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Support Vector Machines with Online Unsupervised Learning Method and its Application to surface-Electromyogram Recognition Problems

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Abstract– The support vector machine (abbr. SVM) is known as one of the most influential and powerful tools for solving classification and regression problems, but the original SVM does not have an online learning technique. Therefore, many researchers have introduced online learning techniques to the SVM. In this paper, we propose the new online unsupervised learning method using a technique of self-organized map for a SVM. Furthermore, the proposed method has a technique for the reconstruction of a SVM. We compare its performance with the original SVM, and also test our proposed method on surface-electromyogram (abbr. s-EMG) recognition problems with changes in the electrode position.

1. Introduction

s-EMG signals 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][9][10].

In this paper, we propose the new online unsupervised 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 with changes in the electrode position.

2. SVM with Online Unsupervised Learning 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 $S=((\mathbf{x}_1,y_1),\ldots,(\mathbf{x}_N,y_N))$ consisting of vectors $\mathbf{x}_i \in R^n$ with $i=1,\ldots,N$, 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:

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

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 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.

$$\text{Maximize margin} \quad \frac{1}{2}(\mathbf{w},\mathbf{w})$$

$$\text{Subject} \qquad y_i((\mathbf{w}\cdot\mathbf{x}_i)+b)\geq 1$$

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 $\mathbf{\Phi}:\mathbf{x}_i \rightarrow \mathbf{z}_i$ and then performing the linear separation. However, it requires an enormous computation of inner products $(\mathbf{\Phi}(\mathbf{x})\cdot\mathbf{\Phi}(\mathbf{x}_i))$ 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).

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

$$K(\mathbf{x},\mathbf{x}_j) = \exp\left(\frac{-\left\|\mathbf{x}-\mathbf{x}_j\right\|^2}{2\sigma^2}\right) \quad (3)$$

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

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

In this paper, we extended the standard SVM based on a pairwise coupling method for multiclass pattern recognition.

2.2. Proposed 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 that 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 importance 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 memory size. Then, we proposed unsupervised online learning method using SOM algorithm for SVM and restructure technique.

Let the input space be denoted by $\mathbf{x}_{in} \in R^n$. $\mathbf{x}_{in}$ $(in \notin \{i = 1,...,N\})$ is the input vector without the label. The training vectors are included in kernel function, $\mathbf{x}_i$ with $i = 1,\dots,N$, belongs to either of the two classes. Thus these are given a label $y_i \in \{-1,1\}$. Each training vector has the same dimension of input space.

Next, the flows of our proposed method are shown.

Step 1: To find the smallest distance 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

$$win = \arg\min_{1\le i\le N} \left\|\mathbf{x}_{in} - \mathbf{x}_i\right\| \quad (6)$$

This selected training vector is called $\mathbf{x}_{win}$, and d_w is the Euclidean distance between $\mathbf{x}_{in}$ and $\mathbf{x}_{win}$.

Step 2: The following processing (Step 3-4) are not done to $\mathbf{x}_{in}$ when the label of $\mathbf{x}_{win}$ is not the same as the label of the output result of SVM of $\mathbf{x}_{in}$.

Step 3: To find the smallest distance 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).

Condition : $\mathbf{x}_j$ 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 $\mathbf{x}_j$.

Step 4: 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).

$$d_w \le d_o \quad (7)$$

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

Parameter η is update parameter. The idea of this rule is an idea near the adaptive resonance theory-like.

Step 5: Step1-4 are done to all input vector.

Step 6: Proposed method repeats *Num* cycles these processing (Step1-5) using same inputs vector $\mathbf{x}_{in}$.

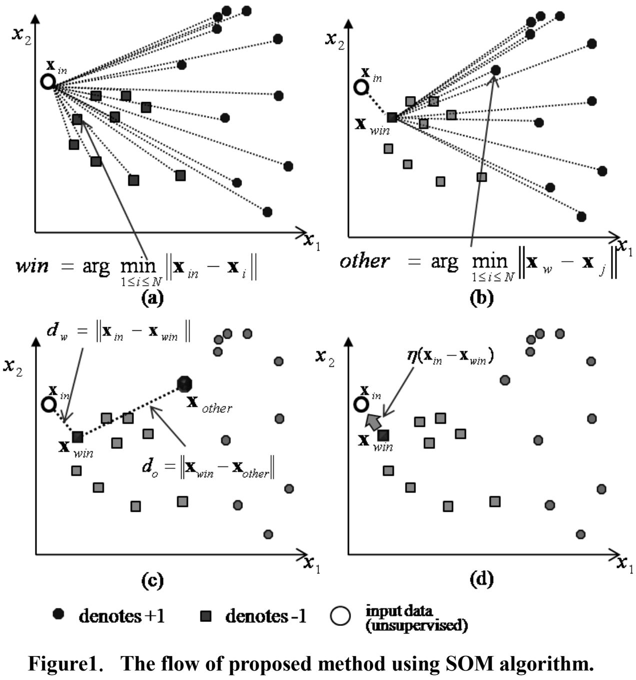


Figure1. The flow of proposed method using SOM algorithm.

If SV changed after the update, SVM is restructured using the updated training vectors. Even if training vectors changes using the Step 1-5, maximizing the margin of SVM is kept from this restructuring processing.

3. Experiments

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

3.1. Experimental Condition

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 to 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 electrode position. We compared proposed method performance with the original hard-margin SVM, soft-margin SVM (C-SVC) and *k*-NN method.

The experimental subjects are 4 healthy men (T.Y, K.F, S.Y, T.M). 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.2). Moreover, the input given to the identification machine is eight inputs. The experiments are conducted for one day.

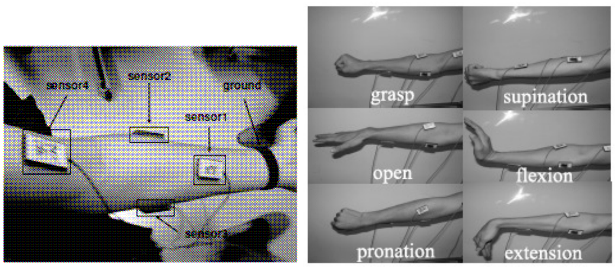


Figure.2. Image figure of forearm motion. 6 motions patterns of forearm are conducted by using s-EMG obtained from four sensors set in the right arm.

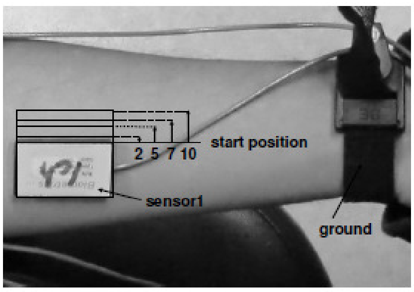


Figure.3. S-EMG recognition problems with changes in the electrode position (2mm, 5mm, 7mm and 10mm).

The experiment method, first acquires the training data from s-EMG concerning the movement of forearm. Next, SVM and C-SVC learn the relation between s-EMG and motion from the training data (the training vectors). And, each motion is identified 60 times. Next, the object moves the electrode position (sensor 1) by 2mm. And, additional unsupervised learning data (the input vector: each motion is 40 times) is obtained from each motion. Afterwards, test data for recognition rate calculation is identified 20 times of each motions. The experiments tested the measurement four times in total by moving the electrode position of 2mm, 5mm, 7mm and 10mm (Fig.3).

The base of proposed method is hard-margin SVM using Eq. (3). Gaussian kernel parameters of SVM were decided from the evaluation that used training data. Subject T.Y was 0.7, K.Y was 2.0, S.Y was 0.9, and T.M was 0.3. In these experiments, the value of parameter η typed two of 0.1 and 0.6. Moreover, the value of *Num* tested five types (*Num*=1, 5, 10, 15, and 20).

3.3. Experimental Result

We showed the comparison experiment results (average result of four subjects) of the value of *Num* and the value of parameter η in Fig.4. Fig.4 shows that *Num*=15 and parameter $\eta = 0.1$ had the better performance. We compared proposed method with SVM and the simulation results (average result of four subjects) are Fig.5. Proposed method is better than original SVM.

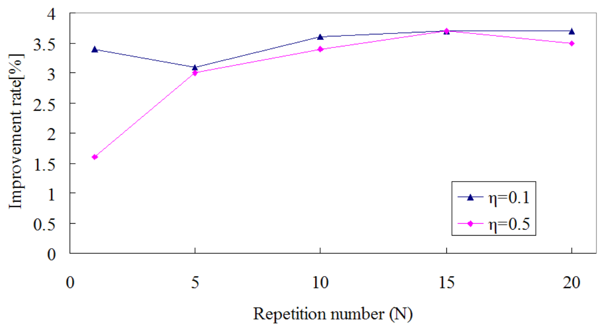


Figure.4. The comparison experiment results of the value of *Num* and the value of parameter η .

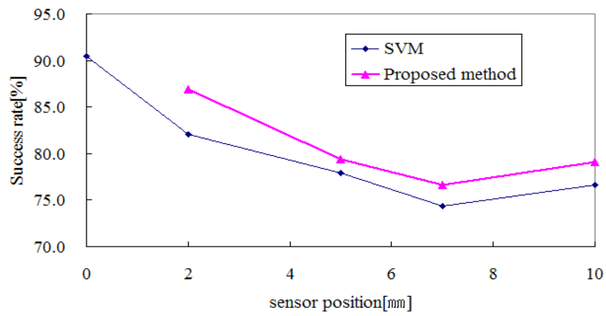
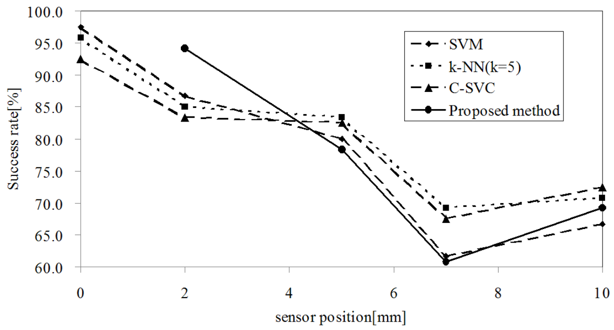
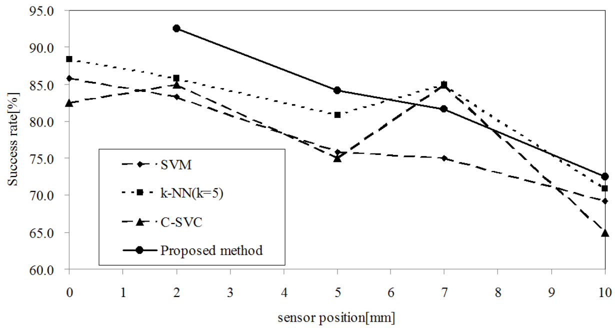


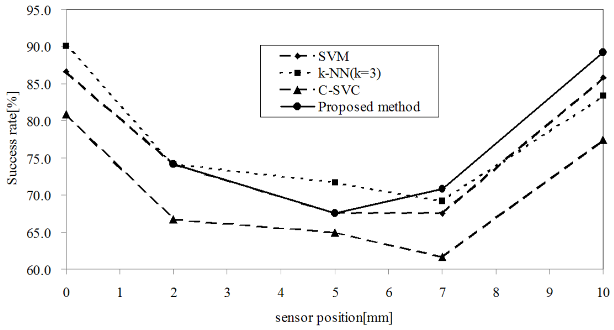
Figure.5. The comparison experiment results of SVM and proposed method (*Num*=15 and $\eta = 0.1$).



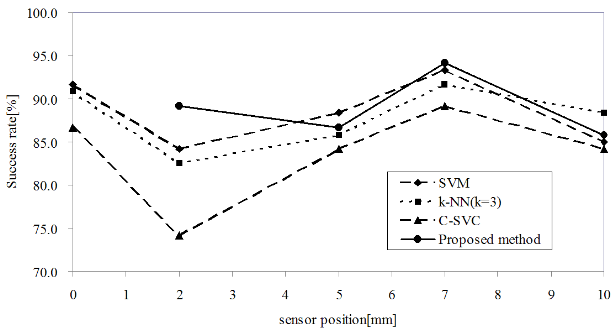
Subject T.Y



Subject K.Y



Subject S.Y



Subject T.M

Figure.6. Experimental results of four subjects.

Next, each subject's results were shown in Fig.6. From Fig.6, our proposed method had the best performance in the sensor gap of 2mm. Moreover, our proposal method had the better results in four techniques in subject K.Y, S.Y and T.M. From these experiment results, we think that proposed method was effective in overcoming the s-EMG recognition problem with changes in the electrode position.

4. Conclusions

In this paper, we proposed unsupervised learning method using SOM algorithm for SVM corresponding for s-EMG recognition problems. The experiment results showed that the proposed method was effective to s-EMG recognition problem with changes in the electrode position. SVM had improved by using our proposed method. Especially, the proposed method had the good performance for the sensor gap of several mm that often happened about a real problem. In future work, we will improve parameter decision method.

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