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EMG based man–machine interaction—A pattern recognition research platform

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HIGHLIGHTS

- Development of indigenous multichannel EMG signals based control.
- Influence of feature ensemble on pattern recognition is studied with five ensembles.
- Feature selective simple logistic regression (SLR) classifier has been proposed.
- Implementation of prosthetic hand control using TMS320F28335eZdsp processor.

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ABSTRACT

This paper describes the proposal of indigenous development of a technological platform for man–machine interaction with the prosthetic hand using a surface electromyogram (sEMG) signals in the laboratory. This work involves the design and the development of the sEMG conditioning system, implementation of EMG pattern recognition algorithm using TMS320F28335 digital signal controller (DSC) and generation of control signals for actuation of hand. In this work, EMG signals were acquired from ten healthy subjects and two transradial amputees for the six hand motions in off-line. The time domain features were extracted from each channel was grouped into five ensembles to understand the importance of selection of features in the identification of intention from EMG signals. Further, the performance of different classifiers namely simple logistic regression (SLR), J48 algorithm for decision tree (DT), logistic model tree (LMT), neural network (NN) and linear discriminant analysis (LDA) were studied. The Kruscal–Wallis test is performed for classification accuracy, computation time and memory space required for different feature ensembles to identify the effective feature ensemble. Also the performance of the classifier was tested in on-line with transradial amputees for actuation of prosthetic hand for two intended motions with TMS320F28335 controller using efficient ensemble and classifier.

1. Introduction

An electromyogram (EMG) based anthropomorphic hand help the amputated people to restore the functionality. Developing an anthropomorphic hand and pattern recognition of EMG signals for actuation of hand are of particular interest to many fervent biomedical researchers in developing countries. In the last few decades, extensive amount of research has been focused either in the development of pattern recognition of intention from surface EMG (sEMG) or in the development of anthropomorphic hand. Surface EMG based pattern recognition groups have focused on developing algorithms to improve the classification accuracy, using the surface EMG measuring instrument in use in clinics or in institutions [1–3]. But other groups have focused on the development of mechanical structure and improving the actuating mechanism of prosthetic hand with multiple degrees of freedom (DoF) [4]. In spite of the advances in pattern recognition and design of the hand, development of sEMG controlled prosthetic hand in a laboratory is still a challenging task for researchers in developing countries. This may be due to the purchase of commercially available sEMG measuring instruments is still a problem for researchers. However, indigenous development of sEMG conditioning system aid development of pattern recognition for different application such as virtual reality, fatigue analysis, prosthesis etc. Further the sEMG signals acquired from the indigenous system might help the researchers of developing countries to study and demonstrate the pattern recognition and man–machine interaction in the laboratory.

In rehabilitation engineering, information about the intention from EMG can be decoded into time domain, frequency domain,

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time–frequency domain and time scale domain features from steady state and dynamic EMG signals for identifying the hidden information to control the assistive devices like prosthetic devices, orthotic devices etc. In the recent years, many feature extraction methods are used by researchers like mean absolute value (MAV) [1,5], number of zero crossings (ZC) [1,5], number of slope sign changes (SSC) [1,5], waveform length (WL) [1,5], mean absolute value slope (MAVS) [1,6], Willison amplitude (WA) [6], variance (VAR) [6], root means square (RMS) [7], histogram (HIST) [8], autoregressive (AR) coefficients [9,10], fast Fourier transform (FFT) coefficients [11], short time Fourier transform coefficients (STFT) [12], cepstrum coefficients (CC) [13], wavelet transform coefficients (WT) [14–16], and wavelet packet transform (WPT) coefficients [17], spectral components [18–21] for pattern recognition. In this paper, simple time domain feature extraction technique is used for the classification of continuous EMG signals which contains both transient and steady state signals. The effectiveness of classifier depends upon various factors such as the types of features, placement of electrodes, and muscle conduction velocity [22,23]. The authors of this paper grouped the extracted features into five ensembles which are widely considered ensembles by the researchers. These ensembles are considered to apprehend the importance of feature selection as well as to demonstrate a larger number of features not necessarily aids classification, but increase the computational cost.

There are several approaches used to classify the extracted features to identify the intended motion. So far, different classification approaches like linear discriminant analysis (LDA) [5,24,25], *k*-Nearest Neighbour (*k*NN) [9,16], neural network (NN) [1,24], fuzzy systems [6], neuro-fuzzy classifiers [26] and support vector classifiers [27–29] were applied for pattern recognition of motion from sEMG signals. The disadvantages of the above classifiers are considering all the input features in building the classification model irrespective of relevance/irrelevance of features that aids in classification. Development of EMG based prosthetic hand control using an extensive number of electrodes has intricacies due to enormous amount features. The concatenation of all the extracted features does not guarantee an optimum performance without time delay [30]. Further, the inclusion of feature reduction/selection algorithm increases computation complexity.

The authors of this paper adopted feature selective classifiers namely simple logistic regression (SLR), decision tree (DT) and Logistic model tree (LMT). These statistical techniques select the most relevant features for classification during training [31]. The capability of selecting features during training reduces the burden of the controller and reduces the processing time if features from multiple locations are considered. Further, these classifiers can classify the smaller number of training sample data, with better accuracy even when the data are noisy [31]. The performances of all the classifiers are compared with traditional classifiers such as linear discriminant analysis and neural network with five feature ensembles in the results section. The identified efficient pattern recognition algorithm is implemented using TMS320F28335eZdsp such a way that the total response time i.e., acquisition of the EMG signals for the actuation of the driving mechanism of the prosthetic hand should be less than 100–175 ms [32].

The development of technological platform for sEMG pattern recognition based prosthetic hand constituting the sEMG conditioning system, pattern recognition system and controller is explored in subsequent sections. Fig. 1 shows the block diagram of man–machine interaction developed in the laboratory to enable the students to understand the integration of electronics and mechanical system, issues related to pattern recognition and motivated them to work in rehabilitation engineering.

2. Surface EMG conditioning system and data acquisition

In this work, sEMG signals are collected, from healthy and transradial amputee subjects using a pair of gold high dome surface electrodes of 10 mm diameter using indigenously developed EMG conditioning system. Since EMG signals have low amplitude, in the range of micro volts to millivolts, with a dominant energy band of 20–500 Hz, influenced by various interferences. It is necessary to design a conditioning system which reduces the interferences due to radio frequency signals, DC offset, movement artefacts and power line interference. DC battery is used to reduce power line interference. The protection circuit has been designed to protect the user and sensitive electronic circuit without distorting the input signal [33]. The first stage consists of resistance–capacitance (RC) combination to suppress the radio frequency signals that enter the amplifier system. The second stage consists of positive negative positive (PNP) and negative positive negative (NPN) transistors that pass signals undistorted less than and equal to 550 mV for frequency less than and equal to 150 kHz.

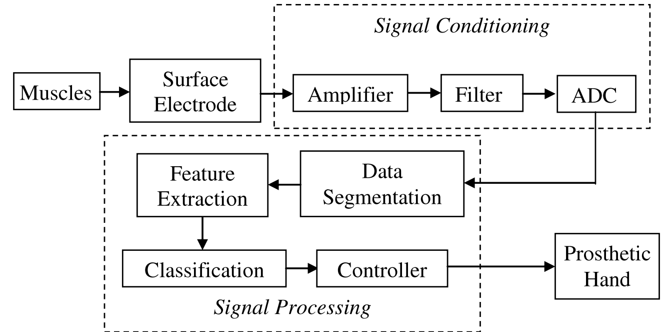

Fig. 1. EMG pattern recognition based prosthetic hand control system.

The quality of the EMG signal, in part, depends on the characteristics of the amplification process. There may be several stages of amplification and the most important stage is pre-amplification. Pre-amplification implies amplification, close to the signal source. With the advent of technology, the process of differential amplification with high input impedance amplifier and high common mode rejection ratio amplifier with a gain of 12 is used to amplify the signals enabled the measurement of EMG signals of low noise and high signal fidelity. High-pass filtering is necessary because movement artefacts are comprised of low frequency components typically less than 10 Hz and to remove DC offset. The second stage amplification is also necessary to optimize the resolution of the recording or digitizing equipment. Amplifiers of high quality with adjustable gains of 6–100 is used to maximize the signal to noise ratio of the EMG signal during each recording. Low pass filtering is desirable to remove high-frequency components to avoid signal aliasing. Since the signal dominant energy band is between 20 and 500 Hz, a band pass filter having a cutoff frequency between 10 and 500 Hz with a gain of 4 was designed using high quality operational amplifiers. It was common to remove power-line noise components by using notch filter. There are problems with notch filtering because EMG has large signal contributions at these and neighbouring frequencies. The result of notch filtering is the loss of important EMG signal information, so notch filtering should be avoided. Further EMG signals can be either positive or negative. This signal must be adjusted by an analogue interface in a range of 0–3 V to allow the analogue to digital conversion module to read both positive and negative values. The analogue offset is made before signal acquisition maintain the voltage into a range of 0–3 V. Fig. 2 shows the single channel surface EMG conditioning system.

EMG signals are collected for six motions of hand i.e., hand close (HC), hand open (HO), wrist flexion (WF), wrist extension (WE), ulnar deviation (UD)/hand supination (HS), radial deviation (RD). These signals are obtained from the forearm of the subjects with brief rest periods of about 60 s between each trial and without any report of fatigue from the subjects. These six motions are collected for the duration of 30 s with recording time of