A MACHINE LEARNING SYSTEM FOR CLASSIFICATION OF EMG SIGNALS TO ASSIST EXOSKELETON PERFORMANCE

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***Abstract*—A surface electromyographic signal can provide information on neuromuscular activity and can be used as an input in a myoelectric control system for applications such as orthotic exoskeletons. In this process, a key step is to extract useful information from the EMG signals using the pattern recognition tools. Our research focus is on identification of a set of relevant features for efficient EMG signal classification. Specifically in this work, from the pre-processed myoelectric signals, we extracted auto regression coefficients, different time-domain features such as Hjorth features, integral absolute value, mean absolute value, root mean square and cepstral features. Next a subset consisting of a few selected features are fed to the multiclass SVM classifier. Using a radial basis function kernel a classification accuracy of 92.3% has been achieved.**

Keywords—*Electromyography, Myoelectric Signal Processing, Time-Domain features, Cepstral Coefficients, Hjorth Features, Support Vector Machines)*

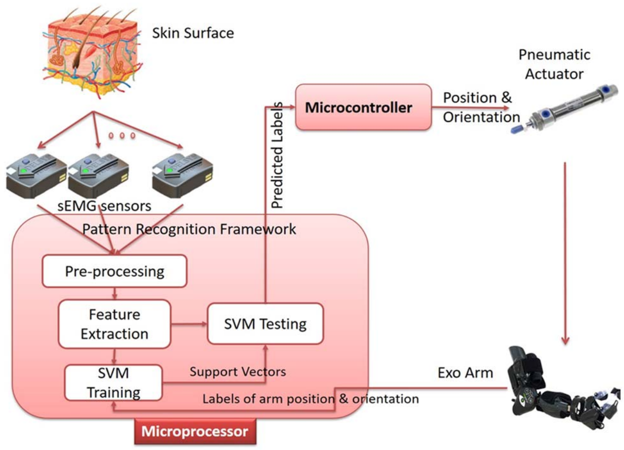

Fig 1. Schematic of the machine learning enhanced exoskeleton system

I. Introduction

A. Problem Description

Some of the goals of wearable robotics specifically orthotic exoskeletons is to assist human beings in either to recover the lost functionality of limbs and the back and to enhance the human capabilities [1]. As shown in fig. 1, an exoskeleton system should consist of (1) an interface with the human wearer usually through a set of sensors that detect biological signals such as the surface electromyography (EMG) and electro-encephalography (EEG). (2) A signal processing and pattern recognition system to extract meaningful content from the bio-signals fed to (3) a microcontroller to command and control the actuators of the orthotic exoskeleton. (4) Finally, various electromechanical components of the exoskeleton including the actuators, sensors and the support structures [2]. An active area of research is related to the second component, i.e., sensing and analysis of bio-electrical activity of the human body [2]. For example, the limb movement can be understood by extracting the surface EMG and processing these signals for relevant movement related parameters. These force parameters can be fed to a controller to guide the exoskeleton movements. In this context, instead of the model inversion, a pattern recognition algorithm can be used to learn the movement intention of the human user which usually can be categorized in discrete terms. Our research focus is on developing a pattern recognition algorithm for learning finger configurations corresponding to various hand gestures. The subsequent goal is to use this configuration information for controlling a orthotic hand to support or enhance human hand's functionality.

In the existing work on pattern recognition of finger configurations, movements and gestures with application toward exoskeleton control, it can be summarized that the time domain statistics, spectral moments and time-frequency features have been commonly used [3, 4, 5, 6]. In this paper, for a multiclass finger configuration problem, we propose an improved feature set consisting of select feature subsets from different feature modalities such as a few time domain and frequency domain features. In the classification scenario, a feature relevance analysis is performed using a wrapper approach. We determined that a combined set of time domain statistics and cepstral features provide superior classification performance.

II. METHODOLOGY

A. Overview

In this work, we address the classification of 10 categories of finger configurations based on multi-channel EMG data. As shown in fig. 2, the classification algorithm can be divided into three stages, namely, (1) the pre-processing, (2) the feature extraction and (3) the classification. In the first stage, we segment the EMG signals corresponding to the individual

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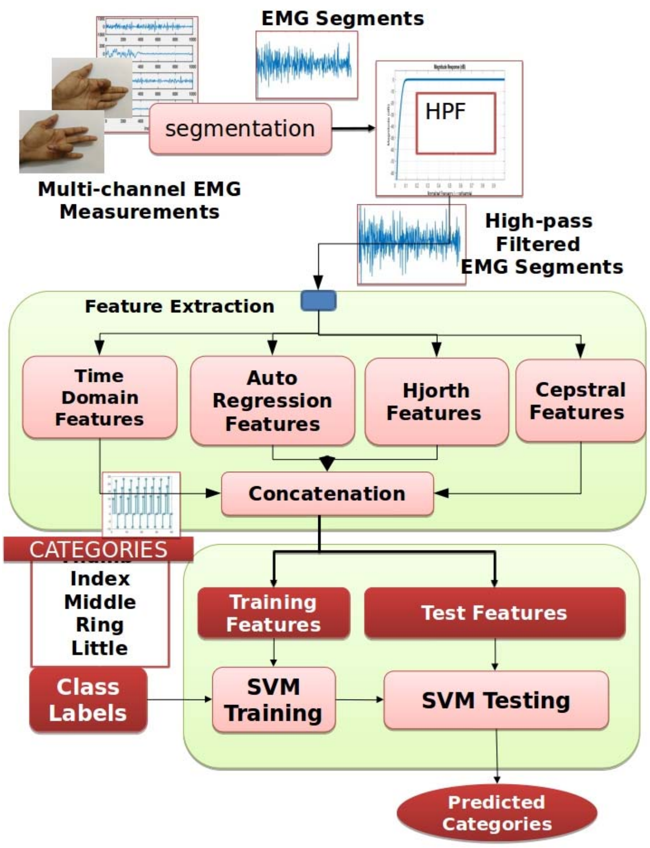

Fig. 2: Block diagram for the proposed EMG classification scheme

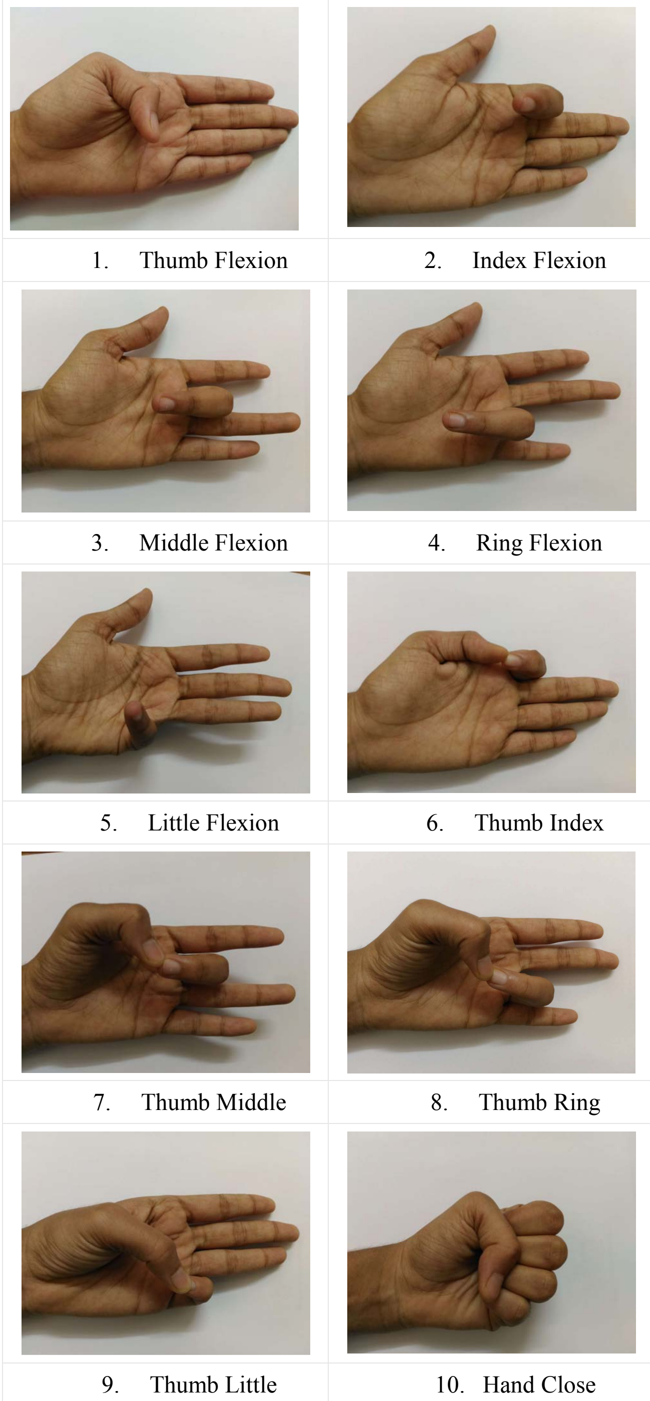

Fig. 3. Finger Configurations

trials. Next the signals are filtered using a bandpass filter with a passband frequency range between 20 and 450Hz designed using a rectangular window of length 125ms with a overlap window of length 25ms. Next DWT decomposition with Daubechies-44 wavelet [7] and manual double thresholding method is used to denoise the signals. Now to facilitate efficient classification of the EMG signals, four modalities of statistical features such as Time Domain Statistics and Hjorth feature, Spectral Statistics, and Autoregression coefficients are computed. Further, the full feature vector is obtained by concatenating the extracted features. In the third stage, a supervised learning algorithm such as the SVM is used to classify the features. Specifically, we use N-fold cross validation for performance evaluation. Finally, we identify the relevant features that contribute to an improved classification performance. Next, the details of feature extraction follow.

B. *Feature Extraction*

The EMG signal is separated into areas of muscle activity, where motor unit action potentials (MUAPs) exist. Consider x[n] be the time series representation of the EMG signal. Next various features from different modalities are extracted as described below.

The Auto Regressive features (AR) The AR features are computed by selecting a proper model order for the EMG data segment and computing the system model coefficients using the Burgs method [8].

Time Domain Statistics (TD) Under the Gaussian random process assumption, the following TD statistics are extracted; (1) the integral absolute value [9], (2) the mean absolute value and (3) the wavelength defined as cumulative length of a segment corresponding to an MUAP [10].

Cepstral Coefficients (CC) Cepstrum Coefficients detect the periodicity in a frequency spectrum for the use in non-linear signal processing. Basically, they analyze the EMG sequences into the sums of their cepstra for linear separation. In [11], Kang et al demonstrated the use of cepstral coefficients for EMG pattern recognition. Here the cepstrum based features are computed using [11]

$$c(n)=\left|F^{-1}\left\{\log\left|F\{x(n)\}\right|^{2}\right\}\right|^{2}$$

Hjorth Features (HF) We compute three Hjorth features namely the activity, the mobility, and the complexity [12]. In EMG analysis, the Hjorth activity α is a measure of variability in the shapes of MUAP and is defined as

$$\alpha_i(x)=\sigma_i^2(x)$$

Where $\sigma_i^2(x)$ is the variance of the i-th segment. The Hjorth-Mobility μ is a measure of the standard deviation to represent the true firing statistics of the MUAP and is given by [13]

$$\mu(x)=\sqrt{\frac{\sigma_i^2(y)}{\alpha_i(x)}}$$

where y[n] = x[n] − x[n − 1] is the first difference of x[n] the Hjorth complexity ζ is a measure of change in frequency of an EMG segment relating turns of the MUAP waveform and it is defined as

$$\varsigma(x)=\frac{\mu(y)}{\mu(x)}$$

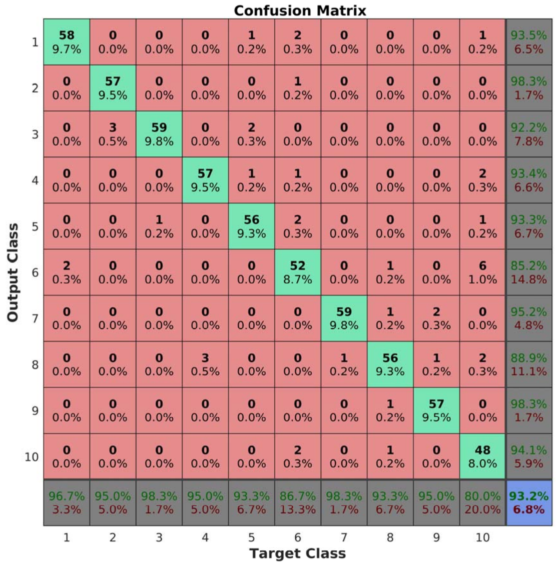

Fig. 4: Confusion Matrix corresponding to the finger configuration classification when selected features from 4 modalities are employed

C. *Feature Selection*

The feature selection is an important stage which determines the feasibility of feature subsets during classification specifically to improve the performance. In our work, we have investigated the feasibility of various feature subsets using the SFS algorithm. This algorithm uses the classifier accuracy as the cost function. The objective of feature selection is three-fold: (1) improving the prediction performance of the learning machines, (2) providing faster and more cost-effective predictors for efficient control input, and (3) providing a better understanding of the underlying bioelectrical process that generated the EMG signals.

D. *Supervised Learning*

The support vector machines (SVM) with a kernel-based approach has become an increasingly popular tool for machine learning tasks. The SVM classifies data by finding the optimal discriminative hyperplane in a high dimensional space. For a k-class problem, k(k − 1) binary classifiers are needed for efficient classification.

III. IMPLEMENTATION AND RESULTS

A. *Data Description*

The dataset was obtained from [3]. In the acquisition process, based on [3], the subjects were instructed to perform finger gestures of ten classes with three major groups: (1) the flexion of all the fingers (2) thumb contact with the other fingers (3) and a clenched fist as illustrated in fig. 3. During experimentation, the myoelectric signals (bandwidth, 50 − 15000 Hz) were detected with surface-skin electrodes on the subjects forearm (each trial with 10 sec of muscle contraction and relaxation) and amplified with a total gain of 3dB. Each subject repeated the physical action R = 6 times. Finally, each channel consists of 20, 000 values. The total sample size becomes P = 10 × 10 × 6 = 600.

B. *Classifier Optimization*

Various features as described in the previous section are extracted and fed to the SVM classifier. We used the radial basis kernel function and the one-against-one approach for 10 class problem which requires 45 binary classifiers. The support vectors are computed by using the iterative single data algorithm (ISDA). We found optimal values for the hyper-parameters as: box constraint as 27 and the kernel scale as 0⊳8.

C. *Analysis*

The features from M (= 2) channels for each modality are computed. Next, these feature subsets from various feature extraction methods are concatenated into a full feature vector. Next the sequential forward selection algorithm is used to identify the relevant features. It is found that 18 out of 30 features are relevant. From the channel I, the selected features are TD (IAV, MAV, RMS), CC, and HF(Activity) . From channel II, the selected features are TD(IAV, MAV, RMS, WL), CC, HF(Activity), and AR. As shown in fig. 4, with the set of the selected features the classification performance is 92⊳3%. As illustrated in fig. 5, the performance is different for different selected feature subsets as follows: TD and the HF features 81%, cepstral features add 6⊳16% and the AR feature subset improves by another 5⊳16% taking the overall accuracy to 92⊳3%. The experiments show that the Channel-II is more relevant for classification compared to Channel-I. This sensitivity can be attributed to the proximity of the electrode II to the area of the bioelectrical activity.

IV. CONCLUSIONS

We implemented a multi-category classification framework based on support vector machines to categorize finger movements using features derived from two channels of surface EMG data. Using the sequential forward selection algorithm, a set of 18 features from above 30 features were found to be relevant for the finger configuration classification.

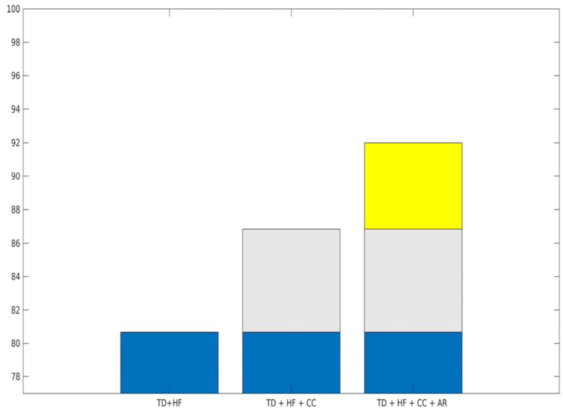

Fig. 5: Classification performance and improvements achieved due to various feature modalities

Based on the selected features using the SVM algorithm, the average kappa accuracy is 0.93.

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