Upper Limb Motion Recognition Based on Two-Step SVM Classification Method of Surface EMG

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Abstract

Robot-assisted self-rehabilitation for patients with stroke is significant for their motor recovery. Meanwhile, the surface EMG can reflect human neuromuscular activity and can be used for rehabilitation robot control. In this paper, we propose a Two-Step SVM classification method based on One-versus-One SVM muti-class classification method in order to improve the time efficiency of upper limb motion classification by sEMG, and then promote the real- time control of upper limb rehabilitation robot. A control experiment is done between the Two-Step SVM classification method and the One-versus-One SVM method. Four muscles in human upper limb are chosen to train and six motions are to recognize according to the aim of rehabilitation and the characteristic of people's daily life. The classifier training and motion recognize times between these two methods are compared. The result shows, the Two-Step SVM classification method proposed is improved in time efficiency, which is meaningful to improve the real time control of the robot during the process of rehabilitation.

Keywords: *TS-SVM, sEMG, upper limb, stroke, rehabilitation*

1. Introduction

Stroke is a leading cause of death in the world and its incidence is high in most countries, such as America, Netherlands and so on according to World Health Organization (WTO) and other reports [1, 2, 3]. Stroke is a disease, which is a sudden ischemic or hemorrhagic disturbance in the blood supply to brain tissue that results in partial loss of brain function [4] and always leads to hemiplegia. Patients with stroke always lose their ability of daily life (ADL), thus need care and treatment, which places a burden on society and families, especially in an aging population.

Stroke makes the cortical tissue partially destroyed, which interferes the formation of the neural control command or cuts down the pathway transmitting neural control command. As a result, the motor intention can't be correctly formatted in the sensorimotor areas of the cortex or transmitted to the target muscles to active them for motion [4]. In this case, the normal motor task is seriously affected, the arm and hand motor function are usually impaired. The restoration of patients' up limb motor function is essential for recovery of their independent ADL. And improve stroke patients' ADL by rehabilitation treatment is meaningful to reduce the burden of family and society.

High-intensity and repetitive rehabilitation training can rebuild the mapping between muscle and nerve, and then improve the motor function restoration of up limb [3, 5], so it is used as one of the most effective approaches. However, the traditional treat methods are carried out in hospitals or rehabilitation centers, which are usually trained between patients and doctors or rehabilitators individually. The training process is always repetitive and lasts a long time. So the method which depends on rehabilitator is time-consuming and labor-intensive, whereas the number of rehabilitators is limited, the prolonged training is likely to cause fatigue of patients that the training time, strength and accuracy cannot be guaranteed. So there is an urgent need for developing new training method for patient after stroke.

Robot aided rehabilitation training [6] method can provide precise and long-lasting control as well as timely feedback to rehabilitator for dominating the treatment, then comes into being and becomes widely used in rehabilitation training. Many research groups have developed robotic devices for upper-limb rehabilitation. Patients after stroke are always unilateral paralysis while the other sides of their bodies are sound. So using the sound side to assist the side of disability to execute rehabilitation training is an optional way. By this method, patients with stroke can train themself independently and most scholars have developed robot devices and training modes to support this manner such as MIME [7] and Bi-Manu-Track [8].

Surface electromyography (sEMG) has some association with active status of muscle, and can reflect neuromuscular activity in a certain extent, meanwhile, it has some advantage such as non-invasive, real-time, easy to operate and multi-point measure [9, 10]. In addition, sEMG controlled assistive devices for the upper limb could be potentially used to augment seniors' force while training their muscles and reduce their fear of frailty [11]. Using sEMG as a control source of robot for stroke patient's rehabilitation is a promising way. SEMG-based control is usually divided into two procedures: feature extraction and pattern recognition. Commonly used feature extraction methods are time domain analysis, frequency domain analysis and time-frequency domain analysis, *etc.* The pattern recognition are treated to identify sample class, let the characteristic values obtained by the feature extraction from original data as input, its classification obtained through a certain algorithm as output. An artificial neural network is a widely used pattern recognition method, however, it depends on experience, and its convergence rate is always slow, easy to over learning with small sample as well as converging to local minima. Support vector machine (SVM) [12] based on principle of structure risk minimization (SRM) can overcome these shortages and becomes a promising approach. SVM is originally used to solve issues of two classifications. In daily life, there are generally issues of multi-classes, such as upper limb motion reorganization. For case of multi-classification, there are One-versus-Rest (OVR) method and One-versus-One (OVO) method [13, 14, 15] *etc.*, by combining multiple binary classifiers. The latter is used more frequently, however, it needs to design $K(K\text{-}1)/2$ classifiers, where K is the number of classes the samples belong to. In this condition, when n is large, the rate of classification is slow.

In previous studies [16, 17] we have already developed an upper limb rehabilitation robot with three degrees of freedom. This robot can do a variety of training modes. The aim of this research is to collect the sEMG form patient's sound arm and recognize its motion type by pattern recognition technology as the control source of the robot to train the disabled arm. A Two-Step SVM (TS-SVM) multi-classification method is proved basing on OVO-SVM classification method to increase the speed of classification. And its performance is verified by experiment.

The remaining of this paper is organized as following: Section 2 presents the upper limb rehabilitation robot system developed in previous studies and basic concepts for this article, including a brief introduction to the surface EMG, feature extraction and support vector machine principle. Section 3 proposes the Two-Step SVM multi-classification methods. The control experiment between TS-SVM multi-classification method and OVO-SVM multi-classification method is executed in Section 4 and the result is analyzed. Finally, in Section 5, the whole article is concluded.

2. Basic Research and Concepts

2.1. Upper Limb Rehabilitation Robot System

Upper limb rehabilitation robot system includes a mechanical arm, control cabinet, PCs and sEMG signal instrument. The robot can do motions of three degrees of freedom (DOF): they are elbow flexion and extension, shoulder flexion and extension as well as shoulder abduction and adduction. It supports active and passive training modes. The workspace of this robot is described in Table1.

Table 1. Workspace of each Degree of Freedom

Degrees of freedom	Range of motion	Speed of movement
elbow flexion and extension	120°	60 °/s
shoulder flexion and extension	90°	60 °/s
shoulder abduction and adduction	90°	60 °/s

Control system includes the motion control hardware, which are controller, driver and motor. The rehabilitation robot hardware control system is shown in Figure 1. Its function is to realize the communication between upper-computer and low computer by TCP/IP protocol and socket interface. When the system is working, the sEMG signal instrument collects the sEMG data from patient and transmits it to PC system. PC system works as upper-computer and generates control information making use of the sEMG signal. The controller transforms the control information into motion control instruction and sends it to servo drivers by rs232 interface, and then achieves the control of the servo motor. When there are errors during system running, this system will show alert. The peripheral circuits are responsible for the system power supply control and provide emergency stop function.

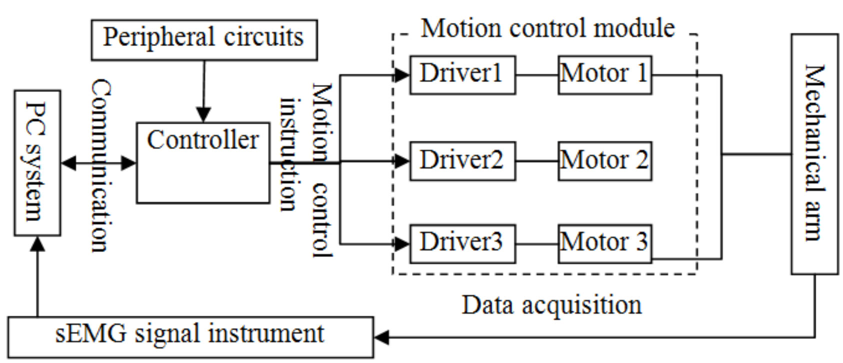


Figure 1. Rehabilitation Robot Hardware Control System

2.2. Surface Electromyography

Skeletal muscle is related to the movement of the human body, and it is a major component of the human movement system. Skeletal muscle attached to the bone produces contraction under the control of the central nervous system, thereby completing a variety of movement of the body limb. Skeletal muscle fibers are dominated by α motor neuron in the spinal nerves, and an α motor neuron dominates multiple skeletal muscle fibers. The Motor neuron excitation causes contraction of skeletal muscle fibers it dominated. An α motor neuron and skeletal muscle fibers it dominated constitute motor unit (MU). Motor neuron is the basic unit of the neuromuscular movement system. The α motor neuron produces potential changes inside and outside the cell membrane, that is nerve impulse under the dominance of innervation or external stimulus. A series of nerve impulses are transmitted to each muscle fiber along the nerve pathway and stimulate muscle contractions to complete the motion. Nervous system control and transmit motion and feedback information through the motor unit action potential (MUAP). MUAP generates from the cell body or axon terminals, and spreads along the nerve fibers. EMG signal is a one-dimensional time series signal. It is the sum of many motor unit action potential sequences in time and space [18], and it is the root cause of the generation of the muscle force on electrical signals. Surface EMG is the combined effect on the electrical activity of the superficial muscle and neural stem, which can reflect neuromuscular activity in a certain extent.

The EMG signals can be divided into the needle EMG signal (nEMG). Surface EMG (sEMG), the former inserts the needle electrode into the internal muscle and directly measure the electrical signal. The latter gets signals by attaching the electrode to the surface of the skin outside the muscle. The detection range of surface EMG is relatively large, and its measurement method has no injury, the testing is more flexible and simple, which is widely used. The surface EMG has the following characteristics:

(1) Surface EMG obtained from the surface of the body skin is a relatively weak signal, which is only 100 μV-5mV.

(2) Surface EMG signal is an AC voltage signal, whose amplitude is proportional to the force generated by muscle contraction. There is approximately linear relationship between the voltage amplitude of surface EMG and muscle relaxation.

(3) The surface EMG is composed of many sine wave signals, the value-added of positive and negative phase tends to zero.

(4) Surface EMG signal is a low-frequency signal, with main frequency range of 0-1000Hz, the maximum energy of the power spectrum concentrated in the range of 0-300Hz and the most spectrums concentrated in the range of 50-150Hz.

(5) Surface EMG is a non-stationary signal, its statistical properties change over time.

(6) The surface EMG signal generated with certain regularity when performing the movement. The EMG signals produced by the same muscle groups are different when performing different movement, while the EMG signals produced by the same muscle groups are similar when performing the same movement even with different individual. This made the interaction between human and machine possible.

Surface EMG has some association with active status of muscle, and can reflect neuromuscular activity in a certain extent. Meanwhile, it has some advantage such as non-invasive, real-time, operate easily and multi-point measure. So in this study, we choose the sEMG as the control source of rehabilitation robot.

2.3. Feature Extraction

The process of feature extraction is using the low-dimensional space to represent the sample by the method of mapping. Feature extraction is a very important part of pattern recognition. There is a direct relationship between the ability of class identification and the selection of the feature vector. The commonly used feature extraction methods include time domain analysis, frequency domain analysis, and time-frequency domain analysis [19]. We choose time domain analysis for feature extraction in this article. There are many methods in time domain analysis, such as the mean absolute value (MAV), variance (VAR), standard deviation (STD), zero crossing (ZC), root mean square (RMS) and so on. The calculation methods of them are as following:

(1) Mean absolute value (MAV)

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

Where N is the number of the sampling points in this period of time, X_i is the amplitude of the ***i***-th sampling point.

(2) Variance (VAR)

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2 \tag{2}$$

Where $\overline{x}$ is the average of the x_i. Because the surface EMG can be approximately regarded as zero mean, in this condition, Variance reflects the frequency of the signal, the formula 3 can be：

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^{\ 2} \tag{3}$$

(3) Standard deviation (STD)

$$STD = \sqrt{\frac{\sum_{i-1}^{N} X_i^2}{N-1}} \tag{4}$$

(4) Zero crossing (ZC)

$$ZC = \sum_{i=1}^{N} \operatorname{sgn}\left(- X_i X_{i-1}\right), \operatorname{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & otherwise \end{cases} \tag{5}$$

(5) Root mean square (RMS)

$$RMS = sqrt\left(\frac{\sum_{k=1}^{n} x_k^2}{n}\right) \tag{6}$$

In this article, the RMS is extracted as feature for upper limb motion classification, because this feature is sample and the calculation algorithm is easy and quick.

2.4. Support Vector Machine

A support vector machine (SVM) is a young method, which is developed on the basis of VC dimension theory of statistical learning theory and structural risk minimization (SRM). SVM can perform better in case of small sample, nonlinear, high-dimension and it can overcome the problem of over learning and converging to a local minimum point. The principle of SVM can be summarized as constructing a hyperplane with the largest margin to separate the two classes of samples. This hyperplane is called optimal classification hyperplane. The support vector refers to those training sample points in the edge of the spacer region. Figure 2 shows this principle, where the circles and the triangles are represent for two classes of the sample and the solid circles and triangles are represent for support vectors, the solid line between this two classes is the optimal classification hyperplane [11, 12].

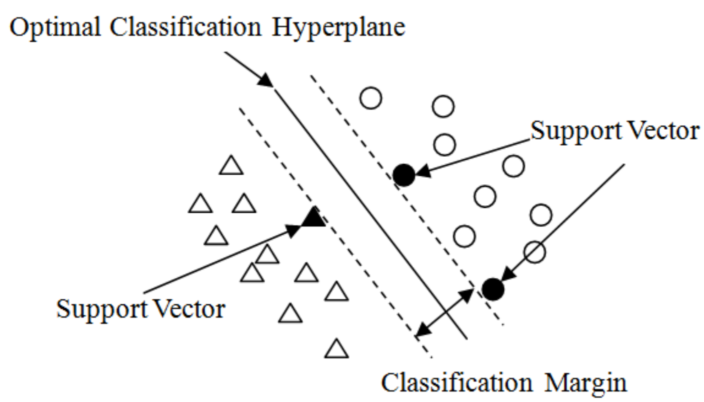


Figure 2. SVM Classification with Optimal Classification Hyperplane

The initial aim of researching on SVM is to solve the two classes of linear separable problem in pattern recognition. In case of linear classification of sample, set the sample feature and its class as (x_i,y_i) $i=1,2,\ldots,n$, $x \in R^d$,$y \in \{-1,1\}$, where x is the sample feature point, y is the class number of the sample, and d is the dimension of the sample feature. Assuming there is a hyperplane, which can separate two classes of samples. This hyperplane can be described as formula 7. W is the weight vector and b is the deviation value.

$$wx + b = 0 \tag{7}$$

When x_i belongs to class 1, that is $y_i=1$, $wx_i+b>0$, and when x_i belongs to class2, that is $y_i=-1$, $wx_i+b<0$. For a classification problem, there may be many hyperplanes meeting the formula 7. And the training process is to find the optimal hyperplane. When solving the linear problem, there need to impose constraints on W and b, for $y_i=1$, let $wx_i+b \geq 1$, and for $y_i=-1$, let $wx_i+b \leq -1$, meanwhile, the distance between hyperplanes $wx_i+b=1$ and $wx_i+b=-1$ is as far as possible. The sample x_i met $y_i(wx_i+b)=1$ is support vector. The problem of finding the optimal classification hyperplane changes into solving quadratic programming:

$$\begin{aligned} & Minimize : \frac{1}{2}\left\|W\right\|^2 \\ & subjectto : y_i\left(WX_i + b\right) \geq 1, i = 1,2...n \end{aligned} \tag{8}$$

For nonlinear classification of sample, map the low-dimensional nonlinear space to high-dimensional linear space through a non-linear mapping $\Phi(x)$. Then, the pattern classification problem in the original space is transformed into a pattern classification problem in higher dimensional space. There is a need to find a new classification hyperplane as formula 9:

$$w\Phi\left(x\right) + b = 0 \tag{9}$$

The new feature space may still be linearly inseparable, so, introduce the non-negative slack variables ξ and penalty factor C. The problem changes into solving the new quadratic programming:

$$\begin{aligned} & Minimize : \frac{1}{2}\left\|W\right\|^2 + C\sum_{i=1}^{n}\xi_i \\ & subjectto : y_i\left(w\Phi\left(X_i\right) + b\right) \geq 1 - \xi_i, i = 1,2...n \end{aligned} \tag{10}$$

SVM uses kernel function of the input space to replace the inner product operation in the high dimensional feature space, which can overcome the dimension disaster. During construction of the discriminant function, it is not to make a nonlinear transformation of sample in the input space, and then solve the issue in the feature space; but to compare the vectors in the input space, and then make a non-linear transformation on the results. In this way, the large amount of work will be done in the input space rather than in the high dimensional feature space.

3. Multi-classification Methods of SVM

SVM is originally used to solve issues of two classes. However, there are generally issues of multi-classification in daily life, such as upper limb motion reorganization. For case of multi-classes, the usual practice is to combine multiple binary classifiers. There are One-versus-Rest method and One-versus-One method etc. the latter is used more frequently.

3.1. OVO-SVM Classification Method

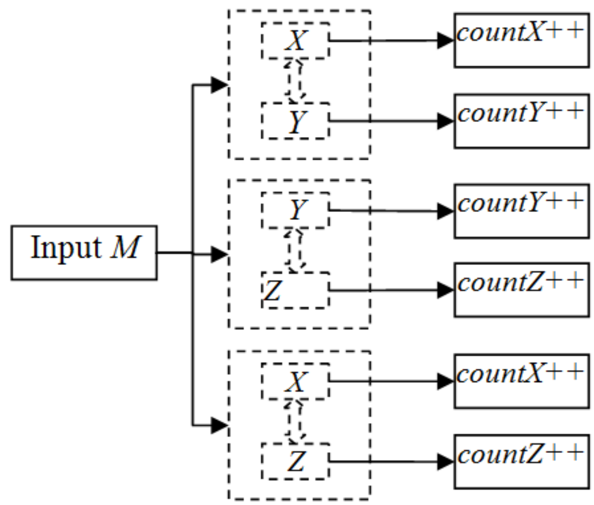


Figure 3. OVO-SVM Method for Three Classes

The algorithm constructs all possible classifiers among classes. That is to train classifier between each two classes. For K classifications, it is needed to train $K(K\text{-}1)/2$ classifiers, where K is the number of classes the sample belongs to. In the classification process, it uses the voting algorithm to count the result of the classification. For input sample M with K classes, there is a need to train K $(K\text{-}1)/2$ classifiers respectively for classification. If M belongs to class i, then the count of i plus one, otherwise, if M belongs to class j, then the count of j plus one. When all this classification tasks finished, the class with the most votes is the input sample belongs to. Figure 3 describes the algorithm principle of OVO-SVM method with three classes. When the number of sample classes is three, it needs to train three classifiers and make three times decision for each sample. The results of each classification are recorded in the counters: *conuntX*, *conuntY* and *conuntZ*, when the classification is finished, the class with biggest counter among *conuntX*, *conuntY* and *conuntZ* is the class of the input sample M.

OVO-SVM muti-class method is better in correct rate of classification, however, it need to design $K(K\text{-}1)/2$ classifiers, where K is the number of classes that the sample belongs to. In this condition, when K is large, the speed of classification is slow. So we proposed the Two-Step SVM classification method.

3.2. Two-Step SVM Classification Method

TS-SVM classification method is based on OVO-SVM muti-classification method. It divides the classification process into two steps, which reorganizes the class of the input sample as two layers accordingly. Define the classes in the first layer as big class, and the classes in the second layer as small class. Each big class contains two small classes and all the small classes are the same as the primitive types. The small class is our final aim. For example, as Figure 4 shows, when the number of classes of sample M is 6, the number of classes in the first layer is 3, and that in the second layer is 6. The algorithm is as follows:

The first step is to make a classification among the big classes in layer1. This classification is based on the OVO method. In example of Figure 4, this step may make 3 times classification among 3 big classes.

After the first step, the big class of the input sample is already certain, and in the second step, we will ultimately determine which class this sample belongs to by using SVM binary classification between two small classes in layer2. In the example of Figure 4, assume the sample belongs to BClass1 in the first step. And in the second step, make a classification between SClass1 and SClass2. After classification, the SClass1 is the class of the input sample.

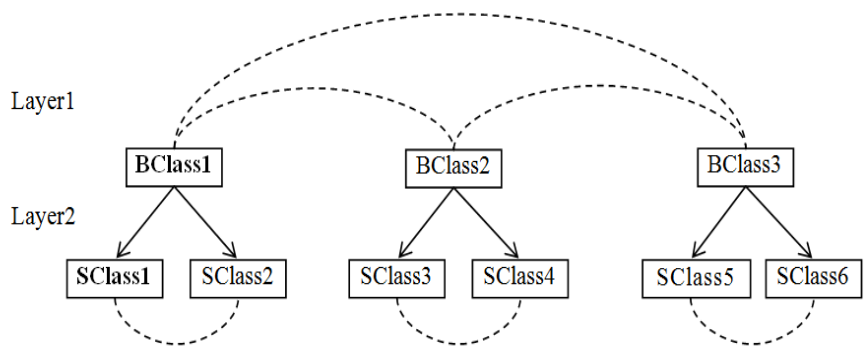


Figure 4. Classification with TS-SVM Method on Six Classes

Set *K* as the number of classes of the input sample. In TS-SVM method, the number of classifiers to train is *(K/2)(K/2-1)/2+K/2* and the time of classifications is *(K/2)(K/2-1)/2+1*. Whereas in OVO method, the number of classifier is *K(K-1)/2* and the number of classification is *K(K-1)/2*. In the example of Figure 4 and Figure 5, *K* is 6. The TS-SVM method needs to train 6 classifiers and make 4 times classifications. And the OVO method needs to train 15 classifiers and make 15 classifications.

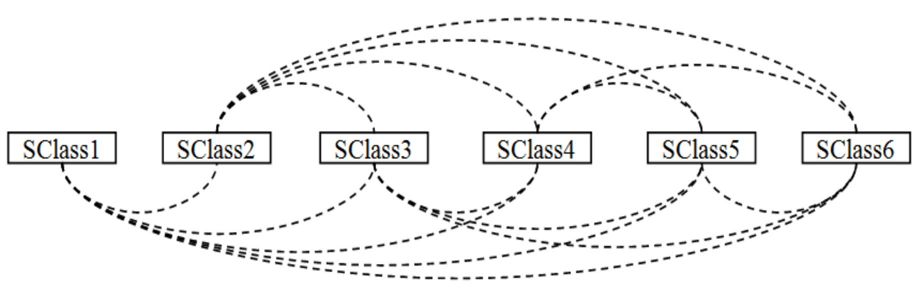


Figure 5. Classification with OVO method on Six Classes

TS-SVM method can reduce the number of classifiers and classifications, and reduce the time of classification. When *K* is large, the TS-SVM method may be well in time efficiency than OVO-SVM method, that will be meaningful to human-computer interaction in real-time.

4. Experiment and Result

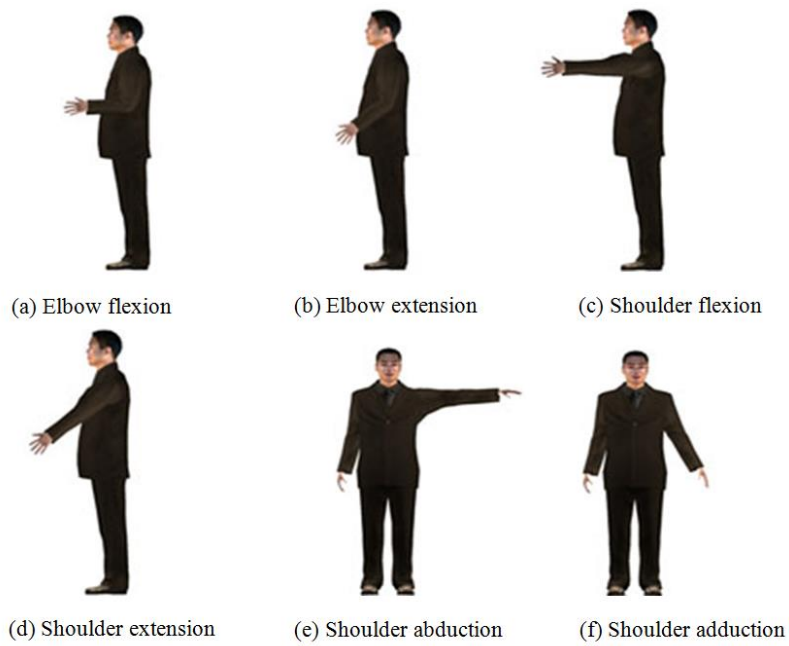


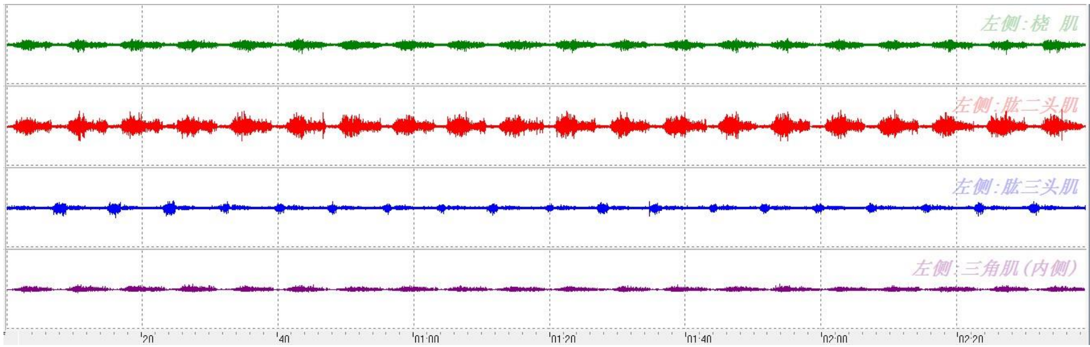
Figure 6. Rehabilitation Training Motions for Upper Limb

In this section, we will test and verify the time efficiency of TS-SVM method. Four muscles in human upper limb are chosen to train according to the aim of rehabilitation and the characteristic of people's daily life, they are: brachioradialis, biceps, triceps, deltoid muscle. We also choose six motions for training as shown in Figure 6, they are: elbow flexion, elbow extension, shoulder flexion, shoulder extension, shoulder abduction and shoulder adduction.

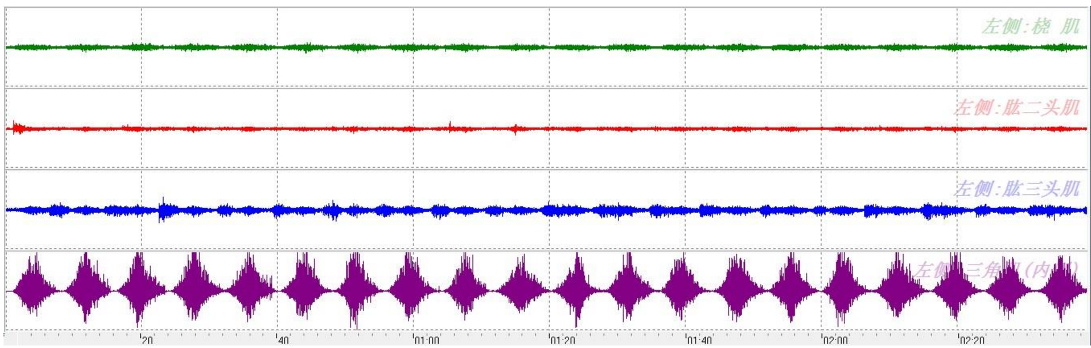
This study is to recognize the motion of the subject's arm for robot control through collecting and analysis the sEMG signal from their upper arm. Two healthy subjects voluntarily participate in this experiment in the laboratory. We do six groups' test in this experiment by each subject. Each group does six motions in pairs: elbow flexion and elbow extension, shoulder flexion and shoulder extension, shoulder abduction and shoulder adduction, and each motion done twenty times in one group in constant speed separately. The execution time of every motion is 3 second with 1second interval between each other. The aim of this experiment is to compare the OVO-SVM and TS-SVM classification algorithms in time efficiency. Then, we will do twice classification by OVO-SVM method and TS-SVM method respectively, meanwhile, record the time consumed by this two methods.

4.1. Data Acquisition and Feature Extraction

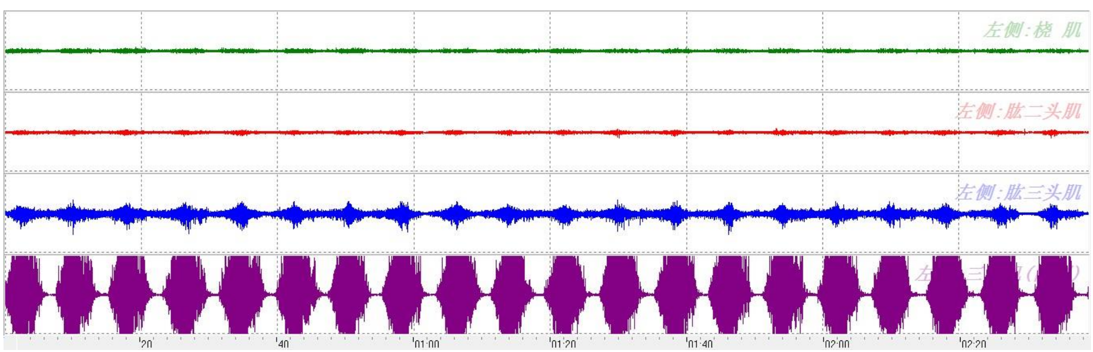
We collect four-channel sEMG signal with the sEMG signal instrument ME6000-T8. And each channel connected with three electrodes, one is reference electrodes and the remaining two are used to get potential difference signal. The electrodes are attached on the arm of the subjects around the four target muscles correspondingly. The sEMG is collected by electrodes attached on the arm of subject respectively, and each muscle with one channel. Channel 1 collects the signal form brachioradialis, Channel 2 collects signal form biceps, Channel 3 collects signal from triceps and Channel 4 collects signal from deltoid muscle. Figure 7 is the original sEMG signal collected from subject 1 with six motions in the first testing group.



(a) The original four-channel sEMG signal form elbow flexion and elbow extension



(b) The original four-channel sEMG signal form shoulder flexion and shoulder extension



(c) The original four-channel sEMG signal form shoulder abduction and shoulder adduction

Figure 7. Original sEMG of Subject 1 with Six Motions in the First Group

After data collection, we will pretreat the original data and make feature extraction from it. And then, two classifications by OVO-SVM method and TS-SVM method will be done.

In the first classification by OVO-SVM method, the original data will be reorganized into six separate variables according to the motion of upper limb. In this experiment, we will try to extract the time-domain feature Root Mean Square for classification, one feature with each motion. After extracting six groups' training data, we will obtain 6*20*4*1 features each type of motion. We define the sample classes in the first classification in

Table 2. The six small classes are elbow flexion, elbow extension, shoulder flexion, shoulder extension, shoulder abduction, and shoulder adduction.

Table 2. The Input Data Sample of OVO-SVM Method

	SClass1	SClass2	SClass3	SClass4	SClass5	SClass6
motion	elbow flexion	elbow extension	shoulder flexion	shoulder extension	shoulder abduction	shoulder adduction
feature	RMS data	RMS data	RMS data	RMS data	RMS data	RMS data
class ID	1	2	3	4	5	6

In the second classification by TS-SVM method, the original data will be reorganized into three separate variables in the first step and six separate variables in the second step according to the motion of upper limb. We will also try to extract the time-domain feature Root Mean Square for classification, one feature with each motion. After extracting six groups' training data, we will obtain 6*20*4*1 features each type of motion. We define the sample classes in the first step in Table 3. And that of the second step is the same as Table 2. The three big classes are: elbow flexion/extension, shoulder flexion/extension, shoulder abduction/adduction. The six small classes are the same as OVO-SVM method.

Table 3. The input data sample in first step of TS-SVM method

	BClass1	BClass2	BClass3
motion	elbow flexion/extension	shoulder flexion/extension	shoulder abduction/adduction
feature	RMS data	RMS data	RMS data
class ID	11	22	33

After feature extraction, the sample data are separated into two parts, one for classifiers' training and the other for classification testing. During the process of motion classification, the feature data is used as input data, and its class is used as output data.

4.2. Motion Classification

We use the OVO-SVM method and TS-SVM method to classify the motion in order to compare the time efficiency between these two methods. The motion classification process is divided into two stages. The two stages are classifier training and motion recognition testing process. In the classification by OVO-SVM method, 15 classifiers among six small classes will be trained as Table 4 shows. After classifier training, the next step is to use the trained classifiers to do motion classification and the testing time will be recorded in order to test the classification results.

In the first step of classification by TS-SVM method, 3 classifiers among 3 big classes will be trained (Table 5) and in the second step will be 3 classifiers among 6 small classes (Table 6).

Table 4. The Classifiers in the Test with OVO-SVM Method

Classifier	Description
Classifier12	The classifier used to classify SClass1 and SClass2
Classifier13	The classifier used to classify SClass1 and SClass3
Classifier14	The classifier used to classify SClass1 and SClass4
Classifier15	The classifier used to classify SClass1 and SClass5
Classifier16	The classifier used to classify SClass1 and SClass6
Classifier23	The classifier used to classify SClass2 and SClass3
Classifier24	The classifier used to classify SClass2 and SClass4
Classifier25	The classifier used to classify SClass2 and SClass5
Classifier26	The classifier used to classify SClass2 and SClass6
Classifier34	The classifier used to classify SClass3 and SClass4
Classifier35	The classifier used to classify SClass3 and SClass5
Classifier36	The classifier used to classify SClass3 and SClass6
Classifier45	The classifier used to classify SClass4 and SClass5
Classifier46	The classifier used to classify SClass4 and SClass6
Classifier56	The classifier used to classify SClass5 and SClass6

Table 5. The Classifiers in the First Step of Test with TS-SVM Method

Classifier	Description
BClassifier12	The classifier used to classify BClass1 and BClass2
BClassifier13	The classifier used to classify BClass1 and BClass3
BClassifier23	The classifier used to classify BClass2 and BClass3

After classifier training in these two methods, the next is to use the trained classifiers to do motion classification and the classification time will be recorded in order to evaluate the classification results. In the experiment of TS-SVM method, for the first step of testing, the task is to distinguish the sample class between bclass1, bclass2 and bclass3 using classifiers bclassifier12, bclassifier13 and bclassifier23. When the big class is certain, the second step becomes a two-classification problems. For example, if we gain the big class of the sample in the first step as BClass1 (elbow flexion/extension), in the second step, we only need to distinguish the sample class between SClass1 and SClass2 using Classifier12.

Table 6. The Classifiers in the Second Step of Test with TS-SVM Method

Classifier	Description
Classifier12	The classifier used to classify SClass1 and SClass2
Classifier34	The classifier used to classify SClass3 and SClass4
Classifier56	The classifier used to classify SClass5 and SClass6

The entire experiment was done in the laboratory with upper limb rehabilitation robot system. The data processing and motion recognition was done with the PC in this system. The configuration of this PC is Intel Celeron 2.5GHz CPU, 3GB RAM and 32bit windows 7 operating system. Mathematical software Matlab R2011a is also used to support this experiment.

4.3 Result and Discussion

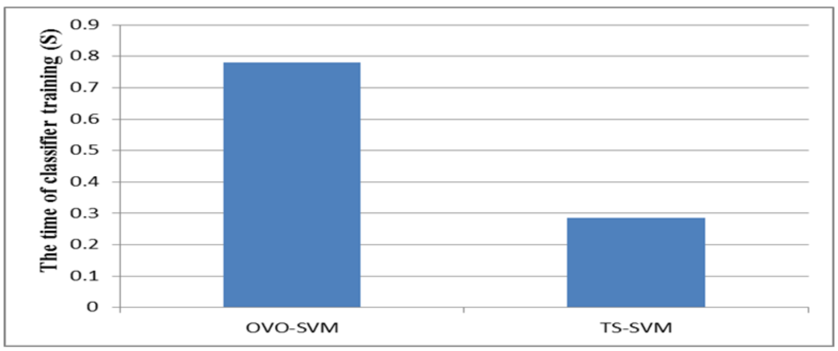


Figure 8. The Time Efficiency Comparison of Classifier Training between OVO-SVM and TS-SVM

During the experiment we record the time of training and classification with both SVM classification methods for comparison and analysis. With the traditional OVO-SVM multi-classification method, there need to train fifteen classifiers. The mean total time of classifier training with this method is about 0.77979798 seconds.

With the TS-SVM multi-classification method, six classifiers need to be trained, three in the first step for distinguishing classes of sample among big classes, and the remaining three classifiers are trained in the second step for distinguishing the ultimate classes of sample between two small classes based on the classification results of first step. The mean total time of classifier training with this method is about 0.28654868 seconds. Figure 8 shows the time efficiency comparison of classifier training between OVO-SVM method and TS-SVM method.

The running time of classification process is a more important aspect in robot control than that of classifier training. So we record and compare the classification time of both methods as Figure 9 shows. Although there need to do twice classifications with the TS-SVM method, the total number of classifier to train is less than the OVO-SVM method. And the total times of classifiers training with TS-SVM is less than OVO-SVM method by about 63.25% from 0.77979798 to 0.28654868. In the experiment of upper limb motion recognition, the total classification time with TS-SVM method is less than that with OVO-SVM method by about 55.80% from 0.169143 to 0.074766.

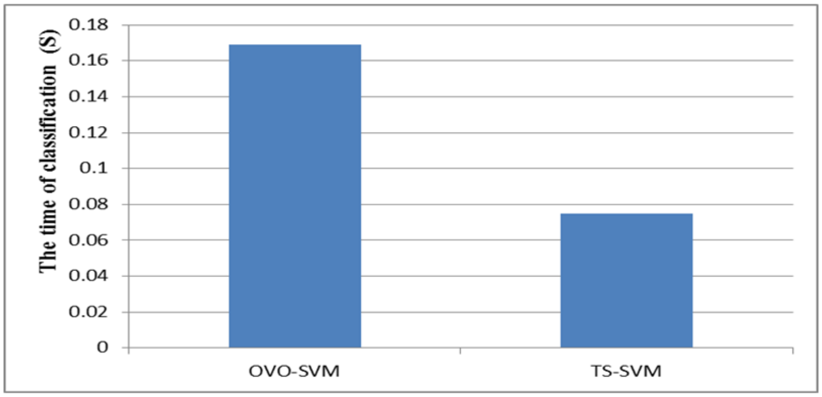


Figure 9. The Classification Time Efficiency Comparison between OVO-SVM and TS-SVM

5. Conclusion

Stroke is a leading cause of death in the world and its incidence is high in most countries. The motor function of patient with stroke is usually restricted. Robot-assisted self-rehabilitation is helpful for their motor function recovery. And the surface EMG can reflect human neuromuscular activity which can be used for rehabilitation robot control. This article based on the method of collecting the sEMG signal form patient's sound arm to control the robot to train the disabled arm by pattern recognition technology. Authors proposed Two-Step SVM classification method based on OVO-SVM muti-class classification method in order to promote the time efficiency of the motion classification. An experiment was done to compare the time efficiency between the TS-SVM method and OVO-SVM method. Authors choose four muscles in human upper limb to train and six motions are to be recognized according to the aim of rehabilitation and the characteristic of people's daily life. After experiment, the mean total classifier training time by TS-SVM method has reduced from 0.77979798 seconds to 0.28654868 seconds which is about 63.25%. After testing, the mean total classification time has reduced from 0.169143 seconds to 0.074766 seconds, which is about 55.80%. The result shows the TS-SVM classification method proposed in this paper is improved more in time efficiency, which in meaningful to improve the real time control of the robot during the process of rehabilitation.

For sEMG based real time robot control, there are several works to do. The study of motion range real time recognition is the future work. And combining visual reality technology and robot technology is a promising way for patient's motor rehabilitation.

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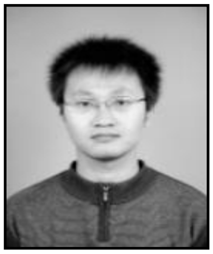

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