EMG ONSET DETECTION USING THE MAXIMUM LIKELIHOOD METHOD

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INTRODUCTION

Electromyography (EMG) is used extensively to determine the muscle activation patterns of neuromuscular functions such as motor control, posture, and movement [1,2]. The onset of the EMG activity is a marker for the onset of active control and therefore is one of the most common parameters evaluated from EMG records [3], but there is no standard method to determine this parameter [4]. The accurate detection of the onset of muscle activity is extremely important since differences in the time from stimulus to EMG onset can be as low as 20 ms [5,6]. Computerized techniques for the determination of the onset of muscle activity exist but their performance varies considerably. Also the accuracy of these methods degrades as the signal to noise ratio is decreased.

In this study we have developed an algorithm to detect the onset of muscle activity from EMG records using the Maximum Likelihood Method. The performance of this method was compared against DiFabio's threshold method [7], and against two experienced human observers in a wide range of standard deviation ratios (SDR) of the samples. The SDR is a measure of the intensity of the signal.

METHODS

EMG Recordings

The EMG records used in this study were from the right Tibialis Anterior (TA) muscles of three healthy young subjects (21-28 years old) during a relaxed state and an ankle isometric dorsiflexion at 10% increments from 10% to 100% of maximum voluntary contraction (MVC). The study was approved by the Advisory Committee for Human Experimentation at the University of Kansas.

The EMG signals were recorded using a Bagnoli-8 double differential surface electrode EMG system by DELSYS (Boston, MA). The signal was sampled at a minimum common mode rejection ratio of 84db. A Cybex II dynamometer was used to measure the net ankle torque and to give visual feedback to the subject using a digital multimeter. The EMG signals were sampled at 1000 Hz using a National Instruments 12 bit A/D board controlled with a LabVIEW (National Instruments, TX) virtual instrument. One hundred and fifty windows of relaxed and active EMG data were randomly selected from the EMG data sets collected. These windows were used to produce 150 data sets, each consisting of a window of relaxed EMG followed by a window of active EMG, thus allowing control of the onset time. The total length of each data set was 1000 ms. The data sets were also divided into 5 different bins based on their SDR level. The SDR was defined as the ratio of the standard deviation of the active state S1 over the standard deviation of the relaxed state S0. The range of values of SDR was from 1 to 31.

EMG Onset Determination

Computerized Methods

Two different algorithms were used to determine the muscle onset time. The first algorithm (A) was based on a threshold method first described by DiFabio, 1987. In this method the EMG signal is first full wave rectified and then filtered using a low pass filter with a cutoff frequency of 50 Hz. A window of 50 ms is used as the baseline. The onset is set at the first point where the filtered EMG signal exceeds 3 standard deviations of the baseline for 25 consecutive ms.

The second algorithm (B) is based on hypothesis testing [8]. To detect the onset of the EMG activity two hypotheses are constructed. The first hypothesis is associated with the relaxed state and is denoted as H0, with a probability density function (PDF) $p0$, and the second hypothesis is associated with the active state and is denoted H1, with a PDF, $p1$. The maximum likelihood test will be used to determine which hypothesis is true at every time step r from 0 to n. The probability that the whole EMG record responds to hypothesis H0 is expressed as:

$$L(0, y_0^n) = p_0(y_0^n) \qquad (1)$$

where y[t] is the EMG sample at every time step from 0 to n.
The probability that the EMG record responds to hypothesis H0 from time 0 to r-1 and to hypothesis H1 from r to n is:

$$L(0,1,r, y_0^n) = p_0(y_0^{r-1}) p_1(y_r^n) \qquad (2)$$

The likelihood ratio is the equal to:

$$\frac{L(0,1,r,y_0^n)}{L(0,y_0^n)} = \frac{p_0(y_0^{r-1})p_1(y_r^n)}{p_0(y_0^n)} = \prod_{t=r}^{n} \frac{p_1(y[t])}{p_0(y[t])} \quad (3)$$

The EMG signal is generally accepted to be stochastic in nature and normally distributed; therefore it is assumed that the corresponding PDF's are Gaussian. The log-likelihood ratio over the whole record is defined as the decision function (DF) and after substitution of the PDF equations into equation (3), the decision function is equal to:

$$DF(0,1,y_0^n) = \left\{ \log \left[\prod_{t=r}^{n} \frac{\frac{1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(y_1(t)-\mu_1)^2}{2\sigma_1^2}}}{\frac{1}{\sigma_0\sqrt{2\pi}} e^{-\frac{(y_0(t)-\mu_0)^2}{2\sigma_0^2}}} \right] \right\} \quad (4)$$

By applying monotonic transformations to eliminate several constants and the exponentials, the final decision function becomes:

$$DF = \left(\frac{\sigma_0}{\sigma_1}\right) S_{y1}^2 - S_{y0}^2 \quad (5)$$

where $\sigma 0$ and $\sigma 1$ are the standard deviations of the parent population and S0 and S1 are the standard deviations of the sample. The values of $\sigma 0$ and $\sigma 1$ were determined from EMG records from previous studies.

The onset of the muscle activity is determined by using a threshold on this decision function.

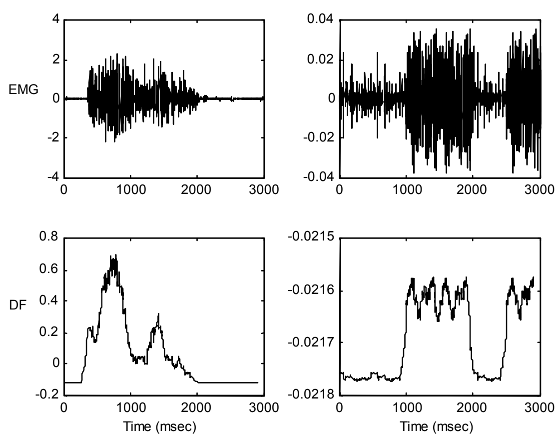

Figure 1. EMG signal and Corresponding DF

Human Observers

Two human observers were asked to identify the onset of muscle activity using a computer interface. Both observers were experienced in identifying EMG activity onset times.

RESULTS

The onset determined from each method was analyzed within each SDR bin. Table 1 shows the success rates of the three different methods for every bin. The determination of the onset was considered successful if it was within ±5 ms of the true onset time.

The success rate of algorithm (B) increased as the SDR level is increased, eventually reaching 100% accuracy. The two human observers exhibited a similar trend although their accuracy never reaches 100%. Algorithm (A) follows the same pattern in the first four bins but at the high SDR level the success rate decreases significantly.

Bin #	SDR	Algorithm (A)	Algorithm (B)	Human 1	Human 2
1	1-6.99	76.6	83.3	50	53.3
2	7-12.99	90	96.6	73.3	83.3
3	13-18.99	90	100	86.6	90
4	19-24.99	80	100	93.3	93.3
5	25-30.99	63.3	100	93.3	90

Table 1. Success Rates (%) vs. SDR

DISCUSSION

The results indicate that the onset times determined by the two algorithms vary significantly. Algorithm (B) works well at SDR levels approaching 1, and is extremely accurate at SDR levels of 13 and above. Algorithm (A) degrades significantly at an SDR level of 19 and above, which can be explained by classifying the incorrect detections as early and late detections. In the first two bins all the incorrect detections were late detections, in bins three and above all of the incorrect detections are early detections. This may be caused by the low pass filter used in the method, as the SDR level increases over 13 the amplitude difference between the active and the relaxed state is relatively large. When the rectified signal is filtered, the envelope of the signal is smoothed, which causes a rise above the threshold before the true onset time. The MLM method appears to perform well in detecting EMG onset times at all levels of SDR used in this study.

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