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Towards a High-Stability EMG Recognition System for Prosthesis Control: a One-Class Classification Based Non-Target EMG Pattern Filtering Scheme

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***Abstract*—This paper aims at dealing with a critical issue for electromyography (EMG) recognition. The issue is related to the stability of an EMG-based prosthesis control. Traditional EMG recognition systems receive EMG patterns and send them into classifiers directly, which generally results in unstable situations if the classes of some of the input EMG patterns are not included in the training of the classifiers. The EMG patterns whose class labels are not defined in the training phase are called non-target patterns. There should be a filter and this filter should be able to reject all non-target EMG patterns. As such, only target EMG patterns are fed into classifier, thus achieving a high-accuracy EMG classification. To this end, we propose in this paper a one-class classification-based non-target EMG pattern filtering scheme. By introducing a novel one-class classifier, called support vector data description (SVDD), into the filtering scheme, the goal mentioned above can easily be achieved. SVDD is a powerful machine learning technique. It can be built on a single class and find a flexible boundary to enclose the target class by using the so-called kernel trick. In experiments, we will show that if the filtering scheme is not performed, the traditional EMG classification system suffers from unstable situations. Contrarily, the whole classification system will achieve satisfactory and stable performance no matter what the input EMG patterns are target or non-target ones, if the proposed filtering scheme is embedded.**

Keywords—Electromyography (EMG) recognition, prosthesis control, one-class classification, support vector data description, machine learning.

I. INTRODUCTION

Electromyography (EMG) signal recognition plays a key role in neural-machine/human-robot interface. The most commonly seen application is the myoelectric prosthesis control. The input of a multifunction prosthetic hand is the EMG signals measured at different sites on the skin surface of a forearm using electrodes. The EMG signals from those recording sites within a timeframe (window) form an EMG pattern representing a specific type of muscle contraction, *i.e.*, a specific type of movement. To execute multiple functions, one has to construct a classifier which receives the EMG patterns and real-time output their corresponding movement labels into the control unit of the prosthetic hand. Various classifiers have been tested, including Bayes classifier [1], *K*-nearest neighbor classifiers [2], [3], linear classifiers [4]-[6], fuzzy logic systems [7], [8], fuzzy clustering-based maximum membership decision criterion [9], neuro-fuzzy systems [10], [11], artificial neural networks (ANN) [7], [12]-[16], Gaussian mixture models [17], and support vector machines (SVM) [18].

A. The Problem

While the existing classifiers have shown different levels of success, there is still a problem that has never been discussed in the research field of EMG recognition. This problem is related to the "stability" of an EMG recognition system. Before the problem statement, we shall define the so-called target pattern and the non-target pattern first.

Definition (*Target pattern and non-target pattern*): Supposing that an EMG pattern classifier (EMG-PC) has N outputs (N classes, i.e., there are N kinds of movements to be classified), if an input EMG pattern X belongs to one of the N classes, then X is called a target pattern; otherwise it is a non-target pattern.

For example, if an EMG-PC has two output classes: hook grasp (HG) and wrist flexion (WF). We need to collect a set of training patterns for each of the two classes in order to train the EMG-PC, because a classifier needs to be trained with a supervised learning manner. After training, the EMG-PC can be used to discriminate test EMG patterns and assign a class labels to each of them. We now consider two different situations:

- Situation I: if an input EMG pattern X enters the EMG-PC, and if X belongs to the class "WF", then there will be two classification results: 1) if X is classified as the class "WF", it is classified correctly, and 2) if X is classified as the class "HG", it is misclassified (an error).

- Situation II: if another input EMG pattern Y enters the EMG-PC, and if Y belongs to the class "*lateral pinch*", then there will be only one classification result: this EMG pattern Y must be a misclassified error because the class "*lateral pinch*" was not defined in the EMG-PC.

From the previous works [1]-[18], it can be seen that no matter what classifier was used, the classifier can only assign a class label to an EMG pattern, and this label must belong to one of the classes that have been included in the training phase. Also, all the experiments were performed on the test EMG patterns that originally belong to these defined classes. Those works did not conduct any experiment on the EMG patterns that do not belong to the defined classes, because it can be expected that the EMG classification rate will be much lower. That is, none of the existing EMG recognition systems considered the second situation (Situation II). If Situation II happens, the prosthesis equipped on an amputee will be out of control: whenever the amputee suddenly thinks of a movement that does not belong to the classes included in the classifier's training, his muscles may start to contract unwittingly. Then, the EMG recognition system would start to perform the classification task on the acquired EMG raw data. As a result, a wrong movement command will be sent to the controller of the prosthesis.

B. Proposed Work

According to the above analysis, we see that a stable EMG recognition system should be able to reject all EMG non-target patterns and accept all EMG target patterns; otherwise the prosthesis will be uncontrollable. To solve this critical problem, we need to design a non-target EMG pattern filter in which a "watch dog" function should be embedded, and the watch-dog function should be capable of rejecting all non-target patterns and accepting all target patterns. In other words, only the target EMG patterns can be authorized to enter the EMG-PC such that the latter prosthesis will only make the desired movements that have been defined. To realize this function, this paper proposes a non-target pattern filtering (NTPF) scheme.

The proposed NTPF scheme is developed based on the concept of one-class classification (also called novelty detection [19], [20]), which has drawn increasingly attention in the pattern recognition filed in the past decade. One-class classifiers are to find a compact description for a specific class (usually being referred to *target class*), and unlike two-class classifiers, such as SVM [21], one-class classifiers can be built on just the target class. Some promising one-class classifiers include the one-class SVM [22], the single-class minimax probability machine (MPM) [23], the support vector data description (SVDD) [24], [25], and the kernel principal component analysis (KPCA)-based method [26]. This paper adopted the SVDD as the basic component of the NTPF scheme for its success has recently been shown in various application requiring novelty/anomaly detections [27]-[30].

SVDD aims at looking for a hypersphere with minimum volume that can enclose all or most of target data. The hypersphere boundary is then used to distinguish target data from outliers (non-target data). What makes SVDD attractive, like SVM, is also the use of the kernel trick, by which the hypersphere boundary can be flexible to fit the shape of an arbitrary target set in the input space. More importantly, training SVDD is easy because only target data are needed in the training phase. We just need to collect EMG target patterns as the training set for training the SVDD-based NTPF scheme. We do not need to make any effort to collect all possible EMG non-target patterns. This can save us much time. For an amputee, this advantage is particularly significant in practical use. In experiment, an illustrative example regarding EMG-based prehensile posture classification will be used to demonstrate the validity of the proposed scheme.

The rest of this paper is organized as follows. Section II first introduces the basics of SVDD. The proposed NTPF scheme will be introduced in details in Section III. The settings of an illustrative example, including the EMG signal acquisition, processing, and feature extraction, are first given in Section IV, and the experimental results are then presented in Section V. Finally, conclusions are drawn in Section VI.

II. SVDD-based Target EMG Pattern Estimation

Given a target training set $T = \{\mathbf{x}_i \in \mathbf{R}^d\}_{i=1}^n$, SVDD aims at finding a minimum-volume sphere with center $\mathbf{a}_F$ and radius R in the feature space F such that all, or most of the target EMG training patterns are enclosed by the hypersphere, which can be formulated as the constrained optimization problem as

$$\begin{aligned} &\textit{Minimize} \quad O_p(R, \mathbf{a}_F, \xi) = R^2 + C\sum_{i=1}^{n}\xi_i \\ &\textit{subject to} \quad \|\phi(\mathbf{x}_i) - \mathbf{a}_F\|^2 \le R^2 + \xi_i, \\ &\qquad\qquad \xi_i \ge 0, \quad \forall i = 1,\dots,n \end{aligned} \tag{1}$$

where C is the penalty weight, ξ_i are slack variables, and ϕ is a nonlinear mapping: $\phi : \mathbf{x}_i \in \mathbf{R}^d \rightarrow \phi(\mathbf{x}_i) \in F$. The primal problem is usually solved by the dual problem as

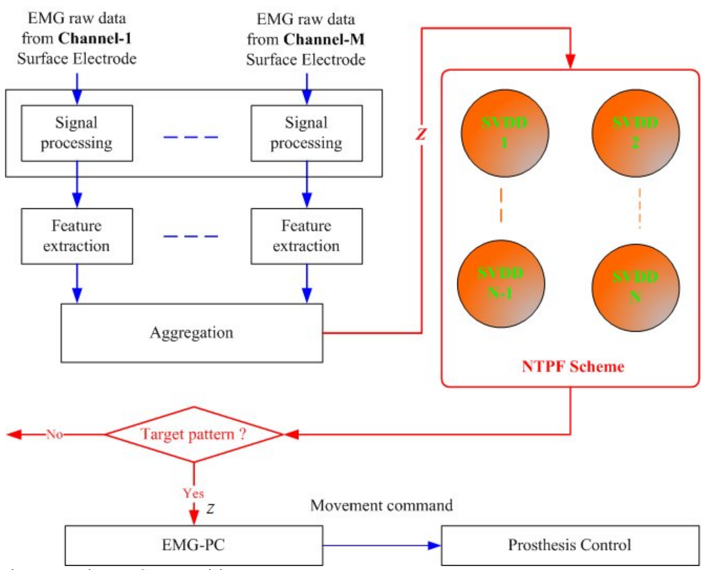

Fig. 1. The proposed NTPF scheme in a generic EMG recognition system.

$$\begin{aligned} &\textit{Maxmize} \quad O_d(\alpha) = 1 - \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j K(\mathbf{x}_i, \mathbf{x}_j) \\ &\textit{subject to} \quad \sum_{i=1}^{n}\alpha_i = 1, \\ &\qquad\qquad\quad 0 \le \alpha_i \le C, \quad \forall i = 1,\dots,n \end{aligned} \tag{2}$$

where α_i are positive weights, and K is the kernel function defined as the inner dot product of feature vectors in feature space F: $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)$. In this paper we consider the radial basis function (RBF) kernel, defined as

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

where σ is the kernel parameter and is specified by the user. According to the Kuhn-Tucker (KT) conditions, the target training data can be classified into the three categories: 1) the data points with $\alpha_i = 0$ are inside of the sphere, 2) the data points with $0 < \alpha_i < C$ lie on the boundary of the sphere, and 3) the remaining data points (with $\alpha_i = C$) fall outside the sphere. The data points whose $\alpha_i > 0$ are called support vectors (SVs). We call the SVs with $0 < \alpha_i < C$ the unbounded SVs (UBSVs), and call the SVs with $\alpha_i = C$ the bounded SVs (BSVs). The center $\mathbf{a}_F$ is expanded by the images of the SVs:

$$\mathbf{a}_F = \sum_{i=1}^{n_s}\alpha_i\phi(\mathbf{x}_i) \tag{4}$$

where n_s is the number of SVs. The radius R can be determined by taking any $\mathbf{x}_k \in$ UBSVs and calculating the distance from its image $\phi(\mathbf{x}_k)$ to the center $\mathbf{a}_F$:

$$R = \left(1 - 2\sum_{\mathbf{x}_i\in \mathrm{SVs}}\alpha_i K(\mathbf{x}_i, \mathbf{x}_k) + \sum_{\mathbf{x}_i\in \mathrm{SVs}}\sum_{\mathbf{x}_j\in \mathrm{SVs}}\alpha_i\alpha_j K(\mathbf{x}_i, \mathbf{x}_j)\right)^{1/2} \tag{5}$$

The output for a test EMG pattern $\mathbf{x}$ is determined by comparing its distance to $\mathbf{a}_F$ with radius R :

$$D_{\mathrm{SVDD}}(\mathbf{x}) = \left\|\phi(\mathbf{x}) - \mathbf{a}_F\right\|^2 - R^2 \tag{6}$$

The kernel expression of the SVDD decision function is given by

$$D_{\mathrm{SVDD}}(\mathbf{x}) = K(\mathbf{x},\mathbf{x}) - 2\sum_{i=1}^{n}\alpha_i K(\mathbf{x},\mathbf{x}_i) + \sum_{i,j=1}^{n}\alpha_i\alpha_j K(\mathbf{x}_i,\mathbf{x}_j) - R^2 \tag{7}$$

If K is a RBF kernel, we obtain the SVDD decision function:

$$D_{\mathrm{SVDD}}(\mathbf{x}) = c - 2\sum_{\mathbf{x}_i\in \mathrm{SVs}}\alpha_i K(\mathbf{x},\mathbf{x}_i) \tag{8}$$

where $c = (1 - R^2) + \sum_{i,j=1}^{n}\alpha_i\alpha_j K(\mathbf{x}_i,\mathbf{x}_j)$ is a constant. If $D_{\mathrm{SVDD}}(\mathbf{x}) \le 0$, $\mathbf{x}$ is accepted as target EMG pattern; otherwise it is rejected as non-target EMG pattern.

III. NON-TARGET EMG PATTERN FILTERING SCHEME

The proposed NTPF scheme is a generic form. Its flow chart is depicted in Fig. 1. Supposing that there are M channels (M

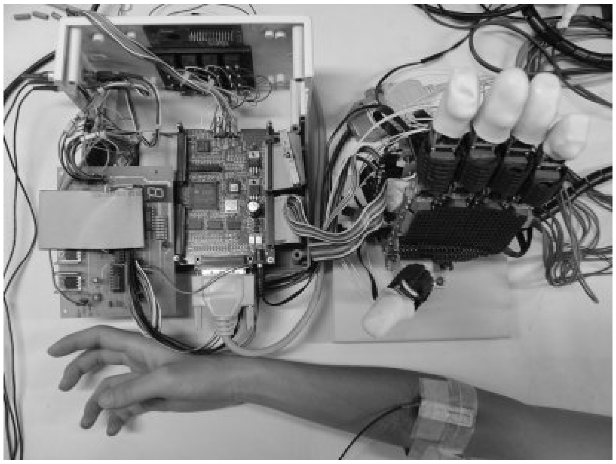

Fig. 2. The DSP-based EMG processing module and the multi-finger prosthesis

surface electrodes at different recording sites), the signal processing and feature extraction tasks perform on each channel independently. Supposing that there are totally d features extracted from the M channels, the d features form a feature vector of d dimension, called an EMG pattern. After the EMG pattern Z arrives, it will not directly go to the EMG-PC for classification, but enters the proposed NTPF scheme first.

Traditionally, the SVDD is trained to enclose the patterns of a specific class. In EMG classification, there are usually many movements (classes) to be classified. The performance of the SVDD may not be the optimum if using only one hypersphere to enclose all the training patterns belonging to these classes, because these patterns would not form a compact distribution but several disjoint clusters in the input space. One remedy is to decrease the value of the kernel parameter σ to sufficiently small. By doing so, all the patterns can be enclosed by the single SVDD hypersphere tightly. However, the generalization performance of the SVDD will drop greatly because a too small σ results in a large number of support vectors. It has been proven that the larger the number of the support vectors, the poorer the generalization performance of the SVDD [24], [25]. Therefore, this paper adopts a “grouping” strategy. Instead of using one single SVDD hypersphere, we propose to use multiple SVDD hyperspheres to learn the data descriptions for the EMG patterns originated from different target classes. Since there are more than one SVDD, we call the SVDDs an SVDD ensemble.

The SVDD ensemble is composed of N SVDDs (SVDD 1, SVDD 2,…, SVDD N), where N is the number of target classes. If the EMG-PC has N kinds of output movements, the SVDD ensemble has N SVDDs. Each SVDD is responsible for enclosing the EMG training patterns of a target class. Therefore, there will be N hyperspheres in the SVDD ensemble after training. The decision making strategy used in the NTPF scheme follows the simple rules as:

(1) *If the EMG pattern Z falls inside any of the N hyperspheres, then it is a target pattern. It will be sent to the EMG-PC for further classification.*

(2) *The EMG pattern Z is classified as a non-target pattern if it does not fall inside any of the N hyperspheres. Since it is a non-target EMG pattern, it will be ignored will not be fed into the EMG-PC.*

Using the simple rules can easily achieve the goal of non-target pattern filtering, and as a result, the EMG recognition system will be stable and will not send wrong motion commends to the prosthesis, unless the classification rate of the EMG-PC itself is not satisfactory.

One may ask the question: since each SVDD in the ensemble is able to describe the distribution of a specific target class, why don’t we use the SVDD ensemble to perform the classification task directly? (because as long as Z falls inside the hypersphere of the ith SVDD, it belongs to the ith class). In theory, it may work. But, using the SVDD ensemble to accomplish the classification task may cause an ambiguous situation in practice. For example, two different hyperspheres may have an overlapping region. Consequently, the pattern Z may fall inside the two hyperspheres at the same time. In this ambiguous situation, the class label of the input EMG pattern Z is unable to determine. Hence, it is still necessary to use a multi-class classifier to accomplish the task of multi-class EMG classification because the SVDD was not designed for multi-class classification, but for outlier/novelty detection.

IV. Illustrative Example

A. EMG Preprocessing

In order to obtain the EMG patterns, we have the hardware and software settings as follows.

1) Recording sites

Three EMG surface electrodes are placed on *palmaris longus*, *extensor digitorum* and *flexor carpi ulnaris* and therefore three channels are used.

2) Signal processing

EMG signals are acquired via the EMG surface electrodes. A 60 Hz. notch filter is used to reduce the effect of noise to the EMG signals. A 30-400 Hz band-pass filter is also used to obtain meaningful EMG signals. After filtering, the EMG signals are sampled by an AD converter with sampling frequency 2.5 KHz and stored in the memory. The sampled EMG raw data are then transferred from the memory to a computer (PC) by parallel ports. The above process is common for all channels, and has been implemented with a digital signal processor (DSP)-based module, as shown in Fig. 2. The details can be referred to the work [18].

3) Feature Extractions

The feature extraction methods include two different methods: autoregressive model (ARM) [31], and the histogram of EMG (HEMG) [32]. For ARM, a 4-th order model is adopted. By using a forth-order ARM, each channel will extract four feature components from EMG raw data. By using HEMG, a feature vector containing nine feature components is obtained from each channel. Therefore, a 13-dimensional feature vector is obtained from each channel. Since there are three surface electrodes, there are totally 39 features. In other words, each EMG pattern is a 39-dimensional vector. Notice that the raw data are received by a window with size of 1000. That is, there would be 1000 EMG raw data collected in 400 ms for each channel since the sampling frequency is set to 2.5 KHz.

4) Classes of postures

In this example, we are interested in several types of postures, including *power grasp (PG)*, *hook grasp (HG)*, *wrist flexion (WF)*, *lateral pinch (LP)*, *flattened hand (FH)*, *centralized grip (CEG)*, *three-jaw chuck (TJC)*, and the *cylindrical grasp (CYG)*. For each of the eight kinds of postures, we collect 20 EMG patterns from an amputee. There are totally 160 EMG patterns.

B. Experimental Results

We design two kinds of circumstances, described as follows.

1) The first circumstance

In this circumstance, we follow the traditional EMG classification schemes. That is, training a classifier that can recognize the classes of the eight kinds of postures. First, for each class, we randomly select 10 EMG patterns as training samples. The remaining 10 EMG patterns are used as the test samples. Hence, we have 80 training sand 80 test samples, respectively. Next, we use the 80 training patterns to train the EMG pattern classifier. The support vector machine (SVM) [21] is adopted as the classifier in this paper for its high generalization performance. However, SVM is a two-class classifier. Hence, we construct a multi-class classifier by using the one-against-one method and the voting strategy [18]. As a result, there are 28 SVMs in total. The Gaussian kernel is used for each SVM. The optimal hyperparameters for the 28 SVMs, the penalty weight and the kernel parameter, are obtained by taking two-fold cross validation. After testing, the classification rate is 87.5%. It is not surprisingly, because the class labels of the 80 test samples have been included in the training. Next, we consider a more practical circumstance.

2) The second circumstance

Here we first define the target class. The target class includes the follow six postures: *PG*, *HG*, *WF*, *LP*, *FH*, *CEG*. Similarly, we randomly select 10 EMG patterns from each of the posture class as the training samples, and the remaining ones are test samples. There are totally 60 training samples. We then use the 60 training samples to train the multi-class SVMs (there are 15 SVMs in total). In addition, all the EMG patterns belonging to the postures TJC and CYG are defined as the non-target EMG patterns, and used as the test samples. Therefore, there are 60+40=100 test samples in total. We then feed the 100 test samples into two different EMG classification systems: one has only the SVM classifier (SYSTEM 1), and the other (SYSTEM 2) involves the proposed non-target EMG pattern filtering (NTPF) scheme, which is placed prior to the SVM classifier. The final classification rates of the two systems are reported in Table 1.

Table 1
Comparisons of the Classification Rates Among Two EMG classification Systems Without (SYSTEM 1) and With (SYSTEM 2) the NTPF Scheme

	SYSTEM 1	SYSTEM 2
Classification rate (%)	51	87

The advantage of the proposed NTPF is clear, which can be seen from Table 1 that the SYSTEM 1 obtains a poor classification performance of 51%. In fact, it is not surprisingly because for SYSTEM 1, the 40 non-target EMG patterns must be misclassifications. On the contrary, SYSTEM 2 achieves a relatively high classification rate (87%) because the NTPF scheme rejects almost all the non-target EMG patterns (in the experiment, there are only 4 non-target EMG patterns are accepted by the NTPF scheme). In other words, 4 non-target EMG patterns enter the SVM classifier. Another 9 classification errors are contributed by the test EMG patterns belonging to the target class.

V. Conclusion

This paper has presented a novel non-target EMG pattern filtering (NTPF) scheme. The results have shown that the proposed NTPF scheme is able to maintain a high EMG classification rate. And as a result, the latter prosthesis can perform more stable. The success of the proposed scheme should be attributed to the use of the one-class classifier, the support vector data description (SVDD). However, the decision function of SVDD is expanded by the images of the training data points, which may result in a great run-time complexity if the size of the target set is larger. To avoid the delay between the EMG classification system and the prosthesis control, in the future, we will design a method to reduce the run-time complexity of SVDD such that it can be used more practically.

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