AUTOMATIC DECOMPOSITION OF SIMULATED EMG SIGNALS

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ABSTRACT

We present an electromyographic signal decomposition program featuring pseudo-correlation, a novel template matching technique. The program performance has been tested with synthetic data. Decomposition was fast and accurate for synthetic signals of moderate complexity, showing capabilities for real-time applications.

INTRODUCTION

During a normal muscle contraction, action potentials propagate along each fiber of their corresponding motor unit (MU) and summate to give a motor unit action potential (MUAP), the shape of which remains fairly constant between each discharges but differs, in general, for different MUs. The electromyographic (EMG) signal collected with indwelling electrodes is composed of MUAP trains that are located within their pick-up volume. During low to moderate contractions, it is possible to *extract* the signal's constituent MUAP trains and to *detect* the individual MUAP occurrences. The combination of both processes is known as *decomposition*. Many algorithms have been developped over the years [1]-[3], but so far none has gained widespread acceptance in the field. One major problem has been the need for frequent adjustments of signal-sentitive parameters to obtain accurate decomposition results, which greatly reduces the overall reliability of the method. The purpose of this work was to develop a program that would decompose EMG recordings typically encountered in research protocols accurately, rapidly and without the need for user intervention.

METHODS

Signals were synthesized so that their characteristics and complexity would match that of experimental recordings stemming from healthy subjects during moderate isometric contractions. Each signal simulated a 10 s long recording sampled at 8 kHz (80000 points).

The MUAP extraction begins by breaking down the input into non-overlapping segments of variable duration. The segments are represented in a 6-dimensional feature space: 1) the sequence of peaks and valleys, 2) the cumulative voltage variation, 3) the peak-to-peak amplitude, 4) the rectified area, 5) the total duration and 6) the peak-to-peak duration. A regression tree is used to recursively partition the feature space into groups of points belonging to the same MUAP train. Templates are obtained through averaging of the waveforms contained in a given group after the MUAPs have been properly aligned. To make sure the templates obtained are genuine and not duplicates of others, we verify their relative similarity using *pseudo-correlation (PC)* defined as:

$$z_k = \frac{\sum_{j=1}^{m}\left(x_j\, y_{k+j} - \left|x_j - y_{k+j}\right| \max\left\{\left|x_j\right|, \left|y_{k+j}\right|\right\}\right)}{\sum_{j=1}^{m}\left(\max\left\{\left|x_j\right|, \left|y_{k+j}\right|\right\}\right)^2}$$

where $\mathbf{x} = \{x_1, x_2, \ldots, x_m\}^T$ is the reference waveform that we are looking for within $\mathbf{y} = \{y_1, y_2, \ldots, y_n\}^T$ ($m < n$), while $\mathbf{z} = \{z_1, z_2, \ldots, z_n\}^T$ contains PC values at different lags of $\mathbf{x}$ with respect to $\mathbf{y}$. Templates that show a PC index greater than a certain similarity threshold are merged.

The detection of individual MUAP occurrences of the extracted trains is carried out in a two-step approach. The first step consists in locating MUAPs that do not significantly overlap with each other by pseudo-correlating each template with the entire signal. Significant PC values indicate the firing of a given train, whose template will be subtracted from the signal. The MUAP template and the time of its occurrences are stored in a matrix to be used to compute firing statistics. The second step deals with waveforms showing a greater degree of overlapping with each other. Here, we use an iterative approach based on a series of peel-off procedures where templates are subtracted from a compound waveform one at a time, which is similar to an algorithm developed by Fang et al. [1].

# Trains	# Total MUAPs	Process time Step 1 (s)	Process time Step 2 (s)	Detections Step 1 (%)	Accurate detections (%)	False positives (%)	False negatives (%)
4	470 (440 - 488)	1.5 (1.4 - 1.5)	1.0 (0.8 - 1.3)	82.1 (79.6 - 86.1)	95.5 (91.8 - 97.6)	0.3 (0.0 - 1.0)	4.5 (2.4 - 8.2)
6	706 (684 - 730)	2.3 (2.2 - 2.5)	1.9 (1.8 - 2.1)	74.3 (70.8 - 82.7)	94.4 (92.5 - 97.5)	0.4 (0.0 - 1.6)	5.6 (2.5 -7.5)
8	1002 (924 - 1103)	3.2 (2.9 - 4.0)	3.7 (2.5 - 6.7)	65.8 (57.7 - 69.9)	90.8 (87.7 - 95.2)	1.5 (0.7 - 4.0)	9.2 (4.8 - 12.3)
10	1228 (1138 - 1273)	4.0 (3.7 - 4.8)	5.0 (3.9 - 7.6)	63.5 (61.4 - 68.8)	86.5 (79.1 - 90.0)	0.7 (0.0 - 1.6)	13.5 (10.0 - 20.9)
12	1462 (1486 - 1598)	4.7 (3.7 - 5.5)	8.3 (5.5 - 12.8)	61.9 (55.0 - 72.7)	82.7 (77.8 - 86.9)	2.0 (1.2 - 3.3)	17.3 (13.1 - 22.2)

Table 1. Detection results obtained for simulated signals. Process times are for a Pentium IV 2.8 GHz processor. Values in parentheses indicate the range of values obtained over each set of 5 signals.

RESULTS

The average time required to perform extraction ranged from 1 to 2 s, while for the detection module it ranged from 2.5 to 13.0 s. With increasing signal complexity, we noticed a steep increase in the processing time of the second detection step, which consists in resolving superimpositions. As seen in Table 1, the percentage of accurate detections steadily decreased from 95.5% to 82.7% with the number of trains varying from 4 to 12, while the average rate for detection errors of the false negative type climbed from 4.5% to 17.3%. The false positive rate remained lower than 3.5%.

DISCUSSION

Accurate extraction of MUAP trains was always achievable, but for complex signals where the train shapes were abnormally similar, it required some minor parameter adjustments. Extraction errors could also occur when trying to extract small-amplitude MUAPs present amidst several larger ones. The detection module was able to produce satisfactory results for signals containing up to 12 trains without any parameter adjustments. Errors arose mostly when trying to resolve superimpositions involving small- and large-amplitude MUAPs. In all, signals showing a limited degree of overlapping (typically fewer than 8 trains) rapidly yielded overall decomposition results that were practically error-free.

CONCLUSION

With an average processing time (extraction + detection) slightly shorter than the duration of the signal, our program could decompose EMG signals containing up to 8 trains in real time. Moreover, since the program performs satisfactorily without relying heavily on MUAP firing statistics, it could be used to analyze various experimental EMG signals such as the ones acquired under varying force or in non-isometric situations.

REFERENCES

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