Fluctuating EMG Signals: Investigating Long-term Effects of Pattern Matching Algorithms

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Abstract— **In this paper, we investigate the behavior of state-of-the-art pattern matching algorithms when applied to electromyographic data recorded during 21 days. To this end, we compare the five classification techniques k-nearest-neighbor, linear discriminant analysis, decision trees, artificial neural networks and support vector machines. We provide all classifiers with features extracted from electromyographic signals taken from forearm muscle contractions, and try to recognize ten different hand movements. The major result of our investigation is that the classification accuracy of initially trained pattern matching algorithms might degrade on subsequent data indicating variations in the electromyographic signals over time.**

I. Introduction

Modern prosthetic hand controllers allow the operation of complex and multi-functional prostheses in a simple and intuitive way by deriving an amputees' intention from muscular activity using pattern matching algorithms. A large part of related work on electromyography (EMG) signal classification focuses on accuracy improvement and the number of discriminated movements. In our work we concentrate on the effects of EMG signals when recorded over a longer period of time. In this context, the main question is whether and how much the classification accuracy degrades over time if the pattern matching algorithms are not being trained recurrently? Assuming a change in the EMG signals, essential issues to study are the nature of the change, the way it can be measured, the effects on the classification accuracy, the appropriate feature extraction schemes compensating EMG signal variations and the effects of the amputee interacting with the prosthesis control. Furthermore, one also has to analyze technical issues such as the amount of training data for reaching nearly asymptotic accuracy, the selection of most stable feature extraction / dimensionality reduction / classification algorithm combination and incremental learning.

In experiments presented in this paper, we investigate the basic question of accuracy deterioration in the case that the pattern matching algorithms are not being retrained periodically. To this end, we collect a data set of 10 hand movements performed by a non-amputee on 21 days and roughly five to six times a day (altogether 121 trials). We classify these data afterwards with five state-of-the-art algorithms: Decision Trees (DT), k-th Nearest Neighbor (kNN), Multi-layer Perceptrons (MLP), Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). We evaluate the algorithms when trained on initial trials, when trained on only the most recent data, and when using all preceding data.

The paper is structured as follows. Section II reviews related work. The setup of the EMG sensor system and the conducted experiments, as well as the signal processing and feature extraction are presented in Section III. The experiments are evaluated using three different schemes in Section IV. Finally, Section V concludes the paper and gives an outlook on future work.

II. Related Work

Early attempts using pattern matching algorithms for prosthesis control have been proposed by Finely [1], Herberts [2] and Graupe and Cline [3]. In today's literature on EMG classification the signal processing chain is often broken down to three algorithmic components: the *feature extraction*, the *dimensionality reduction* and the *pattern classification*. In the feature extraction step attributes are extracted omitting redundancy. In the second step the amount of data is further reduced by selecting or projecting features for more robust and accurate classification. In the last step pattern matching algorithms are applied to detect the category of the input data. The complete processing queue has to be carefully balanced - especially the combination of the pattern matching algorithm and the selected feature contributes significantly to the classification accuracy.

For continuous prostheses control the feature extraction schemes act in a sliding-window manner. That is, a single feature set is calculated on data recorded during typically up to 300 milliseconds. Then, according to the classification rate of the prostheses controller, the next data window is selected and the feature extraction step is repeated.

Computationally efficient algorithms are of utmost importance as prosthesis control is typically implemented on low-performance embedded systems. Here, feature extraction methods acting in the time domain (TD) are well suited due to their simplicity. Mean absolute value (MAV), zero crossing (ZC), slope sign changes (SSC) and waveform length (WL) are often used by EMG classification algorithms [4]–[6].

EMG electrodes, being electrically only loosely coupled to the skin surface, are basically antennas collecting a lot of noise from power lines, adjacent electric and electronic prosthesis subsystems and other electromagnetic sources. Besides this noise, varying skin conductance affects amplitude based TD features. Thus, a significant part of approaches presented

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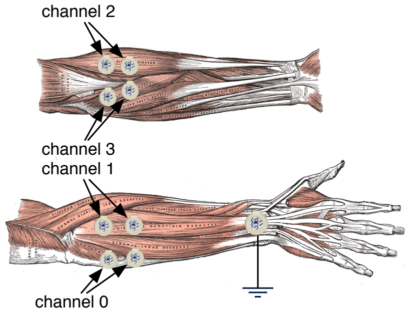


Fig. 1: Sensor placement (muscle anatomy taken from [24]).

in related work concentrate on frequency domain (FD) based feature extraction or on combinations of TD and FD to suppress noisy influences. Fourier transformation (FT), short-time FT (STFT), wavelet transformation (WT) and wavelet packet transformation (WPT) are among the popular methods [7]–[9]. However, FD based feature extraction schemes are computationally expensive and suited for today's high-performance embedded systems.

The second step in the EMG signal processing chain is the dimensionality reduction of features. Reducing feature dimensionality while preserving essential information may increase the generalization ability. Additionally, irrelevant information skipped in this step reduces the amount of processed data. Dimensionality reduction can be implemented as the *selection* of a subset of features that maximizes the probability of an accurate classifier decision [7], [10]. However, for the classification of EMG signals the *projection* of features gained more popularity. Here, a new and generally smaller feature set is derived by linear or non-linear combinations of the features in the original feature set. Principle component analysis (PCA) [7], [10], linear and non-linear discriminant analysis (LDA, NLDA) [11], and self-organizing feature maps (SOFM) [11] are some of the employed algorithms.

In the last step of the signal processing chain the pattern matching algorithms are executed. A dominant part of related work uses artificial neuronal network (ANN) based classifiers [4], [12]–[14]. Newer work also introduces support vector machines (SVM) for EMG signal classification [15]–[17]. Bayesian classifiers [7], [18], [19], fuzzy classifiers [20], [21], Gaussian mixtures [22], and hidden Markov models [23] have also been applied.

y a classification algorithm. No dimensionality reduction is applied on feature vectors.

III. EMG Sensor System and Experiment Setup

We use a portable data acquisition system [25] to continuously monitor four EMG sensor channels with 24 bit resolution at a sampling rate of 2048 Hz. We place the four electrode pairs on the top, bottom, medial, and lateral sides of the forearm with the reference at the wrist (see Fig. 1). The exact electrode positions are determined specifically for the test subject to obtain pronounced signals. After initial calibration we mark the electrode positions to be able to re-establish the experimental setup on different days.

In a single data experiment run, the test subject has to perform a sequence of multiple and different movements. The movements are depicted in Fig. 2. The recording of a movement starts with a four second relaxation phase followed by a five second contraction phase. The EMG signal for the contraction part divides roughly into a one second phase at the onset of the contraction containing the transient components of the EMG signal, and a subsequent steady state phase which corresponds to a constant force contraction phase. We use the data of the steady phase for our classification experiments.

Signal preprocessing and feature extraction is done completely in the digital domain. EMG data from roughly 150 milliseconds is used to calculate the mean absolute value (MAV), zero crossings (ZC), slope sign changes (SSC) and the waveform length (WL) [18]. After finishing the extraction the data window is shifted by roughly 150 milliseconds and the next feature vector is calculated. A compact description of the employed features is given by Zecca et al. [5].

IV. Experiments and Results

The EMG data collected during 21 days (altogether 121 trials) is evaluated in three experiments. For a test trial i, $2 \leq i \leq 121$, we define the indices of the training set trials as:

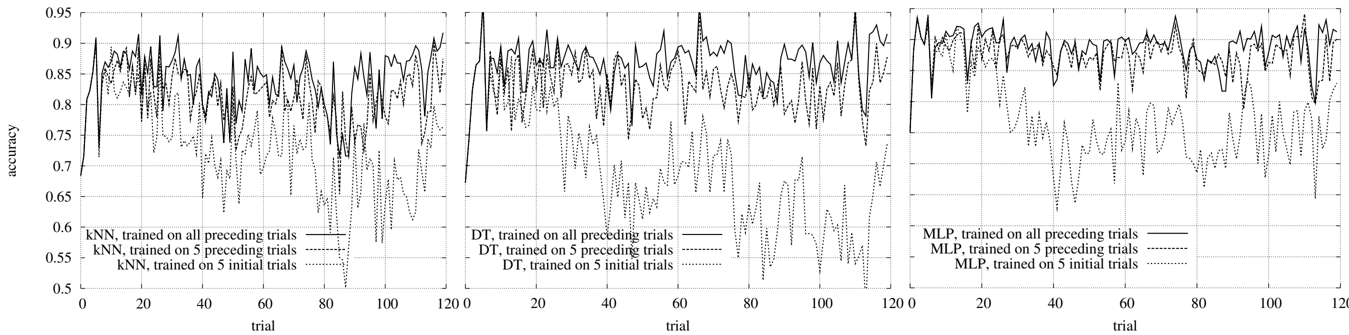
I. $1, \ldots, i-1$,
II. $1, \ldots, \min(s, i-1)$, and
III. $max(i-s, 1), \ldots, i-1$.

s denotes the number of trials that are sufficient to gain high test accuracies for all algorithms. In preliminary experiments we observed for all considered algorithms that data of roughly five trials, which corresponds to the data recorded during one day, is sufficient for gaining high test accuracy. The goal of the second scheme is to check, whether the accuracy degrades if a classifier is trained with the data from the first day only. This test should provide insight into the question, if and how long an initially trained classifier succeeds in keeping high accuracies. The first validation scheme calculates the accuracy by using all preceding data for training. This might however not be the best approach, assuming that for changing EMG signals old data might well cause degradation in accuracy. Moreover, successively growing the training set is computationally expensive. Therefore, the third validation scheme investigates how the accuracy evolves when using only recent data for training. This test calculates a reference accuracy if a practical amount of data storage is to be used.

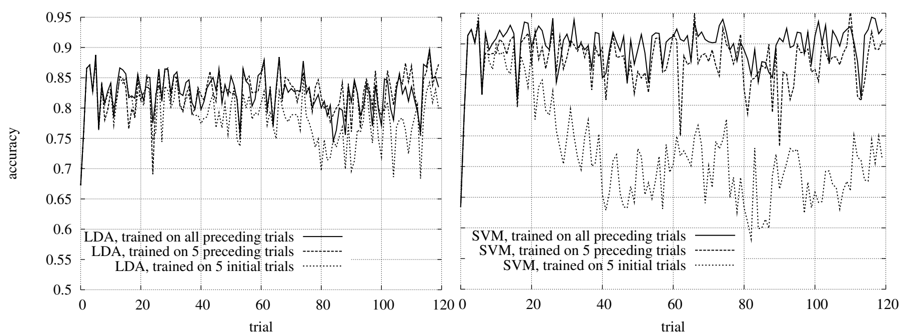
All experiments are conducted with the data mining framework RapidMiner [26]. RapidMiner uses the LIBSVM [27] implementation of support vector machines and the WEKA [28] implementation for decision trees and multi-layer perceptrons.

Fig. 3 presents the results for the defined schemes. The horizontal axis denotes the test trial while the vertical axis shows the corresponding test accuracy. Table I summarizes the averaged behavior over all test trials. The following observations can be derived:

Fig. 2: Motion classes: *1)* extension, *2)* flexion, *3)* ulnar deviation, *4)* radial deviation, *5)* pronation, *6)* supination, *7)* open, *8)*, close *9)* key grip and *10)* extract index finger



(a) kNN (b) DT (c) MLP



(d) LDA (e) SVM

Fig. 3: Generalization accuracy trained on the first five, last five and all preceding trials.

TABLE I: Averaged test errors in % (generalization), when trained on the first five (roughly the data recorded on a single day), recent five and all preceding trials. Bold numbers represent the best error rates achieved.

	test error rates [%]		
	first 5 trials	recent 5 trials	all preceding trials
kNN	27.38	18.75	16.03
DT	31.19	17.02	13.28
MLP	22.84	**12.48**	11.15
LDA	**21.27**	17.63	17.54
SVM	27.35	12.77	**10.34**

- The accuracy degrades with rising time difference between training and test data and drops gradually if not being retrained for all algorithms but the LDA. While there is a difference in accuracy for LDA when looking at the absolute numbers in Tab. I for initially and recurrent trained variants, the distance is small compared to other algorithms. After roughly three days the differences between the fixed and retrained classifiers becomes distinguishable in Fig. 3. Averaged over 121 trials the differences for the kNN, DTs, MLPs and SVMs trained on the first and recent five trials are roughly 8.6%, 14.2%, 10.4% and 14.6%, respectively. Accuracy for LDA drops only by 3.6% when not being trained recurrently.
- Using five recent and all preceding trials for training entails similar shaped graphs in Fig. 3. The averaged numbers from Tab. I shows that more data is beneficial to all algorithms. The differences, however, are small to justify the demanding computation. For a real-world situation the training set has to be reduced in its size by, for example, selecting recent data. Incremental learning [29] might be a solution to approximate the best error rate when using all preceding data for training.

While LDA is robust when not being trained recurrently, SVMs and MLPs excel for the other benchmarks.

V. Conclusion and Future Work

From the viewpoint of the experiments, we can draw two main conclusions: All algorithms manage to calculate differentiated results even when distinguishing between 10 classes. Also, over time degrading classification accuracies for initially trained pattern recognition algorithms suggesting the existence of variably components within EMG signals.

There has been mostly anecdotal evidence that users produce EMG patterns that will differ from trial to trial. The reasons for the changing EMG signals may be due to electrode movement, or behavior factors on the part of the user. It was the intent here to investigate the nature of these changes, how they impact classification performance, and whether retraining may maintain classification accuracy.

In practical use, the user will have visual feedback commensurate with the actuation of the prosthesis, and will experience self-adaptation in the form reflexive error correction and longer-term learning. If the system and the user are both adapting, this might create an unstable situation. For the purposes of this study, we sought to characterize EMG changes without feedback. It is important to determine appropriate adaptation schemes that can coexist with user adaptation in the presence of visual feedback and with the dynamics of electromechanical prostheses worn by the user.

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