

Myoelectric Control of Prosthetic Devices for Rehabilitation

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INTRODUCTION

Bio-signals patterns analysis problems have enjoyed a rapid increase in popularity in the past few years. The electromyography (EMG) signal, also referred to as the Myoelectric signal (MES), recorded at the surface of the skin, is one of the biosignals generated by the human body, representing a collection of electrical signals from the muscle fibre, acting as a physical variable of interest since it first appeared in the 1940s (Scott, 1984). It was considered to be the main focus of scientists, and was advanced as a natural approach for the control of prosthesis, since it is utilising the electrical action potential of the residual limb's muscles remaining in the amputee's stump (which still has normal innervations, and thus is subject to voluntary control) as a control signal to the prosthesis—in other words, it allows amputees to use the same mental process to control their prosthesis as they had used in controlling their physiological parts; however, the technology in that time was not adequate to make clinical application viable. With the development of semiconductor devices technology, and the associated decrease in device size and power requirements, the clinical applications saw promise, and research and development increased dramatically.

This control approach referred to as myoelectric control has found widespread use for individuals with amputations or congenitally deficient limbs. The methodologies used in this approach of control spanned the range from classical multivariate statistical and syntactic methods, to the newer artificial intelligence (symbolic and connectionist) approaches to pattern processing. In these systems, voluntarily controlled parameters of myoelectric signals from a muscle or muscle group are used to select and modulate a function of a multifunction prosthesis. The essential elements of a myoelectric control of prosthesis devices

are shown in the block diagram schematic of Figure 1 (Merletti & Parker, 2004). The Myoelectric control system is based on the noninvasive interfaces designed for casual wear.

In the following sections, the details and related works to the research problem are given; after that, the methodology adopted is explained and discussed, followed by future work, and finalised with conclusion.

BACKGROUND AND RELATED WORK

Continuous myoelectric-controlled devices are one of the challenging research issues, in which the prosthetic is controlled in a manner proportional to the level of myoelectric activity. Although the success of fitting these systems for single device control is apparent, the extension to control more than one device has been difficult (Hudgins, Parker, & Scott, 1993), but, unfortunately, it is required for those with high-level (above the elbow) limb deficiencies, and the individuals who could stand to benefit from a functional replacement of their limbs (Englehart, Hudgin, & Parker, 2001). It has been proved that the MES signal exhibits a deterministic structure during the initial phase of muscle contraction, as shown in Figure 2 for four types of muscle contractions measured using one surface electrode. Based on this principle, a continuous myoelectric control strategy based on the use of pattern classifiers was the main focus during the last years for most scientists in related fields.

The MES patterns exhibit distinct differences in their temporal waveforms. Within a set of patterns derived from the same contraction, the structure that characterizes the patterns is sufficiently consistent to maintain a visual distinction between different types of contraction. Hudgins et al. (1993), and Lighty, Chappelly, Hudgins, and Englehart (2002) aligned the pat-

terns using a cross-correlation technique, and showed that the ensemble average of patterns within a class preserves this structure. The myoelectrical signal is essentially a one-dimensional pattern, and the methods and algorithms developed for pattern recognition can be applied to its analysis. The myoelectric control, system-based pattern classifier consists of four broad system components, which are (Ciaccio, Dunn, & Akay, 1993; Lusted & Knapp, 1996) :

- Myoelectric signal acquisition using surface or implanted electrodes, mostly surface electrodes.
- Signal conditioning and features extraction.
- Pattern recognition algorithms to classify the signal into one of multiple classes.
- Mapping of classified patterns to interface actions that control external devices.

A general look onto the myoelectric control system components reveal that it operates at a few stages of machine pattern recognition or interpretation for bio-signals that were proposed in Ciaccio et al. (1993), and Lusted and Knapp (1996). Also, specific features are extracted usually because the motivation is toward the evaluation of myoelectric signal features in ways which are not tied to accurate estimates of signal characteristics, but rather to the intrinsic quality of the features as control signals for a desired device, which have been usually a prosthetic hand robot for the purpose of rehabilitation.

The features extraction is considered as the most important part, because the success of any pattern classification system depends almost entirely on the choice of features used to represent the continuous time waveforms (Hudgins et al., 1993). Although the

Figure 1. Normal and myoelectric control system

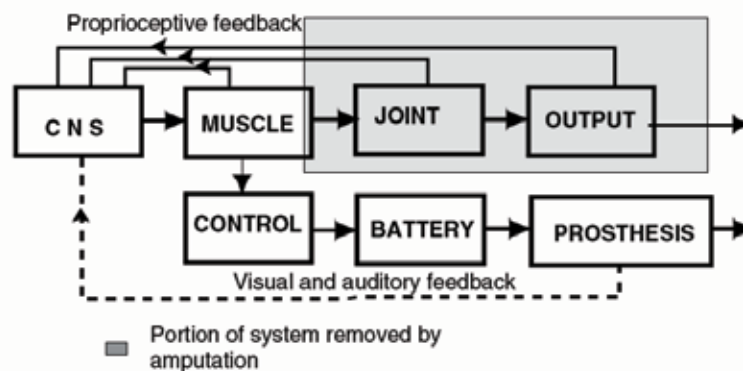
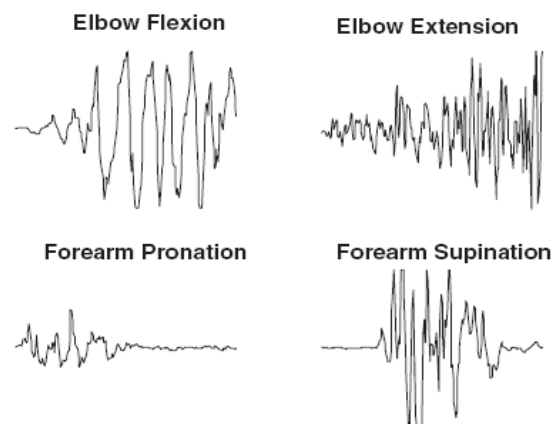


Figure 2. Patterns of transient MES activity recorded using a single bipolar electrode pair, placed over the biceps and triceps



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