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Adaptive myoelectric pattern recognition toward improved multifunctional prosthesis control

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ABSTRACT

The non-stationary property of electromyography (EMG) signals in real life settings usually hinders the clinical application of the myoelectric pattern recognition for prosthesis control. The classical EMG pattern recognition approach consists of two separate steps: training and testing, without considering the changes between training and testing data induced by electrode shift, fatigue, impedance changes and psychological factors, and often results in performance degradation. The aim of this study was to develop an adaptive myoelectric pattern recognition system, aiming to retrain the classifier online with the testing data without supervision, providing a self-correction mechanism for suppressing misclassifications. This paper presents an adaptive unsupervised classifier based on support vector machine (SVM) to improve the classification performance. Experimental data from 15 healthy subjects were used to evaluate performance. Preliminary study on intra-session and inter-session EMG data was conducted to verify the performance of the unsupervised adaptive SVM classifier. The unsupervised adaptive SVM classifier outperformed the conventional SVM by 3.3% and 8.0% for the combination of time-domain and autoregressive features in the intra-session and inter-session tests, respectively. The proposed approach is capable of incorporating the useful information in testing data to the classification model by taking into account the overtime changes in the testing data with respect to the training data to retrain the original classifier, therefore providing a self-correction mechanism for suppressing misclassifications.

1. Introduction

Among the potential biological signals for human–machine interaction (brain, nerve, and muscle signals), electromyography (EMG), directly reflect the human motion intention, may be the only experimentally non-invasive record of the motor commands to the muscles that allows applications in routine clinical use. As a noninvasive measurement containing rich motor control information, surface electromyogram (EMG) signal is an important input for the control of power prostheses, known as myoelectric control [1]. Conventional myoelectric control systems enable users to operate a single device such as a hand or a wrist in an on–off mode or proportional control strategy. Controlling a multiple degree of freedoms (DOFs) prosthetic devices requires more sophisticated technique for identification of various movement intentions from the recorded EMG [2–5]. Because of the inherent non-stationary of EMG signals, the possible EMG variation induced by these factors such as electrode condition, muscle fatigue and so on is a big challenge, which hinders the commercialization of myoelectric controlled prosthetic devices that was developed in a laboratory environment.

While the myoelectric pattern recognition strategy is a promising approach to controlling the multiple DOFs of a multifunctional dexterous prosthesis [6,7], these studies reported low error in a single session, however, robustness over time has rarely been evaluated [8]. Conventional pattern recognition methods are usually accomplished in two independent parts, training and testing steps. The parameters acquired in the training contain limited information because the training EMG data are normally acquired at one time during a short period, which are not representative for the whole period including testing step. Enlarging the EMG recordings in training step that contains more information may be impractical, because it is time-consuming therefore adding additional burden to the users. So far, no clinically prosthetic system utilizing myoelectric pattern recognition control has been commercialized because of the unsatisfactory performance of these existing myoelectric pattern recognition algorithms in real life settings [2] due to the variations in EMG signals in the testing data with respect to the training data, induced, e.g. by electrode shifts [9,10], arm position changes [11,12], fatigue [13], time-related effects [14].

Training a robust myoelectric pattern recognition system is critical due to the changes of EMG signal properties occur over sessions.

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Especially the myoelectric pattern recognition system may have to be retrained if changes in EMG signal properties are substantial. To account for changes, recent studies attempted to use adaptive learning schemes by including testing data into the classifier's training data set [15–17]. However, unsupervised adapting existing myoelectric pattern recognition systems to the overtime changes remains a challenging open problem. Therefore, it is required to develop an adaptive classification algorithm. In particular, it is motivated to incrementally retrain the classifier online with the testing data by taking into account real-time changes in the testing data with respect to the training data.

The current study seeks to develop an adaptive myoelectric pattern recognition system, aiming to retrain the classifier online with the testing data without supervision, thus incorporating the changes in the testing data with respect to the training data, therefore providing a self-correction mechanism for suppressing misclassifications. To achieve this goal, a novel myoelectric pattern recognition approach based on the incremental learning adaptive support vector machine (SVM) is proposed.

2. Methods

2.1. Data set description

The data used in this study are identical to the data in a previous study [18]. Eight-channel EMG data were collected from forearm muscles and the biceps muscle of healthy subjects using Ag-AgCl electrodes. Fig. 1 illustrates the placement of the electrodes, using the right arm as an example. The surface EMG signals were sampled at 3000 Hz per channel. Subjects performed six forearm motions plus rest: hand open, hand close, supination, pronation, wrist flexion, wrist extension and rest. EMG data used in this study were collected from 15 subjects during two sessions completed on two separate days, and five trials were acquired within each session. Each motion was repeated four times with duration of 3 s within each data collection trial. The order of these motions was randomized.

2.2. Incremental learning adaptive SVM

The classical SVM classifier was extended to the incremental learning adaptive SVM classifier, since the SVMs are popular classifiers employed widely in pattern recognition studies [19–21]. Given the initial training data T consisting of N samples $X_j \in R^n, j = 1, 2, \ldots, N$, labeled by $y_j \in \{1, -1\}$, an initial SVM classifier was trained from T by

$$\min_{w,b,\xi P} \frac{1}{2}\|w\|^2 + C\sum_{j=1}^{N} \xi_j$$
$$\text{s.t.} \quad y_j(\langle w, X_j\rangle - b) \geq 1 - \xi_j, \quad \xi_j \geq 0, \quad j = 1, 2, \ldots, N \qquad (1)$$

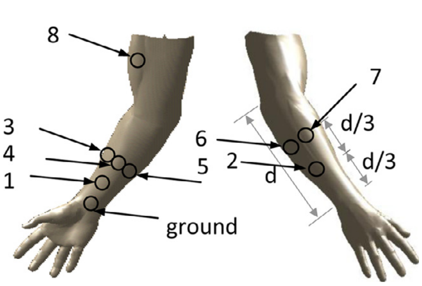

Fig. 1. Illustration of the surface electrode placement on the right arm. Eight surface electrodes (Myotronics, 6140) were placed around the forearm and the biceps, with the electrodes indexed 3, 4, 5, 6, 7 being equally spaced along the circumference of the forearm longitudinally along the muscle fiber approximately one-third the distance between the elbow and wrist. The right panel shows the lateral view of the electrodes with only three electrodes being visible. The left panel shows the medial view of the electrodes for the other electrodes. A ground reference electrode (3 M, 2237) was placed on the wrist.

The SVM computes a decision function $f(X_j) = \langle w, X_j\rangle + b$ such that the sign of the decision function is employed to predict the label of a test sample $X_k \in R^n$. X_k is classified by $z_k = \text{sign}(f(X_k))$. In addition, for the estimation of class label, the posterior class probability $p_k = P(y_k = z_k|X_k)$ can be computed, because the SVM output score can be transformed into the probability estimate using sigmoid transformation [22]. The predicted class label obtained by the posterior class probability is then used for incorporating the testing sample and continuously adapts the classifier.

For this study, Platt's posterior probabilistic output [22] in conjunction with pairwise coupling was employed to obtain k multiclass probability estimates. For the binary SVM of ith and jth classes, given the any sample X and the class label y, let $r_{i,j}$ be the estimates of pairwise class probabilities $u_{i,j} = P(y = i|y = i \text{ or } j, X)$. An improved implementation of Platt's posterior probability estimation algorithm based on Newton's method with backtracking line search [23] was utilized to approximate $r_{i,j}$ by a sigmoid function.

$$r_{i,j} = P(i|i \text{ or } j, X) = P_{A,B}(\hat{f}) = \frac{1}{1 + e^{A\hat{f}+B}}$$
$$\text{where} \quad \hat{f} = f(X) \qquad (2)$$

where A and B are estimated by minimizing the negative log-likelihood function, and $\hat{f}$ are the decision values of training data.

Consequently, a multi-class probability can be estimated by combining all pairwise coupling comparison [24]. From the ith and jth classes of a training set, a model is obtained which, for any new X, calculates $r_{i,j}$ as an approximation of $u_{i,j}$. Then, given all $r_{i,j}$, the goal is to estimate $p_i = P\left(y = i|X\right), \quad i = 1, 2, \ldots, k$ for k classes.

According to [24], optimization formulation is given as follows:

$$\min_{P} \sum_{i=1}^{k} \sum_{j:j\neq i} (r_{ji}p_i - r_{ij}p_i)^2$$
$$\text{s.t.} \quad \sum_{i=1}^{k} p_i = 1 \qquad (3)$$

The objective function of (3) can be written as

$$\min_{P} 2P^T QP = \min \frac{1}{2}P^T QP$$
$$\text{where} \quad Q_{ij} = \begin{Bmatrix} \sum_{s:s\neq i} r_{si}^2 & \text{if } i = j \\ -r_{ji}r_{ij} & \text{if } i \neq j \end{Bmatrix} \qquad (4)$$

Any optimal solution P is a vector of multi-class probability estimates. The objective function (4) is a linear-equality-constrained convex quadratic programming problem. Subsequently, an optimal solution P is a global minimum only if it satisfies the optimality condition: There is a scalar b such that

$$\begin{bmatrix} Q & e \\ e^T & 0 \end{bmatrix} \begin{bmatrix} P \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \qquad (5)$$

where b is the Lagrangian multiplier of the equality constraint $\sum_{i=1}^{k} p_i = 1$, e is the $K \times 1$ vector of all ones and 0 is the $K \times 1$ vector of all zeroes. Therefore, P the solution to (3) can be obtained by solving a simple linear system (5).

As T changes during retraining, Eq. (1) needs to be solved consequently online. Thus the incremental learning method [25] was employed to train the SVM classifier incrementally using the L1 soft margin approach and adapt the classifier to changes via regularization and kernel parameters. Sequential minimal optimization (SMO) is not feasible when used online, because the solution for Eq. (1) needs to be computed from scratch each time T changes [26]. In contrast, the method described in a previous study [25] was used in the current study to train an SVM and incrementally update the solution for Eq. (1) each time when a new testing sample is added and therefore incrementally update the solution every time a new sample is added. All individual classifiers update each time for multi-class classification.