

Electromyographic Signal Processing With Application To Spinal Cord Injury

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To Teresa, for her endless support and love.

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Abstract

An Electromyogram or Electromyographic (EMG) signal is the recording of the electrical activity produced by muscles. It measures the electric currents generated in muscles during their contraction. The EMG signal provides insight into the neural activation and dynamics of the muscles, and is therefore important for many different applications, such as in clinical investigations that attempt to diagnose neuromuscular deficiencies. In particular, the work in this thesis is motivated by rehabilitation for patients with spinal cord injury. The EMG signal is very important for researchers and practitioners to monitor and evaluate the effect of the rehabilitation training and the condition of muscles, as the EMG signal provides information that helps infer the neural activity in the spinal cord. Before the work in this thesis, EMG analysis required significant amounts of manual labeling of interesting signal features. The motivation of this thesis is to fully automate the EMG analysis tasks and yield accurate, consistent results.

The EMG signal contains multiple muscle responses. The difficulty in processing the EMG signal arises from the fact that the transient muscle response is a transient signal with unknown arrival time, unknown duration, and unknown shape. In addition, the EMG signal recorded from patients with spinal cord injury during rehabilitation is very different from the EMG signal of normal healthy people undergoing the same motions. For example, some of the muscle responses are very weak and thus hard to detect. Because of this, general EMG processing tools and methods are either not applicable or insufficient.

The primary contribution of this thesis is the development of a wavelet-based, double-threshold algorithm for the detection of transient peaks in the EMG signal. The application of wavelet transform in the detection of transient signals has been studied extensively and employed successfully. However, most of the theories assume certain knowledge about the shapes of the transient signals, which makes it hard to be generalized to the transient signals with arbitrary shapes. The proposed detection scheme focuses on the more fundamental feature of most transient signals (in particular the EMG signal): peaks, instead of the shapes. The continuous wavelet transform with Mexican Hat wavelet is employed. This thesis theoretically derived a framework for selecting a set of scales based

on the frequency domain information. Ridges are identified in the time-scale space to combine the wavelet coefficients from different scales. By imposing two thresholds, one on the wavelet coefficient and one on the ridge length, the proposed detection scheme can achieve both high recall and high precision. A systematic approach for selecting the optimal parameters via simulation is proposed and demonstrated. Comparing with other state-of-the-art detection methods, the proposed method in this thesis yields a better detection performance, especially in the low Signal-to-Noise-Ratio (SNR) environment.

Based on the transient peak detection result, the EMG signal is further segmented and classified into various groups of monosynaptic Motor Evoked Potentials (MEPs) and polysynaptic MEPs using techniques stemming from Principal Component Analysis (PCA), hierarchical clustering, and Gaussian mixture model (GMM). A theoretical framework is proposed to segment the EMG signal based on the detected peaks. The scale information of the detected peak is used to derive a measure for its effective support. Several different techniques have been adapted together to solve the clustering problem. An initial hierarchical clustering is first performed to obtain most of the monosynaptic MEPs. PCA is used to reduce the number of features and the effect of the noise. The reduced feature set is then fed to a GMM to further divide the MEPs into different groups of similar shapes. The method of breaking down a segment of multiple consecutive MEPs into individual MEPs is derived.

A software with graphic user interface has been implemented in Matlab. The software implements the proposed peak detection algorithm, and enables the physiologists to visualize the detection results and modify them if necessary. The solutions proposed in this thesis are not only helpful to the rehabilitation after spinal cord injury, but applicable to other general processing tasks on transient signals, especially on biological signals.

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