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A Study of SVM using the Combination with Online Learning Method and Midpoint-Validation Method

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Abstract: The support vector machine (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 our former paper, we proposed an unsupervised online learning method using the technique of the self-organized map for SVM. In other paper, we proposed the midpoint-validation method for the improvement of SVM. Therefore, we test the performance of SVM using the combining of two techniques in this paper. Moreover, we compare its performance with the original hard-margin SVM, soft-margin SVM and *k*-NN method, and also experiment our proposal method on surface electromyogram recognition problems with changes in the electrode position. From these experiments, our proposal method has the best performance in the technique of other SVM and corresponds to the changing data.

Keywords: Support vector machine, Online learning, Midpoint-validation, Pattern classification problem, Surface-electromyogram.

I. INTRODUCTION

The SVM proposed by Cortes and Vapnik [1] is one of the most influential and powerful tools for solving classification problems [2][3][4][5].

We are studying the surface-electromyogram (s-EMG) recognition of using SVM. The purpose is development of the human interface of using s-EMG. In this study, we pay attention to problems such as the change of the s-EMG pattern by the muscle fatigue and the position gap of the sensor to measure. And in our former paper [6], we proposed the 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.

In addition, we are studying SVM which is not limited to recognition of s-EMG. In this study, we pay attention to a problem of the deflection of the separating hyperplane in the input space of non-linear SVM and proposed the improvement method [7][8]. We call this method Midpoint-Validation Method. This Method assumes a Midpoint between the classes of training data an index of the deflection and moves the separating hyperplane according to the index. This method also has a technique for the reconstruction of a SVM.

These two studies achieve good result each. However, we have not combined two methods so far. Therefore, we test the performance of SVM using the combining of two techniques in this paper. Moreover, we compare its performance with the original hard-margin SVM, soft-margin SVM and *k*-NN method, and also experiment our proposal method on s-EMG recognition problems with changes in the electrode position.

II. PROPOSED METHOD

In this section, we introduce SVM, our Online Learning Method and Midpoint-Validation Method. And we propose the method that combined Online Learning Method with Midpoint-Validation Method.

1. SVM

The SVM is a mechanical learning system that uses a hypothetical space of linear functions in a high-dimensional feature space.

Nonlinear SVM is expressed by the three equations (Eq. (1), Eq. (2) and Eq. (3)). Here, we used the Gaussian kernel given in Eq. (1) as the kernel function, while the SVM decision function $g(\mathbf{x})$ and the output of the SVM are as given in Eqs. (2) and (3).

$$K(\mathbf{x},\mathbf{x}_i) = \exp\left(\frac{-\|\mathbf{x}-\mathbf{x}_i\|^2}{2\delta^2}\right) \tag{1}$$

$$g(\mathbf{x}) = \sum_{i=1}^{N} w_i K(\mathbf{x},\mathbf{x}_i) + b \tag{2}$$

$$O = sign(g(\mathbf{x})) \quad (3)$$

2. Online Learning Method [6]

In this subsection, we introduce unsupervised online learning method using SOM algorithm for SVM and restructure technique.

Let the input space be denoted by $\mathbf{x}_{in} \in R$. $\mathbf{x}_{in}$ ($in \notin \{i = 1,...,N\}$) is the input vector without the label. The training vectors are included in kernel function, $\mathbf{x}_i$ with $i = 1,\ldots, N$, 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 online learning method are shown in Fig.1.

Step 1: To find the smallest distance of 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 compute (Fig.2.a).
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.2.b).
Step 4: If d_w is condition of rule of Eq. (4), $\mathbf{x}_{win}$ is update according to the learning rule of Eq. (5) (Fig.2.c and Fig.2.d).
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 $\mathbf{x}_{in}$.

$$d_w \le d_O \quad (4)$$

$$\mathbf{x}_{win}^{new} = \mathbf{x}_{win}^{old} + \eta(\mathbf{x}_{in} - \mathbf{x}_{win}^{old}) \quad (5)$$

Fig.1 Flow of the Online Learning Method

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

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. Midpoint-Validation Method [7][8]

In this subsection, we introduce Midpoint-Validation Method. Midpoint-Validation Method adjusts the SVM output with Midpoint data. Here, Midpoint is a point to be located on midway between two classes on input space. In Fig.3, we showed a change of the improvement rate when Midpoint-Validation Method

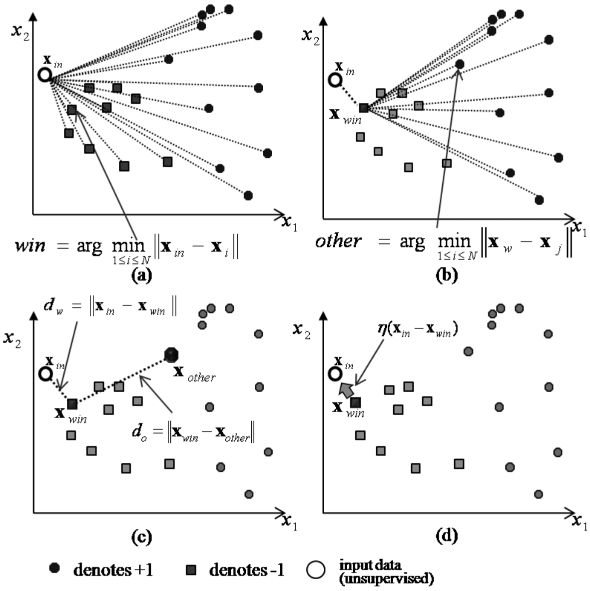

Fig.2. The flow of Online Learning Method

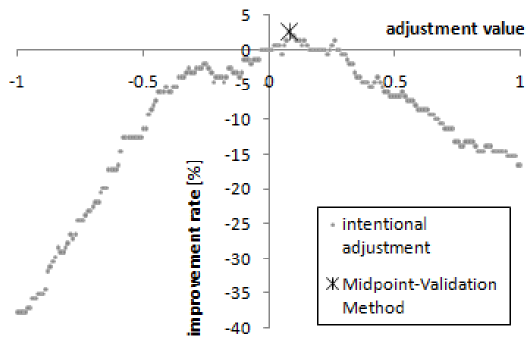

Fig.3 Adjustment value and improvement rate (Pima-indians-diabetes data)

Step 1: SVM is created by the known training data.
Step 2: Create the midpoint data.
Step 3: The output value of SVM of the midpoint data and training data computed.
Step 4: The value of B is computed according to Eq. (8).
Step 5: The output of the proposed SVM is also computed according to Eq.(6) and Eq.(7).

$$h(\mathbf{x}) = g(\mathbf{x}) + B \quad (6)$$

$$O = sign(h(\mathbf{x})) \quad (7)$$

$$B = -\frac{1}{M}\sum_{m=1}^{M} g(\mathbf{x}_m) \quad (8)$$

Fig.4 Flow of the Midpoint-Validation Method

added adjustment value B to the SVM output. We showed a procedure of Midpoint-Validation Method in Fig.4.

By past study, we know that this method improve success rate with high probability when satisfies condition $|B| \geqq 0.50$. And we know that the classifier is a high tendency when the value of $|B|$ is small [8].

4. Combination with Online Learning Method and Midpoint-Validation Method

In this subsection, we propose combination method using above-mentioned 2 methods. The procedure at first, we perform Online Learning Method. Next, we create SVM by the updated training data. Finally, we perform Midpoint-Validation Method. By this procedure, we can complete the proposed method.

III. EXPERIMENTS

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.

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 [9]. Paper [9] 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 Hz to 500 Hz.

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 Online Learning Method, Midpoint-Validation Method, the original hard-margin SVM, soft-margin SVM (C-SVC) and *k*-NN method. Proposed method and Midpoint-Validation Method have two results.

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.5). Moreover, the input given to the identification machine is eight inputs. The experiments are conducted for one day.

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.6).

The base of proposed method is hard-margin SVM using Eq. (1). 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 was 0.1. And the value of *Num* was15.

3. Experimental Result

We performed with each method and the simulation results are table 1. In table 1, we showed the average of success rate. Here, "*k*-NN with Online Learning" is *k*-NN method using training data updated by Online Learning Method. From the table 1, proposed methods are the highest value and the second highest value.

In Fig.7, we showed the success rate by 3 methods, Proposed Method ($|B| \geqq 0.25$), SVM, *k*-NN with Online Learning. The horizontal axis expresses the sensor position. Proposed method has improved SVM at 14

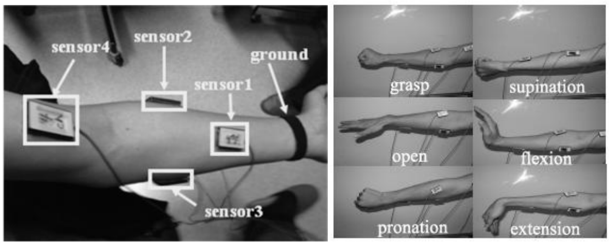

Fig.5. Image figure of forearm motion

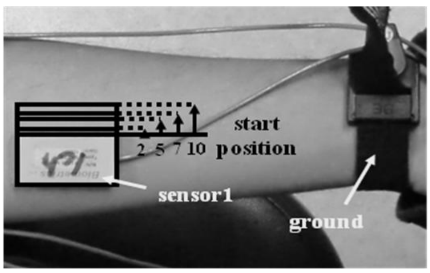

Fig.6. S-EMG recognition problems with changes in the electrode position (2mm, 5mm, 7mm and 10mm)

Table 1. Success rate average [%]

Proposed Method (|B|≧0.25)	Proposed Method (|B|≧0.50)	Midpoint Validation (|B|≧0.25)	Midpoint Validation (|B|≧0.50)	SVM with Online Learning	SVM	C-SVC	*k*-NN with Online Learning	*k*-NN
82.8	**82.7**	78.8	79.9	80.7	77.8	76.1	80.8	79.8

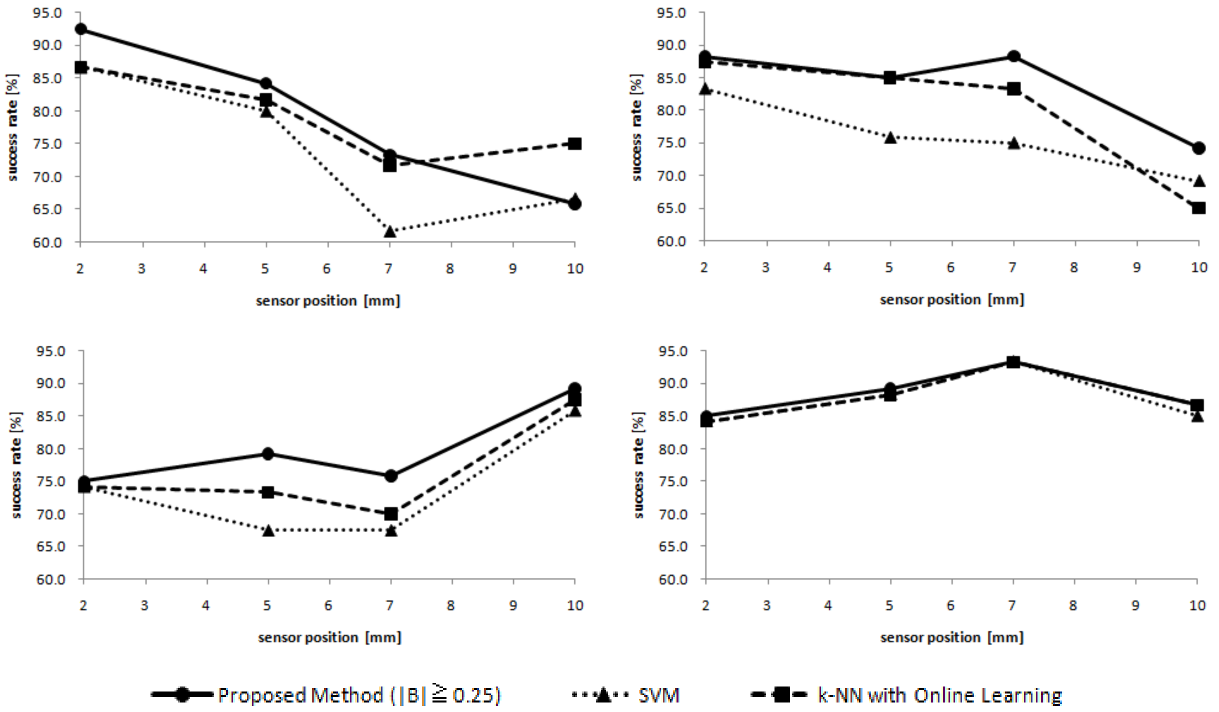

Fig.7 Experimental results of four subjects

items among 16 items. In comparison with *k*-NN with Online Learning, Proposed method gets high success rate generally. From these simulation results, it is shown that the combination of proposed method is effective.

VI. CONCLUSION

In this paper, we proposed the improvement method for SVM that is the combination with Online Learning Method and Midpoint-Validation Method. 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. In future work, we will experiment on the effectiveness of the proposed method by the other recognition problems.

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