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Technical note

High energy spectrogram with integrated prior knowledge for EMG-based locomotion classification

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ABSTRACT

Electromyogram (EMG) signal representation is crucial in classification applications specific to locomotion and transitions. For a given signal, classification can be performed using discriminant functions or if-else rule sets, using learning algorithms derived from training examples. In the present work, a spectrogram based approach was developed to classify (EMG) signals for locomotion mode. Spectrograms for each muscle were calculated and summed to develop a histogram. If-else rules were used to classify test data based on a matching score. Prior knowledge of locomotion type reduced class space to exclusive locomotion modes. The EMG data were collected from seven leg muscles in a sample of able-bodied subjects while walking over ground (W), ascending stairs (SA) and the transition between (W-SA). Three muscles with least discriminating power were removed from the original data set to examine the effect on classification accuracy. Initial classification error was <20% across all modes, using leave one out cross validation. Use of prior knowledge reduced the average classification error to <11%. Removing three EMG channels decreased the classification accuracy by 10.8%, 24.3%, and 8.1% for W, W-SA, and SA respectively, and reduced computation time by 42.8%. This approach may be useful in the control of multi-mode assistive devices.

1. Introduction

Lower limb amputation is a major cause of disability in the world. In the United States alone, 45% of the estimated 1.6 million individuals with limb loss experienced lower limb amputation [1]. To restore the locomotion capabilities of lower limb amputees many microprocessor controlled prosthetic legs have been developed [2,3] differing in pattern recognition algorithms, source of information [2,3], and data source [4]. Accurate and timely classification of locomotion modes and transitions are crucial for locomotion mode control. This requires efficient representation of signal source to develop efficient pattern recognition (PR) systems.

With recent advances in signal processing and pattern recognition algorithms, electromyography (EMG) has emerged as a source of neural information to facilitate motion classification and device control [5]. Pattern recognition systems rely on strict repeatability of EMG signal feature sets corresponding to particular locomotion modes [6]. This leads to the selection of unique feature sets providing robust locomotion classification. For control of lower limb prosthetics, time domain features including auto-regressive coefficients (AR) [7–9] have been used more often than frequency domain features due to their relative simplicity in computation and implementation in real time. However, limited signal representation in the time domain demands a high number of features [10], leading to high dimensionality for good classification accuracy.

Frequency domain features provide important contributions to the classification process. Using accelerometer data to classify dynamic activities, some groups have demonstrated that primitive frequency domain features from Fast Fourier Transform (FFT), in addition to time domain measures, can increase classification accuracy significantly compared to time domain features only [11–13]. Combined analysis of time and frequency EMG signal has been noted in kinesiology literature [14,15], though not in the areas of prosthetic mode control or classification of locomotion and transition modes. More recently, time and frequency domain features have been used to classify dynamic activities using accelerometer data, with highest classification accuracy of 97%, when using FFT components [16]. However, the frequency domain approach has not been thoroughly explored for EMG based locomotion transition classification; the exception being a conference report of early efforts [17].

The following approaches are generally used to introduce frequency domain information for classification problems: (i) frequency component using FFT, (ii) frequency component along with time domain measures, and (iii) time-frequency component including wavelet transform [16]. The wavelet transform has flexibility in

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time-frequency resolution, and is thus well suited to analyze short transient bursts typical in EMG signals. However, wavelet transforms can lead to redundant wavelet coefficients [18, 19] which may overburden the classifier, requiring an additional step of principal component analysis (PCA) before final classification. Further, wavelet bases are not well adapted to represent signals with narrow "high" frequency spectrum because of poor resolution at higher frequencies. Instead, wavelet packet transform (WPT) has been recommended for such signals [20]. One attractive approach is to use the basic time-frequency energy distribution, termed 'spectrogram', which supports narrow "high" frequency signals similar to WPT, with fixed time-frequency resolution.

The application of a spectrogram for feature extraction in non-stationary signals is not new [21], however little is known about its potential application in EMG for prosthetic control. Spectrogram representation of EMG was first presented to analyze fast movement and constant contraction of human hand muscles [22], however little is known about its utility in classifying locomotion modes or transitions using lower extremity EMG.

For the choice of pattern classification system, LDA has been commonly used [10,23,24]. The LDA is relatively efficient in computation and is considered to be equal to optimal Bayes classifiers, when care is taken with model assumptions. Further, in choosing a pattern recognition system, especially in lower limb prosthesis, usability of the system for the patient and clinician must be taken into consideration.

In previous attempts, EMG based locomotion classification has resulted in acceptable accuracy utilizing the time domain [23,25]. Enhanced classification accuracy in daily activities using frequency domain features of acceleration data [26,27] suggests that it is reasonable to explore the frequency characteristics of EMG for locomotion and transition classification. Spectrogram (time-frequency) representation of EMG signal is segmented into bins and is thus well suited to the histogram model of classification without transformation. Such a histogram model leads to simple if-else rules for classification. Spectrogram analysis has been shown to have superior accuracy compared to a Gaussian mixture model in the challenging task of color modeling for skin and non-skin image classification [28].

In this paper, we demonstrate the use of a time-frequency representation of EMG to classify locomotion and transition between modes using simple if-else rules for future application in prosthetic lower limbs. We present a spectrogram-derived histogram model for classification. We further present a prior knowledge approach to be integrated with the classifier. Lastly, we identify the discriminating power of each muscle for different classes using Euclidean distance between histograms, allowing for critical evaluation of classifier performance with reduced neural information.

2. Methods

2.1. Data collection

This study was approved by the university's Institutional Review Board. All subjects provided written informed consent prior to involvement in the study. Surface EMG data were recorded from leg muscles of 13 healthy young adults (11 male, 2 female; age 23 ± 4 year, height 172.8 ± 9.9 cm, mass 74.2 ± 12.1 kg) while walking over level ground (W), ascending stairs (SA), and the transition between states (W-SA). Passive surface electrodes (Ag/Ag-Cl) were placed in bipolar single differentiation configuration on the tibialis anterior (TA), medial gastrocnemius (MG), rectus femoris (RF), vastus lateralis (VL), biceps femoris (BF), gluteus maximus (GMax), and gluteus medius (GMed) (Fig. 1). Cohesive flexible bandage was used to secure wires and transmitters to reduce motion artifact (not shown in figure).

Subjects were asked to complete a total of three successful level-ground to stair ascent trials (including transition). Each trial was constructed so the subject would have at least 10 gait cycles pre-transition, continuing on to ascend a full flight of stairs. The final two pre-transition gait cycles and transition cycle were used for further analysis, to observe the efficiency of the prior knowledge scheme. Subjects were asked to walk at a self-selected pace throughout each trial. The EMG data were sampled at 1500 Hz and band-pass filtered between 3 and 500 Hz, utilizing full EMG power spectrum, using the Telemyo DTS system (Noraxon, Scottsdale, AZ). All post-processing of the EMG signals was conducted using custom-written programs in Matlab (Mathworks, Natick, MA).

Fig. 1. Anterior, posterior and lateral views of EMG electrode setup.

2.2. Spectrogram formation

We selected the data from heel strike of one locomotion mode to heel strike of the next locomotion mode as a gait cycle. Heel strikes were identified using foot switch (Noraxon, Scottsdale, AZ) activation profiles. Each gait cycle was further divided in 256 ms data segments for continuous decision making. A recent report of a real time prosthetic control system indicated that the optimal window length was between 150 and 250 ms [29]. We selected 256 ms, a value closer to the higher reported range to avoid large variance (or classification error) due to shorter window size. A shorter window size has the benefit of more continuous decision making, leading to a tradeoff between accuracy and controller delay. Within locomotion mode detection, a delay of 50–400 ms has been reported as acceptable for decision making in real time prosthesis control [30,31]. However during transition, the classification decision for upcoming locomotion state must be made within stance phase of the transitional cycle so that appropriate damping of swing phase can be provided. Hence, we restricted the number of data segments in a gait cycle so that they covered a minimal portion of swing phase. A spectrogram for each 256 ms data segment was developed with 64 ms of sliding window and 50% overlap, as shown below in Fig. 2.

We used a periodogram approach to calculate the spectral density of the data segment as

$$P_x(m,\omega) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) \times W(n-m) \times e^{-j\omega n},$$

where N is the total number of data points in the data segment, ω is the frequency and m is the length of window. The spectrogram was then calculated as the magnitude square of each periodogram as

$$\text{Spectrogram}\{x(n)\}(m,\omega) = |P_x(m,\omega)|^2.$$

The periodogram gives a good estimate of spectral density of non-stationary signals like EMG, calculating the Fourier transform of autocorrelation to give a better estimate of signal. A detailed description of periodograms can be found in [32].