



Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features



Rami N. Khushaba^{a,*}, Maen Takruri^b, Jaime Valls Miro^a, Sarath Kodagoda^a

^a School of Electrical, Mechanical and Mechatronics Systems, Faculty of Engineering and Information Technology, University of Technology, Sydney (UTS), Australia

^b American University of Ras Al Khaimah, Ras Al Khaimah, United Arab Emirates

HIGHLIGHTS

- Human limb position has a substantial impact on the robustness of EMG pattern recognition.
- Invariant power spectral moments described as a solution.
- Real time classification experiments were carried out on 11 subjects.
- Limb position invariant myoelectric pattern recognition achieved.

ARTICLE INFO

Article history:

Received 12 December 2012
Received in revised form 2 March 2014
Accepted 6 March 2014
Available online 28 March 2014

Keywords:

Electromyogram (EMG)
Spectral moments
Signal processing

ABSTRACT

Recent studies in Electromyogram (EMG) pattern recognition reveal a gap between research findings and a viable clinical implementation of myoelectric control strategies. One of the important factors contributing to the limited performance of such controllers in practice is the variation in the limb position associated with normal use as it results in different EMG patterns for the same movements when carried out at different positions. However, the end goal of the myoelectric control scheme is to allow amputees to control their prosthetics in an intuitive and accurate manner regardless of the limb position at which the movement is initiated. In an attempt to reduce the impact of limb position on EMG pattern recognition, this paper proposes a new feature extraction method that extracts a set of power spectrum characteristics directly from the time-domain. The end goal is to form a set of features invariant to limb position. Specifically, the proposed method estimates the spectral moments, spectral sparsity, spectral flux, irregularity factor, and signals power spectrum correlation. This is achieved through using Fourier transform properties to form invariants to amplification, translation and signal scaling, providing an efficient and accurate representation of the underlying EMG activity. Additionally, due to the inherent temporal structure of the EMG signal, the proposed method is applied on the global segments of EMG data as well as the sliced segments using multiple overlapped windows. The performance of the proposed features is tested on EMG data collected from eleven subjects, while implementing eight classes of movements, each at five different limb positions. Practical results indicate that the proposed feature set can achieve significant reduction in classification error rates, in comparison to other methods, with $\approx 8\%$ error on average across all subjects and limb positions. A real-time implementation and demonstration is also provided and made available as a video supplement (see [Appendix A](#)).

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Human–computer interfaces play a very important role in the advancement of methods enabling humans to interact with and

control a specific machine. One such interface directly senses and decodes the Electromyogram (EMG) signals from human muscles, utilizing these in developing various applications including a control source for powered prosthetic and rehabilitation devices (Englehart & Hudgins, 2003; Hudgins, Parker, & Scott, 1993; Merletti & Parker, 2004), speech recognition (Chan, Englehart, Hudgins, & Lovely, 2002; Scheme, Hudgins, & Parker, 2007) and more recently a muscle–computer interface for gamers (Saponas, Tan, Morris, & Balakrishnan, 2008; Saponas, Tan, Morris, Turner, & Landay, 2010). The control scheme denoted as myoelectric control employs a

* Corresponding author. Tel.: +61 295147629; fax: +61 295142655.

E-mail addresses: Rami.Khushaba@uts.edu.au (R.N. Khushaba), Maen.Takruri@aurak.edu.ae (M. Takruri), Jaime.VallsMiro@uts.edu.au (J.V. Miro), Sarath.Kodagoda@uts.edu.au (S. Kodagoda).

pattern recognition approach to discriminate between the EMG signals that belong to different arm movements (Hudgins et al., 1993). The main assumption is that, at a given surface electrode location, the set of parameters, i.e., the extracted features, describing the EMG signal will be more or less the same for a given pattern of muscle activation. In addition, such features will also differ from one pattern or mode of muscle actuation to another at the same electrode location (Graupe, Salahi, & Kohn, 1982). Based on this assumption, successful off-line classification results on pre-recorded signals have been reported in the literature (Li, 2011; Oskoei & Hu, 2007).

Recent interest towards advancing real-time and clinical application of myoelectric control revealed a gap between research findings and a clinically viable implementation (Lock, 2005). This gap is mainly formed by several contributing factors, many of which can significantly affect the performance of an EMG pattern classifier, thereby resulting in an unusable controller. As an example, Hargrove, Englehart, and Hudgins (2008) showed how electrode displacement during usage can adversely affect the accuracy of EMG classification; however this effect can be mitigated by training the system to recognize plausible displacement locations. The conventionally defined classification accuracy was also recognized as an idealistic measure that may not reflect true clinical performance. To this end Scheme, Englehart, and Hudgins (2011) proposed a selective multiclass one-versus-one classification technique which allows for an independent adjustment of individual class-pair boundaries making it flexible and intuitive for clinical use. Cipriani, Controzzi, Kanitz, and Sassu (2012) showed that variations in the weight of the prosthesis and upper arm movements significantly influence the robustness of a traditional EMG classifier, thus causing a significant drop in performance. It was further suggested that a robust classifier should add some inertial transducers to myoelectric signals such as multi-axes position, acceleration sensors, and sensors able to monitor the interaction forces between the socket and end-effectors. An additional factor, specifically the effects of a limb position on pattern recognition based myoelectric control, has been examined on normal and amputee subjects (Chen & Li, 2011; Scheme, Fougner, Chan, Stavadahl, & Englehart, 2010). Fougner, Scheme, Chan, Englehart, and Stavadahl (2011) proposed two possible solutions to reducing adverse limb position effect including training in multiple limb positions and using accelerometers to measure position. Additional factors affecting the myoelectric pattern recognition performance could also include minimizing EMG electrode numbers, determining acceptable electrode locations, optimizing electrode recording configurations, and dealing with additional challenges of EMG recording in a dynamic environment (Zhang & Zhou, 2012). Jiang, Dosen, Muller, and Farina (2012) indicated that unlike the fixed arm/trunk positions exhibiting stationary EMG statistical properties under controlled laboratory conditions, EMG signal characteristics can change readily in a dynamic environment. This is due to factors like sweat, fatigue, or different adaptation strategies employed by the user. The fact that literature indicates very few myoelectric control systems which are able to adapt to such changes is, in itself, reasonable grounds for the lack of usability of these systems in practice. Additional factors to be reported include that the majority of pattern classification methods fail to provide simultaneous and proportional control, are not implemented with sensory feedback, and do not integrate with other sensor modalities to allow for complex actions.

The focus of this paper is also targeted on the effect of upper-limb position on EMG pattern recognition, as a complementary study to that reported in Fougner et al. (2011). In this paper we investigate a new feature extraction method, as an alternative solution to the use of accelerometers. The method is based on local and global spectral characteristics of the EMG signal and the utilization of these characteristics to form a set of invariants to the

changes in EMG signals which belong to the same movements. The main arguments here to justify the need for the new feature extraction method include first that the effectiveness of any pattern recognition system is mainly dependent on the quality of the extracted features, and their ability to provide an accurate representation of the underlying activity. Thus, investigating a new feature set to overcome the effects of limb position is of significant importance and should be considered as an initial solution before employing additional inertial sensors. Secondly, regardless of the limb position, and the generated EMG activities at the different positions, the EMG pattern classifier should be able to accurately recognize the hand movements. Put simply, when implementing the same arm or hand movement at different limb position one would intuitively assume that the underlying relation between the EMG activities generated by the different muscles should be the same, to some extent, as these muscles are collaborating to induce the same movement. However, as indicated by Fougner et al. (2011) this is not the case as different muscle combinations, in order to stabilize the limb, can be recruited at different limb positions to perform specific tasks. Additionally, variations in the underlying EMG activities should be captured and recognized as they belong to the same movement class. Notably, these activities are induced by the change in the muscle's shape and length while the user attempts to do the same movement at different positions. Such variations can easily change the amplitude, shape, and frequency-domain characteristics of the EMG signal upon what the classifier was initially trained on causing degradation in EMG recognition performance. According to all of the above, we propose a set of power spectrum features which may act as invariants to signal amplification, translation and scaling as a possible solution to this problem.

The structure of this paper is as follows: Section 2 first reports a background on EMG feature extraction, followed by a description of the proposed feature extraction method. Section 3 describes the data collection procedure. Section 4 presents the experimental results and finally, conclusions presented in Section 5.

2. The proposed feature extraction method

In an attempt to enhance the performance of an EMG-driven pattern recognition system, a new feature extraction method is presented here based on spectral moments. However before proceeding to describe our proposed method, we proceed first with a background review on feature extraction in EMG classification before linking the effect of limb position changes with variations in the EMG signal characteristics.

2.1. EMG feature extraction—literature review

Feature extraction addresses the problem of locating the most compact and informative feature set that can accurately describe the EMG signal in a condensed representation. According to Boostani and Moradi (2003), a feature space should have a maximum class separability for a feature set to be suitable for EMG-based control. It should also be robust in a noisy environment as much as possible with an associated low computational complexity. To this end, various temporal and spectral approaches to feature extraction have been utilized to derive an EMG-based controller (Boostani & Moradi, 2003; Du & Vuskovic, 2004; Hannaford & Lehman, 1986; Hudgins et al., 1993; Oskoei & Hu, 2007; Phinyomark, Phukpattaranont, & Limsakul, 2012; Rafiee, Rafiee, Yavari, & Schoen, 2011; Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995).

A primary advantage of employing time-domain characteristics is the reduction in complexity associated with the feature extraction process. Hudgins et al. (1993) had been among the first to consider time-domain features in myoelectric control while

Download English Version:

<https://daneshyari.com/en/article/403966>

Download Persian Version:

<https://daneshyari.com/article/403966>

[Daneshyari.com](https://daneshyari.com)