The Fourteenth International Symposium on Artificial Life and Robotics 2009 (AROB 14th '09),
B-Con Plaza, Beppu, Oita, Japan, February 5 - 7, 2009

# Unsupervised Learning Method for Support Vector Machine and its Application to Surface-Electromyogram Recognition

Shuji KAWANO Hiroki TAMURA Koichi TANNO

Faculty of Engineering, University of MIYAZAKI
1-1 Gakuken kibanadai-nishi, Miyazaki-shi, 889-2192 Japan
(Email:htamura@cc.miyazaki-u.ac.jp)

**Abstract**

Support Vector Machine (abbr. SVM) is known as one of the most influential and powerful tools for solving classification and regression problems. But original SVM does not have online learning technique. Therefore, online learning techniques of SVM were introduced by many researchers. In this paper, we propose unsupervised online learning method using self organized map for SVM. Furthermore, the proposed method has the technique of reconstruction of SVM. We compare it performance with the original SVM, supervised learning method of SVM, neural network, and also test our propose method on surface electromyogram recognition problems.

**keywords:**Surface-Electromyogram, Support Vector Machine, Self-Organizing Map, Pattern Classification Problem

## 1 Introduction

Surface electromygram signals (abbr. s-EMG) are detected over the skin surface and are generated by the electrical activity of the muscle fibers during contraction [1]. The load of s-EMG that rests upon the user for non-erosion is less than that of other biological signals. Therefore the application that uses s-EMG is actively developed. s-EMG recognition of using the conventional neural network is a method which learns the relation between s-EMG patterns and is reproduced using a neural network. In the recognition system, there are some problems that the s-EMG changes by the muscle wasting. In general, the muscle wasting will cause a decrease in the frequency of s-EMG and the tension. This is assumed to be the one due to the decrease at the muscle fiber conduction velocity [2]. Therefore, an additional learning function that corresponds to the muscle wasting is necessary for the s-EMG application. Support Vector Machine is known as one of the most influential and powerful tools for solving classification and regression problems [3]. But original SVM does not have online learning technique. Therefore, online learning techniques of SVM were proposed by many researchers [4] [5] [6].

In this paper, we propose unsupervised online learning method using self organized map (abbr. SOM) [7] for SVM. Furthermore, the proposed method has the technique of restructuring of SVM. Our proposed method has the advantage of small required memory size and small computational complexity. We test our proposed method to the s-EMG recognition problems.

## 2 Proposed Method

In this section, we introduce SVM and propose unsupervised learning method for SVM based on SOM.

### 2.1 Introduction of SVM

In this subsection, we summarize support vector machines for two-class problems. Assume the training sample $S = ((\mathbf{x}_i, y_i), ..., (\mathbf{x}_i, y_i))$ consisting of vectors $\mathbf{x}_i \in R$ with $i = 1, ..., N$, and each vector $\mathbf{x}_i$ belongs to either of the two classes. Thus it is given a label $y_i \in \{-1, 1\}$. The pair of $(\mathbf{w}, b)$ defines a separating hyper-plane of equation as follows:

$$(\mathbf{w}, \mathbf{x}) + b = 0 \tag{1}$$

However, Eq.(1) can possibly separate any part of the feature space, therefore one needs to establish an optimal separating hyper-plane (abbr. OSH) that divides $S$ leaving all. The points of the same class are accumulated on the same side while maximizing the margin which is the distance of the closest point of $S$. The closest vector $\mathbf{x}_i$ is called support vector (abbr. SV) and the OSH $\mathbf{w}', b'$ can be determined by solving an optimization problem. We explain how to select candidates for SV. The solution of this optimization problem is given by the saddle point of the Lagrangian.

$$\begin{array}{ll} \text{Maximize margin} & \frac{1}{2}(\mathbf{w},\mathbf{w}) \\ \text{Subject to} & y_i((\mathbf{w}\cdot\mathbf{x}_i)+b) \geq 1 \end{array}$$

to solve the case of nonlinear decision surfaces, the OSH is carried out by nonlinearly transforming a set of original feature vectors $\mathbf{x}_i$ into a high-dimensional feature space by mapping $\Phi : \mathbf{x}_i \rightarrow \mathbf{z}_i$ and then performing the linear separation. However, it requires an enormous computation of inner products $(\Phi(\mathbf{x})\cdot\Phi(\mathbf{x}_i))$ in the high-dimensional feature space. Therefore, using a Kernel function which satisfies the Mercer's theorem given in Eq.(2) significantly reduces the calculations to solve the nonlinear problems. In this paper, we used the Gaussian kernel given in Eq.(3) as the kernel function. The SVM decision function $g(\mathbf{x})$ and output of SVM are as given in Eq.(4) and Eq.(5).

$$(\Phi(\mathbf{x})\cdot\Phi(\mathbf{x}_i)) = K(\mathbf{x},\mathbf{x}_i) \tag{2}$$

$$K(\mathbf{x},\mathbf{x}_i) = \exp\frac{-||\mathbf{x}-\mathbf{x}_i||}{2\sigma^2} \tag{3}$$

$$g(\mathbf{x}) = \sum_{i=0}^{N} w_i K(\mathbf{x},\mathbf{x}_i) + b \tag{4}$$

$$O = sign(g(\mathbf{x})) \tag{5}$$

### 2.2 Unsupervised Learning Method

The SOM algorithm was introduced by Kohonen [7]. SOM is a kind of artificial neural network that is trained using unsupervised learning. In the basic version, only one map winner at a time is activated corresponding to each input. And, the vector corresponding to the map vector who is called a reference vector was adjusted by learning rule. This model and its variants have been very successful in several real application areas. In this paper, the training vector is used as learned object instead of the reference vector. When SVM maps input data to a nonlinear space, training vectors have very important action. However, the changing input data cannot be correctly mapped using SVM with the training vector at the beginning. The recognition mistake happens when the recognition data changes in the time series like the muscle wasting of s-EMG. To solve this problem, the training vectors are adjusted sequentially according to the SOM algorithm. The possibility of not satisfying the solution of the condition of the margin maximization that is the feature of SVM is caused by updating SOM algorithm. Therefore, this problem is solved by retraining SVM based on changing SV. Moreover, the number of training vectors must be limited for real problems of

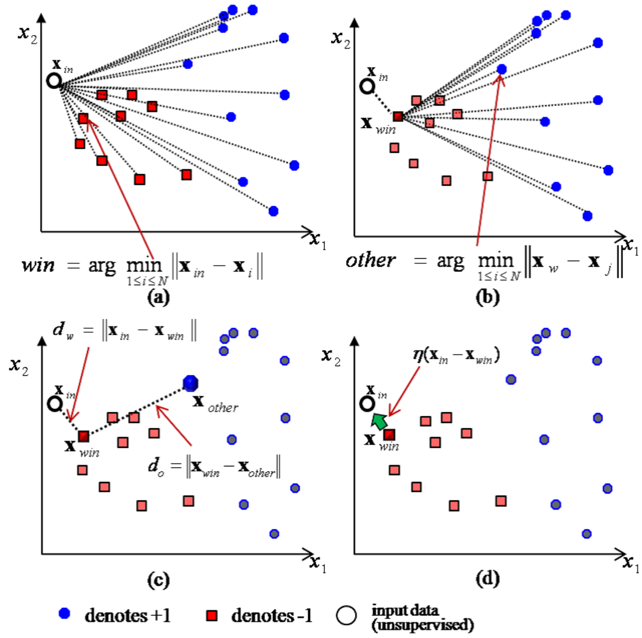


Figure 1: The flow of proposed method using SOM

memory size. Then, we proposed unsupervised online learning method using SOM for SVM and restructure technique.

Let the input space be denoted by $\mathbf{x}_{in} \in R$. The training vectors are included in kernel function, $\mathbf{x}_i$ with $i = 1,...,N$, belongs to either of the two classes. Thus it is given a label $y_i \in \{-1, 1\}$. Each training vector has the same dimension of input space. To find the best match of the input vector $\mathbf{x}_{in}$ with the training vectors $\mathbf{x}_i$, the euclidean distance between $\mathbf{x}_{in}$ and each $\mathbf{x}_i$ is computed (Fig.1.a). Then the $\mathbf{x}_{in}$ with the smallest distance is selected as

$$win = arg \min_{1\leq i\leq N} ||\mathbf{x}_{in} - \mathbf{x}_i|| \tag{6}$$

The particular processing element that satisfies this condition is called the winning training vector $\mathbf{x}_{win}$, for the input vector $\mathbf{x}_{in}$. $d_w$ is the euclidean distance between $\mathbf{x}_{in}$ and $\mathbf{x}_{win}$. Next, find the best match of the $\mathbf{x}_{win}$ with the training vectors $\mathbf{x}_j$, the euclidean distance $\mathbf{x}_{win}$ and each $\mathbf{x}_j$ is computed (Fig.1.b). However, $\mathbf{x}_j$ should be a different class from $\mathbf{x}_{win}$. The $\mathbf{x}_j$ which becomes the smallest distance is selected. This selected training vector is called $\mathbf{x}_{other}$, and $d_o$ is the euclidean distance between $\mathbf{x}_{win}$ and $\mathbf{x}_j$. If $d_w$ is condition of rule of Eq.(7), $\mathbf{x}_{win}$ is updated according to the learning rule of Eq.(8) (Fig.1.c and Fig.1.d).

$$d_w \leq \zeta \times d_o \tag{7}$$

$$\mathbf{x}_{win}^{new} = \mathbf{x}_{win}^{old} + \eta(\mathbf{x}_{in} - \mathbf{x}_{win}^{old}) \tag{8}$$

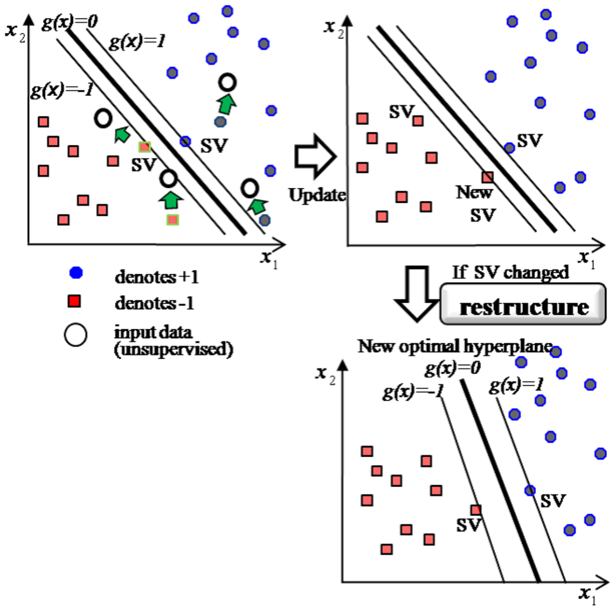


Figure 2: The technique of restructuring of SVM

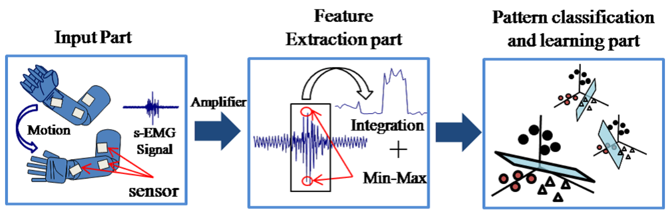


Figure 3: Structure of the EMG recognition system

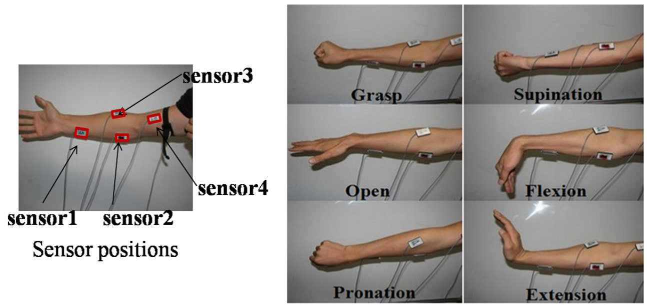


Figure 4: Image figure of forearm motion

Parameter $\zeta$ is allowable parameter. Parameter $\eta$ is update parameter. In this paper, we used parameter $\zeta = 0.7$, and $\eta = 0.1$. If SV changed after the update, SVM is restructured with the updated training vectors (Fig.2).

## 3 Computer Simulations

In this section, the system configuration for recognition experiments of forearm motions using s-EMG is explained. Next, the result of computer simulations is described.

### 3.1 Experimental Condition

The construction of proposed s-EMG pattern recognition system is shown in Fig.3. The system consists of an input part, a feature extraction part and pattern classification and learning part. S-EMG of each movement pattern is measured with electrode sensors, and the feature quantity is extracted from the s-EMG. The feature quantity is given to the recognition machine as an input and each movement pattern that generates s-EMG is presumed. The feature quantity uses minimum-maximum (abbr. min-max) values and integration values [8]. Paper [8] showed that technique of min-max values and integration values are more easy and superior than FFT processing. The sampling frequency of the measurement data is 1 KHz. And the band is from 0 KHz to 500 KHz.

### 3.2 Experiments of Forearm Muscles

We experimented on the effectiveness of the proposed method by the s-EMG recognition problem that the feature quantity changes by the muscle wasting. We compared proposed method performance with the original SVM, MLP, supervised learning method [9] and other unsupervised learning method. Supervised learning method of paper [9] is a method of adjusting threshold $b$ of SVM (Eq.(4)) by online additional learning. This technique was effective to s-EMG recognition problem. In this paper, SOM only method (without part of restructured technique) and every time restructured SVM (SOM with restructured technique when training vectors were updated) are used as additional unsupervised learning method to compare the effectiveness of proposed method. The experimental subject is healthy man (S.K). The subjects sit on a chair. The recognition experiment of the 6 motions pattern is conducted by using s-EMG obtained from four sensors set in the arm of the right hand (Fig.4). Moreover, the input given to the identification machine is eight inputs. The experiments are conducted for three days.

The experiment method, first acquires the training data from s-EMG concerning the movement of forearm. Next, SVM and MLP learn the relation between s-EMG and motion from the training data. And, each motion is identified 20 times. Next, the subject trains few minutes with watching the recognition result on the display. Afterwards, additional supervised learning data is obtained from each motion. The experiment repeats the measurement nine times.

### 3.3 Experimental Result

We performed with each method and the simulation results are Fig.5. Proposed method is better than original SVM. And, proposed method had better performance in unsupervised learning method, because the recognition calculation of the proposal method is fast. The 3 days average of muscle wasting experiment results MLP was 86.7%, original SVM was 85.7%, supervised learning method was 89.2%, every time restructured using SOM was 90.4%, SOM only 89.5%, and proposed method was 90.1%. We compared proposed method with total restructuring frequencies, proposed method was 16, every time restructured method was 601. We approached t-test (significance level of 5%) that changed parameter $\zeta$ and $\eta$. The t-test had a similar tendency of the results of Fig.5. The simulation results showed that the recognition rate of proposed method has improved by unsupervised learning method and original SVM.

## 4 Conclusion

In this paper, we proposed unsupervised learning method using SOM for SVM corresponding to s-EMG recognition problems. The experiment results showed that the proposed method was effective to s-EMG recognition problem.

## Acknowledgements

This research has been supported by TATEISHI Science and Technology Foundation (No.1081019).

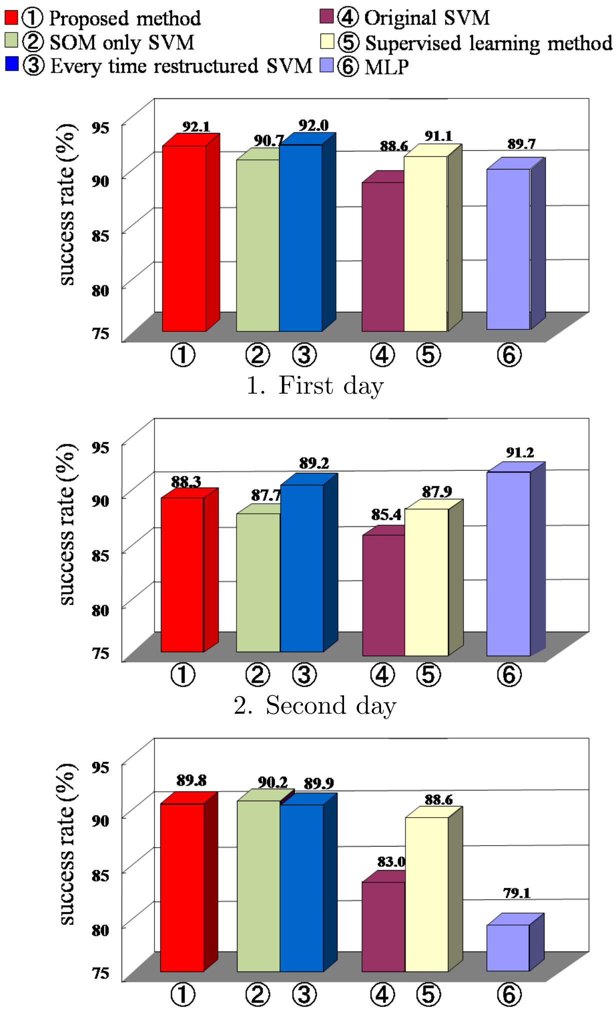


Figure 5: Average of recognition results

## References

[1] Kizuka Tomohiro, Masuda Tadashi, Kiryu Tohru and Sadoyama Tsugutake, " Practical Usage of Surface Electromyogram ",Biomechanism Library, 2006.

[2] De Luca C.J. and Knaflitz M, Surface Electromyography:What 's New?, CLUT Publishers, Torino,Italy, 1992.

[3] C.Cortes and V.N. Vapnik, " Support Vector Networks ",Machine Learning, 20(3), pp. 273-297, 1995.

[4] C.J.C Burges, " A Tutorial on Support Vector Machine for Pattern Recognition ",Data Mining and Knowledge Discovery, vol.2, no.2, 1998.

[5] Nello Cristianini, John Shawe-Taylor, " An Introduction to Support Vector Machines and Other Kernel-based Learning Methods ",Cambridge University Press, 2000.

[6] Nobuhiko Ogura, Sumio Watanabe, " Online Learning for Support Vector Machine using Necessity Estimation ",Techinical report of IEICE PRMU,Vol,99,No,182,pp. 45-52,1999.(Japanese)

[7] Teuvo Kohonen. " Self-Organizing Maps ". Springer-Verlag Tokyo, 1996. Translation of Self-Organizing Maps by Teuvo Kohonen, Springer-Verlag Berlin Heidelberg,1995.

[8] Hiroki Tamura, Takafumi Gotoh, Dai Okumura, Hisashi Tanaka, and Koichi Tanno, " A Study on the s-EMG Pattern Recognition using Neural Network ",2008 International Symposium on Intelligent Informatics (ISII 2008).(acceptance)

[9] Shuji Kawano, Hiroki Tamura, Dai Okumura, Hisasi Tanaka, and Koichi Tanno, " Online Learning Method using Support Vector Machine for Surface-Electromyogram Recognition ", AROB2008 (CD-ROM) pp. 227-230, 2008.