PATTERN RECOGNITION IN SURFACE ELECTROMYOGRAPHY

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Abstract: In this paper, a method is proposed to differentiate patterns in one-channel surface electromyography. This particular method uses an example signal containing all relevant patterns to learn spectral coefficients. These coefficients are used to analyze unknown signals. An example of finger recognition algorithm based on a signal from forearm muscles is shown and discussed.

Keywords: EMG, pattern, recognition, Fourier, Teager-Kaiser

1. INTRODUCTION

Surface electromyography (EMG) is widely used for controlling various types of limb prostheses. Pattern recognition from the remaining muscles of the amputated limb is the key component to comfortable and ergonomic control. Improved prostheses control leads to better quality of life of the amputee.

EMG signal is the result of a non-stationary stochastic process and as such is difficult to analyze. To aid the analysis, short periods of this signal can be viewed as deterministic and time-frequency analysis in the form of short-time fourier transform (STFT) can be performed as shown in [1].

Signals were captured using long rectangular surface electrodes in the forearm area by BIOPAC acquisition unit. Key muscles contributing to the signal were Flexor Digitorum Superficialis and Extensor Digitorum. Analysis was then performed using MATLAB.

2. ENERGY ESTIMATION AND ON-SET DETECTION

A precise detection of the beginning and end of a muscle contraction is essential to allow the algorithm to learn correctly. Movement artifacts are filtered out with a finite impulse response high-pass filter at 20 Hz cutoff frequency and the Teager-Kaiser Energy Operator [2] (TKEO) is applied. To improve detection, a smoothing median filter is applied after TKEO to minimize valleys and peaks of the signal. A simple threshold method is used to discriminate between the on and off states. The threshold is derived from the first 50 samples of the signal. This part of the signal is defined as contraction-less. Figure 1 shows the results of signals before and after TKEO with detected contractions. The value of the threshold is strongly dependant on how and where the signal is measured from.

3. LEARNING PHASE

The learning sequence used to test this method is as following: 5 s pause, 5 s 50% of maximum voluntary contraction of a pattern, repeated four times, once for every finger.Thumb movement is not distinguished as there is no direct connection between thumb movement and contraction of any muscles in the vicinity of the electrodes.

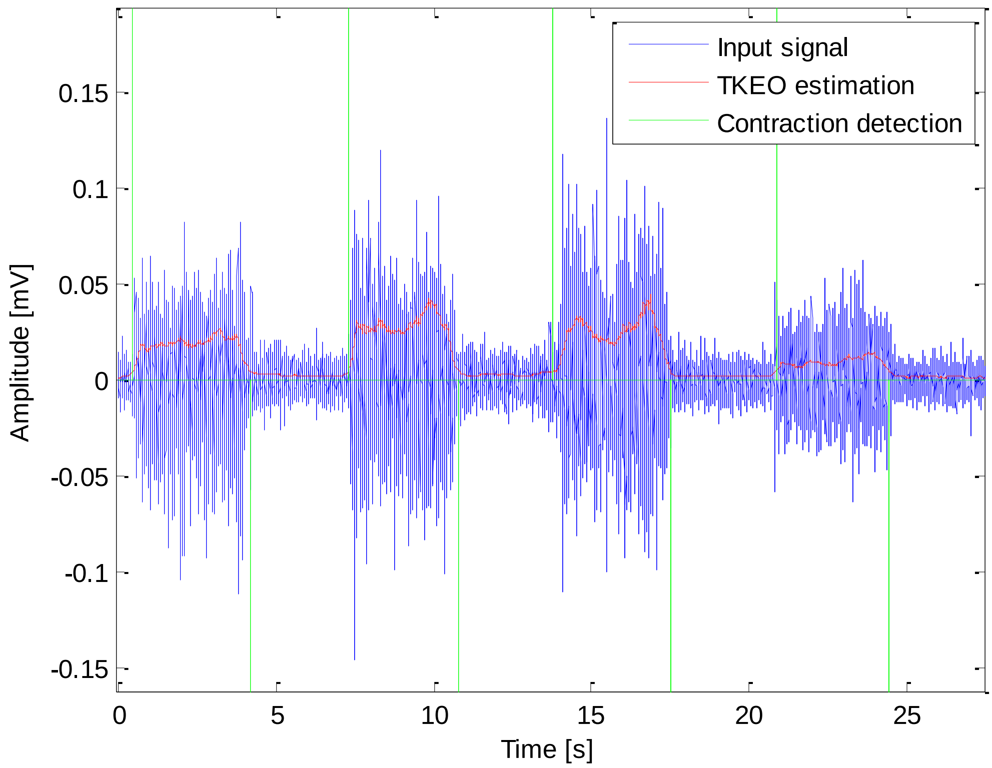

Figure 1 - EMG signal before and after TKEO, with true positive onset and off-set detection

The beginnings and ends of every pattern must be detected correctly prior to obtaining spectral coefficients via STFT. Mean frequency, median frequency and low to high frequencies ratio are computed in each of the STFT sections. These sets of coefficients are then averaged accordingly for every pattern. Standard deviation of the coefficient sets is also saved to form field of effect. Outptut of the learning phase can be represented in 3d space with coefficients being position of points in the center of boxes whose size is determined by the fields of effect (Figure 2).

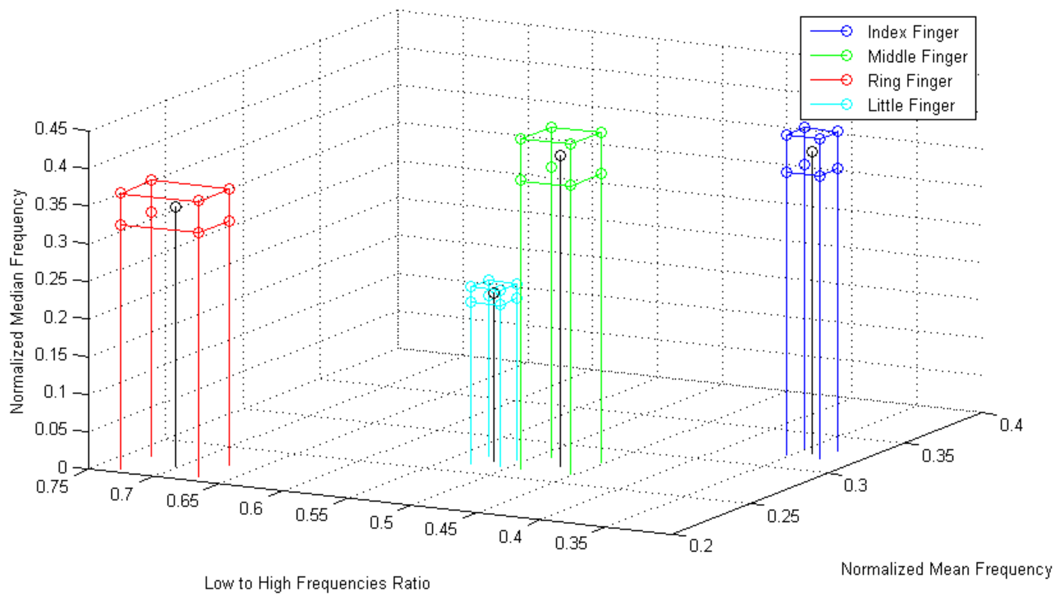

Figure 2 - Representation of learning phase output

4. OPERATIONAL PHASE

The operational phase is similar to the learning phase except averaging of spectral coefficients. The signal is filtered and TKEO is applied to detect contraction. When onset energy is detected, STFT is applied until the end of contraction. Spectral coefficients are computed in fashion similar to the learning phase. Euclidean distance is measured between all of the specified patterns and the most recent part of the test signal. If the current coefficients all lie within the field of effect, the distance is set to zero. All of the previous distances of the same contraction are summed at any time of the contraction.

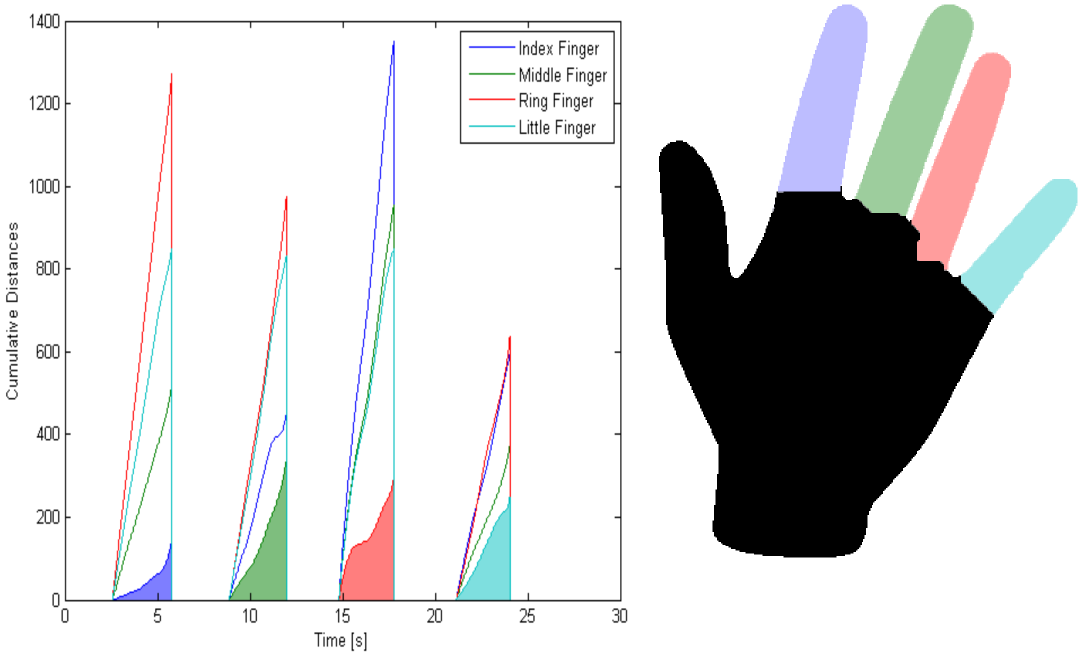

Figure 3 - Output of the algorithm shows cumulative distances on the left and corresponding fingers

5. RESULTS AND CONCLUSION

For basic testing purposes, five signals were acquired from a subject asked to isometrically push the four fingers, one at a time with a 5 s pause between 5 s pushes. One of the signals was used as input for the learning phase, the others as input for the operational phase. During this basic test 100% of beginnings and ends of contractions were detected with no false positive results. The pattern differentiation was 93.75% accurate with one falsely recognized contraction.

These results were acquired in a controlled environment; the subject was always sitting and the contractions were always isometric. Therefore more complex tests with additional subjects need to be performed to further confirm the reliability of the algorithm.

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