, mean squared error (MSE) was used for measuring the performance of models.

2.3.4 Back-Propagation Neural Network

ANN proved by mathematical theory to have the ability to map any complex nonlinear function is one of the common methods for sEMG based movement recognition and classification of realizing a mapping function from input to output virtually. In this paper, BPNN algorithm (Buscema, 1998) is selected to establish the quantitative model between sEMG signals and joint angles. The BPNN has a structure of 3 layers with a hidden layer with 4 neurons.

It is difficult to choose an appropriate learning rate for some specific problems. The learning rate is usually given by experience or experiment, thus, it is difficult to apply to the entire training process. In order to address this problem, an adaptive learning rate is selected in the paper.

3. EXPERIMNETS ANG RESULTS

3.1 Comparison of SVM and BPNN model

The activation function of the hidden layer in BPNN is logsig function, while the output layer is purelin function. The hidden layer consists of one layer of four neurons selected out of *a* range of zero to eight determined by empirical function $n=\sqrt{n_{in}+n_{out}}+a$. The SVM method was compared with BPNN of trainlm, traingdx, and traingda training function. We compared the prediction accuracy of SVM and BPNN model in the three series of experiments including vertical movement, horizontal movement, and consecutive movement in 3D space. Those movements were chosen in the experiment since rehabilitation needs from simple to compound according to the theories of rehabilitation medicine. The performance indexes of models are *MSE* and degree of correlation *r*.

A. Single Joint Single DOF

The vertical movement (Fig.3.1) of the shoulder joint was selected in this experiment. This action is suitable for cerebral apoplexy patients in early rehabilitation training since it is easily be implemented by a robot and simple enough for patients. The results of two methods SVM model and BP neural network model were shown in Table 3.1.

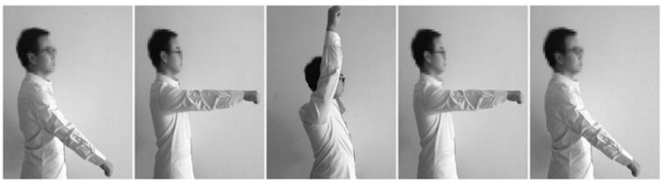

Fig.3.1 Vertical motion of the shoulder joint

Table 3.1 Comparison of single joint

evaluation		SVM	BP neural network		
			trainlm	traingdx	traingda
r	*MAV*	0.9877	0.9779	0.9756	0.9826
	SSC	0.9856	0.9837	0.9683	0.9704
	ZC	0.9923	0.9902	0.9765	0.9413
MSE	*MAV*	68.009	116.498	125.5847	114.6294
	SSC	85.316	88.5142	157.5692	163.5864
	ZC	41.377	57.3797	123.9226	291.5652

From the data in the table, SVM outputted a little more accurately than BPNN. And from the aspect of feature comparison, *ZC* feature was most optimal. So we took this as input in the follow-up experiments.

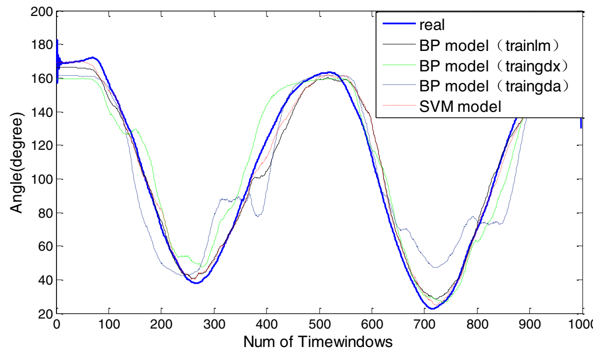

Fig.3.2 Characteristic ZC corresponding test curve

B. Two Joints Two DOFs

The horizontal movement (Fig.3.3) of the shoulder joint and elbow joint was selected in this experiment and parts of the results were shown in Table 3.2.

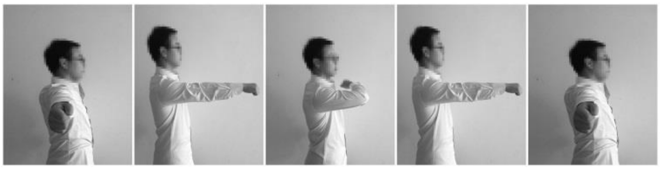

Fig.3.3 Horizontal motion of two joints

Table 3.2 Comparison elbow horizontal movements

evaluation		SVM	BP neural network		
			trainlm	traingdx	traingda
r	*MAV*	0.9238	0.9258	0.9077	0.7885
	SSC	0.9728	0.9706	0.9475	0.8930
	ZC	0.9285	0.9350	0.9301	0.9276
MSE	*MAV*	75.921	73.9084	92.1062	196.9809
	SSC	34.042	33.6153	54.2710	114.4728
	ZC	78.194	66.8504	70.1596	78.4655

Due to space limitations, just a part of the results was shown in the table and only elbow test curve was given in Fig.3.4.

From experiments above, it could be concluded that different inputs of features would lead to different prediction results, so that it is meaningful to select suitable sEMG features for the model. From the experimental curves, the prediction performance of the SVM model was more effective. The motion in the horizontal plane is much more complicated than the first one and can be used for cerebral apoplexy patients in the middle of rehabilitation training.

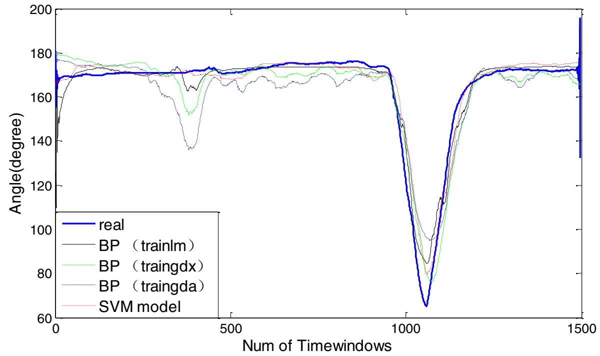

Fig.3.4 Horizontal movement of elbow test curve with SSC

C. Two Joints three DOFs

In this experiment, a consecutive movement in 3D space was chosen (Fig.3.5). In the 3D space, the angle between the forearm and the z axis was redundancy. Hence angles of the elbow, shoulder-x, and shoulder-y were taken as output. The only trainlm function was used in the BP neural network because the BPNN does not have much difference when three functions were used respectively in the previous experiments.

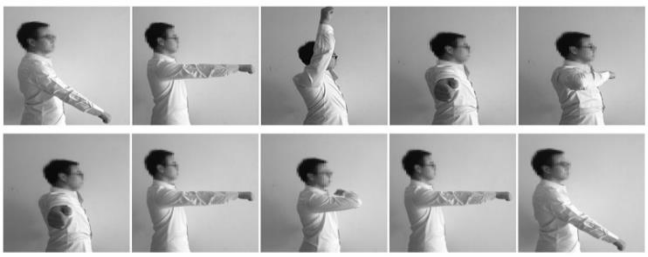

Fig.3.5 Motion with 3DOFs of two joints

The results of SVM model were obviously better than the result of BP when a consecutive movement was selected in 3D space. Due to space limitations, just a part of results were shown in in Fig.3.6 and Fig.3.7.

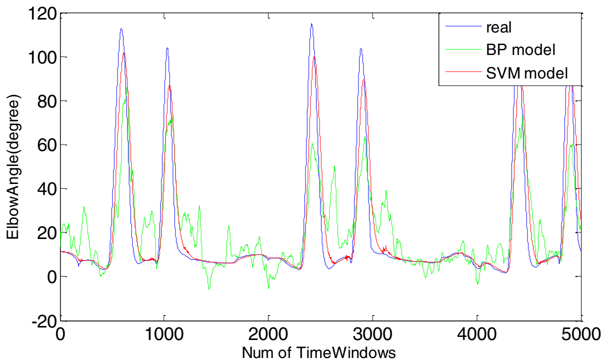

Fig.3.6 Consecutive movement of the elbow test curve

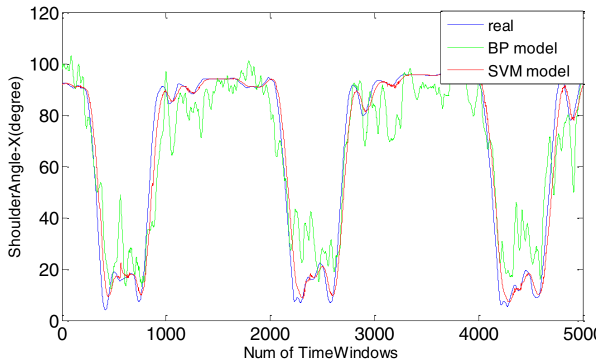

Fig.3.7 Consecutive movement of the shoulder-x test curve

From output curves of the experiment, SVM model had a satisfactory output result and could make the prediction curves smooth, which would be suitable for the actual situation of continuous movement, while BPNN output had a large error. Even though BPNN performed a similar tendency, it couldn't satisfy the actual demand.

3.2 Experimentation

The upper limb rehabilitation robot adopted in our experiments has the design of exoskeleton arm to be in accordance with physiological features of the human upper limbs. The robot is able to accomplish the movement of shoulder adduction/abduction, flexion/stretch and elbow flexion/extension in 3D space. In order to be suitable for different patients in the clinical situation, the size of the robot was designed to be adjustable. Upper limb rehabilitation robot is constituted by robotic arm, control system and sensor system. In order to avoid injuring the participant, four force sensors were installed under the shoulder joint to get the force information corresponding to the intention of movement between the participant and robot. One healthy volunteer was selected as the subject of robot online experiments. Experimental process: 1) Building training data sets by the acquisition system of sEMG and joint angles. 2) Processing the raw data and extract the sEMG signal features. 3) Training SVM model by the selected features. 4) Getting the trained model into the control system. 5) Conducting online experiments using the output of SVM model as a control signal. The information of position and force was illustrated in fig.3.8 and fig.3.9 when the trial was conducted.

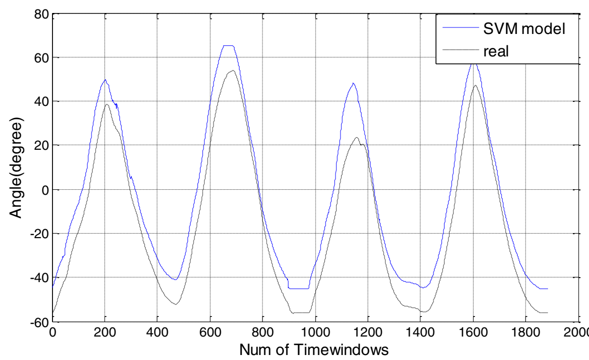

Fig.3.8 Position of the output test

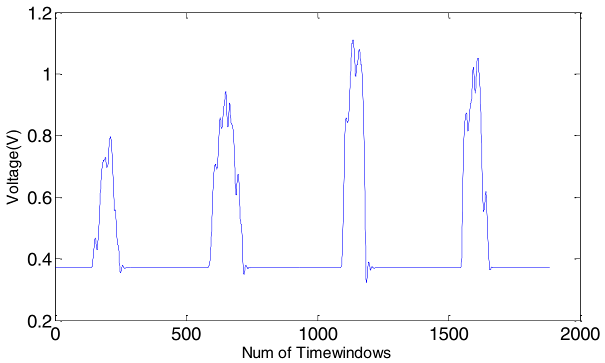

Fig.3.9 Force of the output test

The movement of health arm could be tracked by the upper limb rehabilitation robot from the curve of position. In spite of the error about compensation to angles by the force information was not so accurate, but impedance control could guarantee the safety of participants by stopping the movement immediately when the accidents occurred.

4. CONCLUSION AND DISCUSSION

In this paper, the control method of the rehabilitation robot based on sEMG signals suiting for the specific application of unilateral hemiplegic patient impaired motor function rehabilitation was developed. The sEMG signals were analyzed with the time domain method so that 5 kinds of time domain features were extracted. A continuous quantitative model of SVM was established to describe the relationship between joint angles and sEMG signals based on these sEMG features. The model was modified by a large amount of data collected from the experiment to predict the joint angles according to the sEMG signals. Experiments showed the prediction of SVM model was more precise than the model of improved BP neuron network especially for continuous motion. It must be noticed that the test motion and the train motion must be exactly similar so that the model can perform well. Based on the SVM model, the real time control of rehabilitation robot was accomplished with sEMG features selected through the comparative experiment. According to the experiment in volunteer subjects, the model and control strategy was confirmed with a superior prediction result, which is of great significance in the field of upper limb rehabilitation robot.

It is worth noting that the online experiments were done in an ideal situation instead of conducting on the patients, so the reliability and practicality of the method should still be tested and verified in the clinical application. The future work will focus on improving the method of robustness and the method verification in the clinical experiments.

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