Online Learning Method using Support Vector Machine for Surface-Electromyogram Recognition

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Abstract: Research s-EMG recognition of using neural network is a method which learns the relation between s-EMG patterns. But it does not sufficiently for user, because of s-EMG changes by the muscle wasting and gap of the electrode position etc. SVM is one of the most powerful tools for solving classification problems. But it does not have online learning technique. In this paper, we proposed online learning method using SVM with pairwise coupling technique for s-EMG recognition. We compared it performance with the original SVM and neural network. Simulation results showed that our proposed method is better than original SVM.

Keywords: Surface-Electromyogram, Support Vector Machine, Neural Network, Pattern Classification Problem

I. 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]. Moved muscle can be presumed by analyzing s-EMG. Therefore, s-EMG is used to control artificial leg etc. 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. But it does not sufficiently for user, because of s-EMG changes by the muscle wasting and gap of the electrode position etc.

Support Vector machine (abbr. SVM) proposed by Vapnik [2] is one of the most influential and powerful tools for solving classification and regression problems [3][4]. But it does not have online learning technique. Therefore, Online learning techniques of SVM were proposed by many researcher (for example: Ogura & Watanabe [5] etc,.). But, these techniques needed many computing time. In this paper, we propose simple online learning method using SVM for s-EMG recognition. We compare it performance with the original SVM, and neural network, and also test our propose method on online s-EMG recognition.

II. Review of SVM

The SVM is a mechanical learning system that uses a hypothesis space of linear functions in a high dimensional feature space. The simplest model is called Linear SVM, and it works for data that are linearly separable in the original feature space only. In early 1990s, nonlinear classification in the same procedure as Linear SVM became possible by introducing nonlinear functions called Kernel functions without being conscious of actual mapping space. This extended techniques of nonlinear feature spaces called as Nonlinear SVM.

Assume the training sample $S = ((\mathbf{x}_i, y_i), \ldots, (\mathbf{x}_i, y_i))$ consisting of vectors $\mathbf{x}_i \in R$ 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:

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

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 x_i is called support vector and the OSH $(\mathbf{w}', b')$ can be determined by solving an optimization problem. The solution of this optimization problem is given by the saddle point of the Lagrangian.

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

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

To solve the case of nonlinear decision surfaces, the OSH is carried out by nonlinearly transforming a set of

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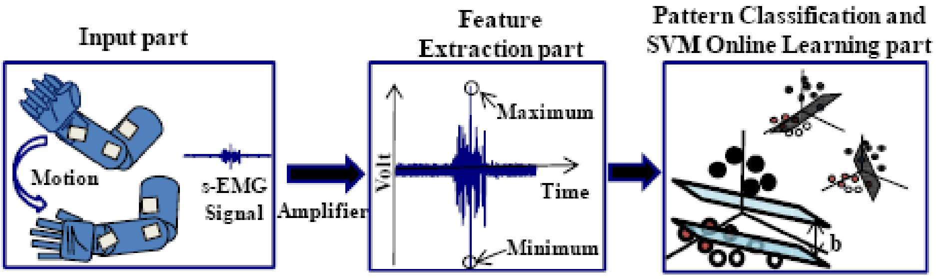

Fig.2. Structure of the s-EMG recognition system.

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).

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

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

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

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

III. Proposed method

In this section, we propose the method of decreasing the deviation of SVM by online learning method for s- EMG recognition problem.

It is widely recognized that SVM is binary pattern recognition machine. However, s-EMG recognition problems need multi-class pattern recognition machine. Thus we extend standard SVM based on pairwise coupling method to enable a multi-class pattern recognition problem for s- EMG recognition. Number of SVM necessary for n pattern classification, N is defined by Eq. (6).

$$N = \frac{n(n-1)}{n} \quad (6)$$

Proposed method is a method of adjusting threshold b of SVM (Eq. (4)) by online additional learning. Threshold b is decided by solve Lagrange multiplier equation. However, many experiment results showed that the boundary line created by SVM has deviation. Then threshold b of SVM adjusts in the rule of Fig.1. In $t(x)$ is supervised information and $y(x)$ of the class (+1 or -1) to which input $\mathbf{x}_i$ belongs are the outputs of SVM to input $\mathbf{x}_i$. The proposed method adjusts the threshold b of SVM that the output result is wrong when identification fails.

if ($t(\mathbf{x})$=+1 and $y(\mathbf{x})$<0) or ($t(\mathbf{x})$=-1 and $y(\mathbf{x})$>0)
then

$$b^{new} = b^{old} - \eta \cdot y(\mathbf{x});$$

else

$$b^{new} = b^{old};$$

Fig.1. Online learning method.

VI. Experimental method

In this section, two experiments are conducted to confirm the effectiveness of the proposed method. The construction of proposed s-EMG pattern recognition system is shown in Fig.2. The system consists of an input part, a feature extraction part and a learning discrimination 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 the maximum value and the minimum value of the s-EMG signal [6][7]. Paper [6][7] showed that technique of paper [6][7] is 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.

3.1. Experiments of muscle wasting

In this subsection, we experimented on the effectiveness of the proposed method by the s-EMG recognition problem that the feature quantity changes by the muscle

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wasting. We compared proposed method performance with the original SVM, and neural network. Neural network used is Multilayer Perceptron (abbr. MLP) that composed of three layers. Moreover, the back-propagation algorithm is used for learning. The experimental subjects are two healthy men (S.K, D.O) in twenties whom the physique looks like. The subjects sit on a chair. The recognition experiments of the 6 motions pattern of fingers is conducted by using s-EMG obtained from two sensors set in the neck of the right hand (Fig.3). The experiment method, first acquires the training data from s-EMG concerning the movement of each finger. Next, SVM and MLP learn the relation between s-EMG and motion from the training data. And, each motion is identified 20 times with these recognition machines. The subjects train ten minutes with seeing the recognition result on the display. Afterwards, additional supervised learning is done nine times about each motion. The experiment repeats the measurement nine times (recognition rate calculation). As a result, the muscle wasting is artificially caused, and the feature quantity is changed. Total experiment time is about three hours.

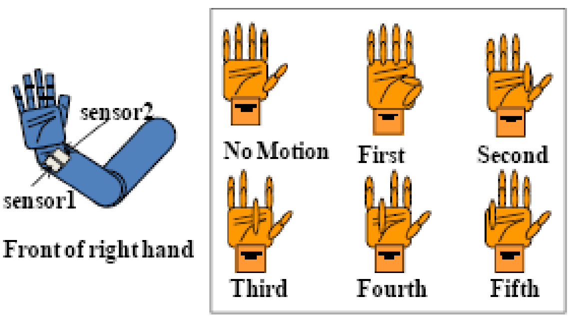

Fig3. Image figure of finger motion.

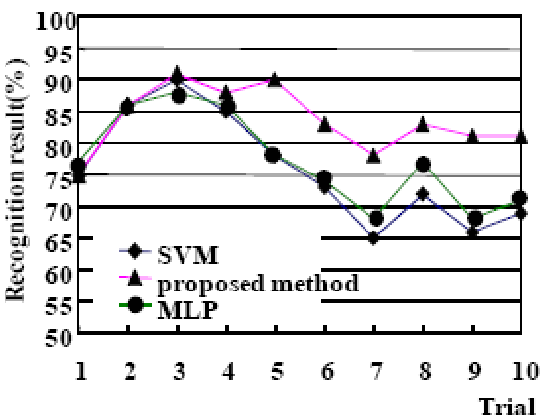

Fig.4. Experiment results of Subject D.O.

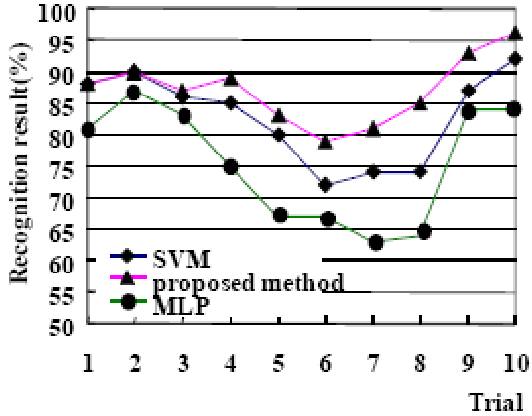

Fig.5. Experiment results of Subject S.K.

Fig.4 and Fig.5 show the recognition results. Experimental results showed that our proposed method is better than original SVM. And, proposed method performs best results in either case of S.K and D.O.

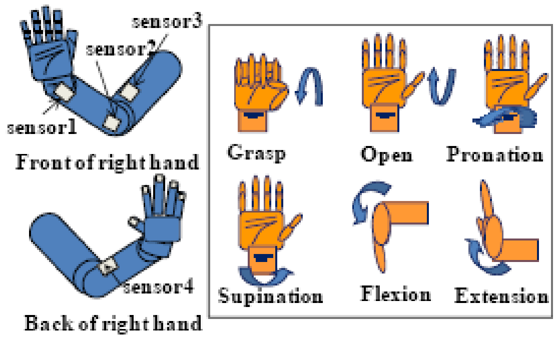

Fig.6. Image figure of forearm motion.

3.2 Experiments of electrode position gap

In this subsection, we experimented on the effectiveness of the method proposed by the s-EMG recognition problem that the feature quantity changes by the gap of electrode position. We compared proposed method performance with the original SVM, and MLP. The experimental subject is healthy man (S.K). 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.6). The experiments are conducted for three days. This purpose is to move the sensor position artificially, and to change the feature quantity. The subject trains few minutes with seeing the recognition result on the display. Afterwards, additional supervised learning is done nine times about each motion. The experiment repeats the measurement nine times (recognition rate calculation). When the experiment finished, subject S.K removes the sensor. SVM constructed with the training data of the first day is used in the second day and third day experiments. From experimental results of Fig.7, our proposed method is better than original SVM. And, proposed method had best performance in S.K. Fig.8 shows the recognition result in second day.

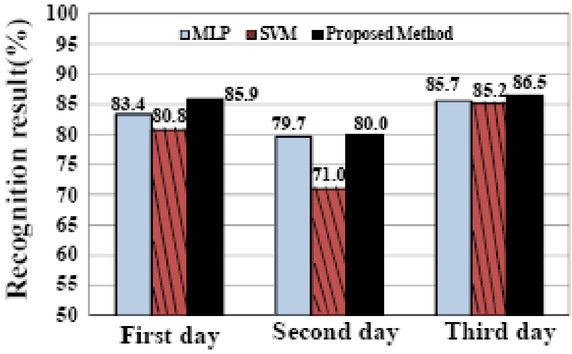

Fig.7. Average of recognition results.

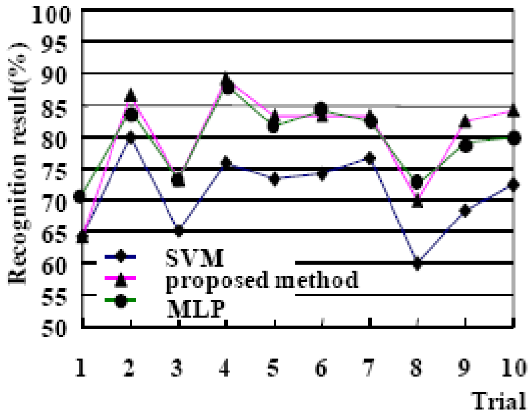

Fig.8. Experiment results of gap of electrode position (Second day).

V. Results

The average of subject D.O muscle wasting experiment results of SVM was 75.9%, MLP was 77.3% and proposed method was 83.6%. The average of subject S.K muscle wasting experiment results MLP was 75.5%, SVM was 82.8% and proposed method was 87.1%. We compared it with Nearest Neighbor method. The result using Nearest Neighbor method of subject D.O was 71.5% and subject S.K was 65.2%.

The average of experiment of electrode position gap results of MLP was 82.9%, SVM was 79.0% and proposed method was 84.1%. The results showed that the recognition rate of SVM has improved by doing online learning.

IV. Conclusion

In this paper, we proposed online learning method using SVM for s-EMG recognition problems. The experiment results showed that the proposed method was effective to s-EMG recognition problem. In the application, we had succeeded in performing robot control (Fig.9) using the technology of this paper. The robot control experiments could perform control which moves a robot in 4-directions from s-EMG of human face.

Future of works are 1) propose the technique of unsupervised learning, 2) miniaturize our system in hardware developments and 3) apply to medical.

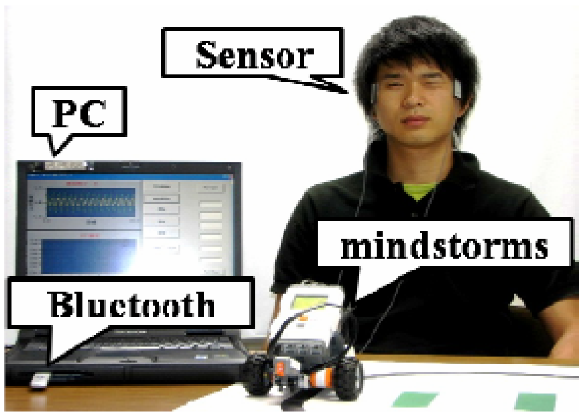

Fig.9. Robot control.

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