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Real-Time Segmentation and Feature Extraction of Electromyography: Towards Control of a Prosthetic Hand

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Abstract: Surface electromyographic (sEMG) signals can be used as inputs to control a myoelectric prosthetic hand. This requires the discrimination of sEMG associated with different hand movements. The signals for key unilateral hand movements such as wrist extension, wrist flexion, and power grip are similar, making the classification and control of these hand movements challenging. This preliminary study explores the viability of classifying the sEMG signals of these hand movements in real-time, in order to control a software simulation of a prosthetic hand. sEMG data was recorded from two bipolar electrodes for offline classifier training purposes. A novel segmentation technique was used to separate the muscle contraction and rest periods of the sEMG time-series data. A time-frequency algorithm was then applied for the first time to extract sEMG-based features from the segmented data. Features were used to train four support vector machines offline, in a one-versus-all architecture. The classification system was tested offline and in real-time. The system yielded accuracies of 89.39% and 84.93% for offline and real-time testing respectively. Real-time classification was done in 10.2 ms when processing 0.5 s of input sEMG data. This shows that the system is accurate and computationally efficient, even with limited electrodes. Thus, it can serve as a foundation for further work in the implemented segmentation and feature extraction methods, for an inexpensive alternative to commercial myoelectric prosthetic devices.

Keywords: sEMG, segmentation, feature extraction, SVM.

1. INTRODUCTION

Following the partial or complete amputation of a limb, people lose the ability to perform several activities of daily living (ADLs) (Sollerman & Ejeskär 1995). As a result, many amputees seek prostheses that are usually body-powered or myoelectric (Young et al. 2013). Myoelectric prostheses allow for more intuitive control than body-powered prostheses, as well as a greater range of degrees of freedom (Young et al. 2013). Intuitive control means that the prosthesis is neurally controlled in a manner similar to that of the lost limb. Myoelectric prostheses commonly use surface electromyography (sEMG) to measure the electrical activity of muscles as control inputs to the device (Shenoy et al. 2008). Classification techniques make it possible to identify intended movements from features extracted from the obtained sEMG signals (Young et al. 2013). Such prostheses allow amputees to perform some of the lost ADLs and in turn improve their quality of life (Shenoy et al. 2008).

To control a myoelectric prosthetic hand (MPH), sEMG information from an amputee's remaining muscles is required to be measured and processed. Segmentation is used to identify periods of contraction (corresponding to periods of movement) and periods of rest (occurring in between contractions). Features can be extracted from these periods for use in a learning algorithm, that can in turn be used to control a MPH. The aim of this research is to extract more relevant information from the sEMG signals to yield more accurate and intuitive control.

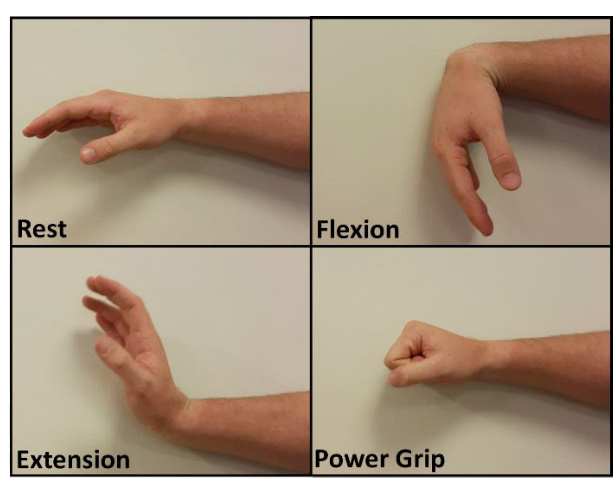

Figure 1: Static hand movements.

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Segmentation of sEMG signals can be performed manually or by correlating muscle contraction to a video recording of the movement (Sedlák et al. 2013). These methods are time consuming and are improved by automatic segmentation algorithms (El Falou et al. 2005). Owing to the non-stationary properties of sEMG (Seven et al. 2013), it is possible to use time-frequency analysis to characterise the changes in sEMG signals over time. An algorithm, previously applied to music recognition (Haitsma & Kalker 2003), is adapted and applied to sEMG, which to the authors' knowledge has not been done before. Other feature extraction methods include variance, the energy of wavelet coefficients of sEMG in nine scales and Cepstrum coefficients (Boostani & Moradi 2003).

In this study, four static hand movements are classified both offline and in real-time to assess the validity of the novel segmentation and feature extraction processes. These movements can be seen in Figure 1: rest, wrist flexion, wrist extension, and power grip are key to allow the performance of ADLs (Trombly & Radomski 2002). Support vector machine (SVM) classification is used to validate the segmentation and feature extraction processes (Shenoy et al. 2008). The latter is the focus of this paper, aimed at improving the discrimination of sEMG of key hand movements and is an initial step towards controlling a MPH (represented in this study by a simulated prosthetic hand) in real-time.

An overview of the system and data collection process is presented. This is followed by details of the novel segmentation method and the adapted sEMG feature extraction technique. The classification system and simulations used for testing are discussed. Thereafter, a discussion and future recommendations are presented.

2. METHOD

2.1 Overview

The system block diagram is shown in Figure 2. Each aspect of the system is further elaborated in the upcoming sections.

2.2 Data Collection

All recorded datasets (offline and real-time) were filtered by a 4th order bandpass Butterworth filter of bandwidth 20 – 450 Hz (Young et al. 2013; De Luca et al. 2010). Two offline sEMG datasets were recorded over the period of one day. Dataset 1 was used for training of the classification system and preliminary offline testing. Dataset 2 was used as a simulation of real-time processing.

Data was collected from two, right-handed, healthy, young male subjects (Subject 1 was age 24 and Subject 2 was age 23) over a total of 15 sessions each per dataset. sEMG data was recorded with a PowerLab 26T in conjunction with LabChart 7 (both by ADInstruments) and was processed in MATLAB. The two available channels for sEMG recording were used, where bipolar sEMG electrodes were placed over the right forearm flexor (channel 1) and the right forearm extensor (channel 2) muscle groups (Criswell et al. 2011). The ground electrode was placed on the left forearm.

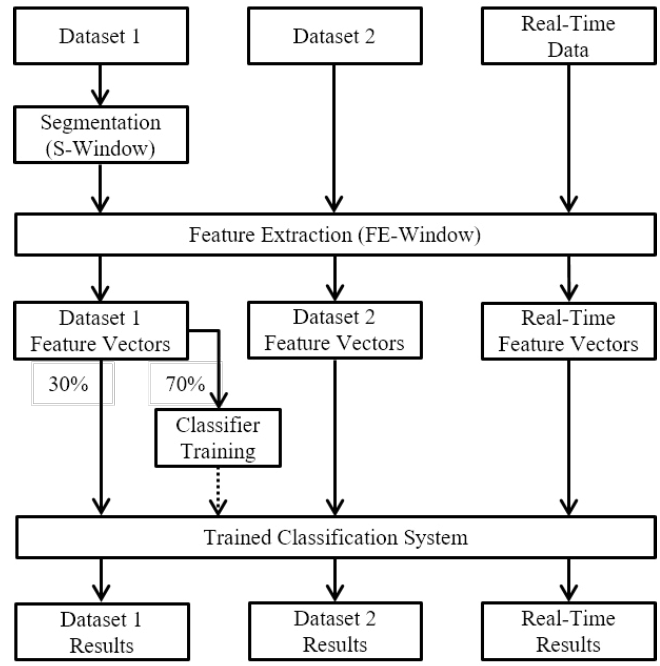

Figure 2: System block diagram.

The subjects were seated with the right arm resting on a level surface. Five sessions were performed for each movement i.e. wrist flexion, wrist extension and power grip. A session began at rest and was comprised of 20 repetitions of one of the three movements. Each repetition consisted of three seconds of sustained contraction followed by four seconds of rest. There were two minutes of rest between sessions. For the power grip sessions, contractions were performed at approximately 50% maximum voluntary contraction (MVC) while gripping a stick of diameter 2.7 cm (Lazaro et al. 2014). The data was sampled at 2 kHz (Shenoy et al. 2008) and was collected simultaneously for both channels. The data was filtered with a 50 Hz notch zero-phase-lag FIR filter by the LabChart software to remove line noise. Each subject was instructed not to observe the sEMG signals during recording as visual bias might have been introduced (Shenoy et al. 2008).

After development of the system, real-time sEMG data was recorded from the same two subjects under the same device settings and filtering as before. This was used for real-time testing. The data was passed to MATLAB using the real-time LabChart to MATLAB module. 1024 voltage-time values were passed to a buffer in MATLAB, which corresponded to approximately 0.5 s of data.

2.3 Segmentation

Segmentation was performed on each channel of recorded data per session from Dataset 1. Owing to the highly variable amplitudes that occur in sEMG signals, each voltage-time value in the channels was amplified per Equation 1, before segmentation could occur.

$$channel_{amp}(t) = |\, channel(t)\, |^{1.5} \tag{1}$$