INVESTIGATION OF OPTIMUM PATTERN RECOGNITION METHODS FOR ROBUST MYOELECTRIC CONTROL DURING DYNAMIC LIMB MOVEMENT

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ABSTRACT

The control of upper limb prostheses based on surface electromyogram (EMG) pattern recognition has long been the focus of many researchers as an important clinical option for amputees. More recently, it has been shown that changes induced during use, such as changes in limb position and performing dynamic activities, can have a substantial impact on the robustness of EMG pattern recognition. This work investigates whether there are alternative EMG features and classifiers which can outperform the commonly used time domain (TD) features and linear discriminant analysis (LDA) classifier in the context of limb positional changes and performing dynamic activities of daily living. A variety of EMG feature combinations and popular classifiers are compared in this study. The bases of comparison are classification accuracy and class separability. The results showed that adding Willison amplitude (WAMP) feature to the commonly used TD feature set combined with LDA classifier reduces the averaged absolute classification error by 1.4%.

INTRODUCTION

Surface electromyogram (EMG) has been used as one of the major neural control sources for powered upper limb prostheses for many decades. It contains useful information about the neuromuscular activity from which it originates. Various EMG signal processing methods have been used to extract user's intent for movement of the prosthetic limb.

Pattern recognition-based myoelectric control is an intelligent and advanced signal processing technique that can potentially be used to control multiple degrees of freedom (DOF). In this approach, a set of features containing spatial and temporal information about the acquired signals are extracted and form an input pattern to a classifier which determines the user's intended movement. Many researchers have reported high classification accuracies using various combinations of preprocessing, feature extraction, classification, and postprocessing [1-3]. However, most of these studies were done in unrealistically ideal conditions performing static contractions in fixed positions. Contrarily, in real-world prosthetic use, the user is required to elicit contractions in a variety of positions and orientations, and under different loading conditions. Newer studies [4-6] have shown that these conditions might affect signal patterns and erode the robustness of the EMG pattern recognition.

Feature sets and classifiers used for EMG pattern recognition may provide different levels of robustness when using data collected during dynamic limb movements compared to data from static tasks. Englehart and Hudgins [1] showed that Linear discriminant analysis (LDA) classifier combined with four time domain features including mean absolute value (MAV), wave length (WL), zero crossing (ZC), and slope sign change (SSC) can be used as an effective real-time control scheme for EMG pattern recognition for static conditions. This combination has since been widely reported in the literature as a promising myoelectric control scheme [1, 4, 5]. Herein, we investigated the general impact of limb positional changes and performing dynamic activities on the robustness of various feature sets and classifiers to explore alternative feature sets and classifiers that may outperform the commonly used LDA classifier and TD features during dynamic movement.

METHODOLOGY

Data Collection and Experimental Protocol

We used the data that was acquired as a part of a study by Scheme *et al.* [5]. Subjects were prompted to elicit a set of contractions at a repeatable 'medium' force level consisting of the following eight classes of motion: wrist flexion/extension, wrist pronation/supination, hand open, power grip, pinch grip, and a no motion (i.e. rest) class. These sets were repeated during three sessions, each involving a different form of positional variation.

In session 1, the contractions were sustained while holding the arm in five different static positions. In session 2, subjects executed motions while performing two dynamic activities, and in session 3, four activities of daily living (ADLs) were completed while holding each of the eight classes of motion [5]. Four sets of contractions were collected in each of the sessions. Two of these sets were used for training and two were used for testing. The ADLs were only used for testing. Contractions were held for 3, 8, and 4 seconds when performing static tasks, dynamic tasks, and ADLs, respectively, with 3 second inter-repetition delays. Similarly to [5], nine training and testing scenarios (SC) were investigated which are listed in Table 1. The scenarios in which only one static or dynamic position was used for training were repeated for every possible position and the results were averaged.

Table 1: Training/Testing scenarios

Title	Training Data	Testing Data
SC1	One static position	All static positions
SC2	One static position	Same static position
SC3	All static positions	All static positions
SC4	One static position	All ADLs
SC5	All static positions	All ADLs
SC6	One dynamic motion	All static positions
SC7	All dynamic motions	All static positions
SC8	One dynamic motion	All ADLs
SC9	All dynamic motions	All ADLs

Data Processing and Feature Extraction

EMG data were notch filtered at 60Hz using a 3rd order Butterworth filter in order to remove any power line interference. Data were segmented for feature extraction using 200ms windows, with processing increments of 50ms.

Nine frequently reported time-domain features for pattern recognition of myoelectric signals were extracted within each analysis time window. We chose only time-domain features that do not require additional signal transformation to keep computational complexity low.

The following features were extracted [1, 7]: Mean Absolute Value (MAV), Mean Absolute Value Slope (MAVs), Waveform Length (WL), Zero Crossings (ZC), Slope Sign Changes (SSC), Willison Amplitude (WAMP), Variance (VAR), Log-Detector (LD), and 4th order Autoregression Coefficients (AR).

Classification

Data were classified using six commonly used classification techniques including K-nearest neighbor (KNN) [8], support vector machines (SVM) [9], neural network (NN) [2], Fuzzy clustering (FC) [10], linear discriminant analysis (LDA) [11], and Mahalonobis distance (MD) [12].

Evaluation

Two metrics were computed to evaluate the suitability of features and classifiers:

1) *Class Separability:* Feature sets that provide higher class separability are expected to result in lower misclassification rates.

We used the *Davies-Bouldin cluster separation measure* [13] to quantify class separability, which is obtained by averaging the worst case separation of each cluster from the others. In fact, the DB metric indicates how badly the clusters overlap their nearest neighbors. A lower DB means higher cluster separability. This index has been used in a variety of classification problems [7, 13].

2) *Classification Error:* In general, the optimum pattern recognition method is expected to be the one that provides minimum classification error.

RESULTS

We tested all possible combinations of nine TD features described in the feature extraction section and picked the ten most interesting feature sets based on classification accuracy and feature combination. These feature sets are listed in Table 2.

Table 2: Selected feature sets

Title	Feature Combination
FS1	MAV, WL, ZC, SSC
FS2	WL, ZC, WAMP
FS3	MAV, ZC, SSC, WAMP
FS4	MAV, WL, ZC, WAMP
FS5	WL, ZC, WAMP, VAR
FS6	WL, ZC, SSC, WAMP
FS7	MAV, WL, ZC, SSC, WAMP
FS8	MAV, WL, ZC, SSC, AR
FS9	MAV, WL, ZC, SSC, WAMP, AR
FS10	MAV, WL, ZC, SSC, MAVS, VAR, WAMP, LD, AR

Class separability

Figure 1 shows the average DB index along with the standard error for all ten feature sets. Each feature was normalized between zero and one for this test. An analysis of variance (ANOVA) was completed using the DB index for all scenarios. A general linear model was used with subject as a random factor, and scenario and trial as fixed factors. The ANOVA showed that all of the feature combinations except FS8 were significantly better ($p < 0.05$) than FS1 which implies that these feature combinations provide higher class separability and consequently are likely to provide higher classification accuracy.

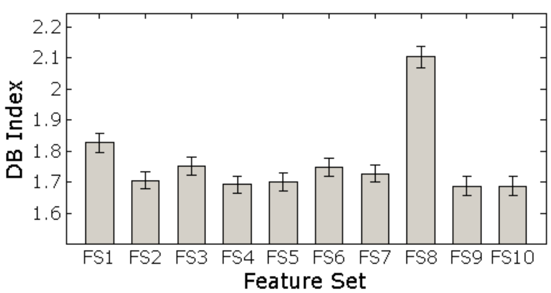

Figure 1: Comparison of feature sets using DB

Classification Error

Classification error (CE) was calculated for each of the aforementioned classification schemes taking into consideration everything including data from all users using all ten feature sets and for all training and testing scenarios. Figure 2 shows the mean classification error using these classifiers. The results of performing the ANOVA test using the classification error showed that LDA is significantly better ($p < 0.05$) than other classifiers. Subject was considered as a random factor and scenario, trial and used feature set were considered as fixed factors.

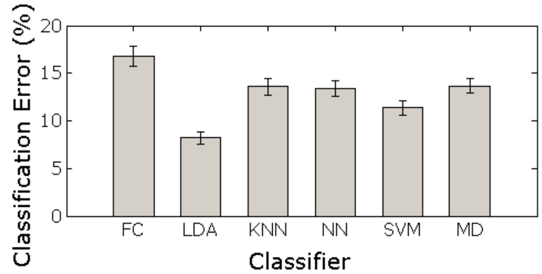

Figure 2: Comparison of classifiers using CE

In another test, CE was calculated for each of the ten feature sets using only the LDA classifier and for all scenarios. The averaged CE along with standard error is depicted in Figure 3. An ANOVA test showed that FS6, FS7, FS9 and FS10 are significantly ($p < 0.05$) better than FS1. Also, FS9 and FS10 were significantly better than all other feature sets except FS7. Subject was a random factor, and scenario, trial and applied classifier were fixed factors.

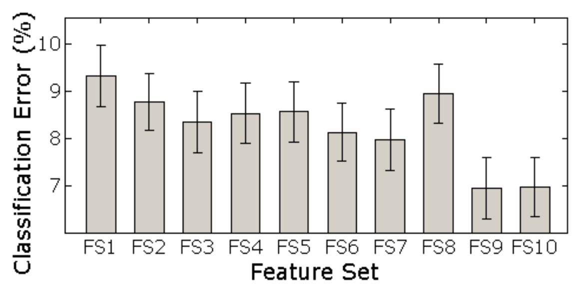

Figure 3: Comparison of feature sets using CE

DISCUSSION

The comparison of classifiers (see Figure 2) showed that LDA can still be considered as a good classifier with regard to classification accuracy in the context of dynamic movements. Its high performance along with its ease of implementation makes it an ideal real-time classifier for myoelectric pattern recognition.

Results of comparing all ten feature sets listed in Table 2 (see Figure 3) are to some extent in agreement with the results of comparing class separability provided by each of these feature sets (See Figure 1). As the class separability increases, classification error decreases. These results show that performance of the commonly used TD feature set can be improved by adding or replacing

	AR4	AR3	AR2	AR1	LD	WAMP	VAR	MAVS	SSC	ZC	WL	MAV
MAV	0.0719	-0.0472	0.2178	-0.2208	0.9481	0.7771	0.9638	0.1915	-0.078	0.1537	0.9198	1
WL	0.0431	-0.0087	0.2219	-0.0061	0.8585	0.8557	0.8933	0.1509	0.072	0.3609	1	
ZC	-0.0224	0.1073	0.0401	0.4319	0.1549	0.4061	0.1257	-0.0265	0.4184	1		
SSC	0.0058	0.0706	-0.2273	0.4493	-0.0727	0.0842	-0.0798	-0.0741	1			
MAVS	0.0315	-0.0426	0.0921	-0.116	0.1792	0.1154	0.1955	1				
VAR	0.065	-0.0517	0.2331	-0.2389	0.8631	0.7081	1					
WAMP	0.0454	0.0043	0.1713	0.0153	0.7601	1						
LD	0.0681	-0.0417	0.178	-0.187	1							
AR1	-0.0879	0.5253	-0.5034	1								
AR2	0.2735	-0.6078	1									
AR3	-0.5214	1										
AR4	1											

Figure 4: Averaged computed correlation between different features (darker means closer to 1)

some of its features with other features. This could be explained as added or replaced features contain complementary information that is particularly useful for myoelectric pattern classification. Figure 4 shows the averaged correlation between different features within a trial using data from all static and dynamic training scenarios. Features that are less correlated are expected to provide complementary information about the signal. However, their degree of correlation does not relate directly to the amount of useful information they provide for classification.

Amongst the feature sets tested, FS8, FS9, and FS10 contain AR feature which is not a practical real-time feature for clinical embedded system implementation. Excluding these three feature sets, FS6 and FS7 seem to be most promising feature sets which are both significantly better than FS1 (See Figure 3). The former, however, is the best choice if increasing the dimensionality of the problem is not desired. Figure 5 compares averaged classification error using FS1, FS6, and FS7 combined with LDA classifier for each of nine scenarios described in Table 1. As it can be seen, error has been consistently reduced for all static and dynamic training/testing scenarios. Results showed that FS6 and FS7 reduce averaged absolute classification error, with respect to FS1, by 1.2% and 1.4% respectively (13% and 15% relative reduction).

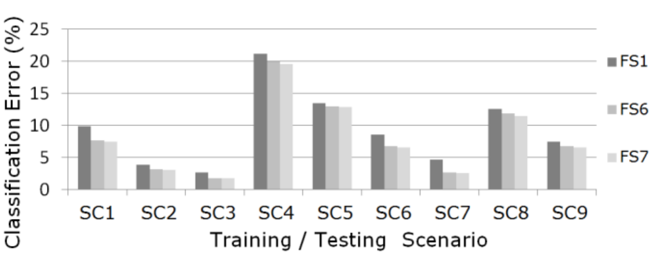

Figure 5: Comparison of FS1, FS6, and FS7

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