Proceedings - 19th International Conference - IEEE/EMBS Oct. 30 - Nov. 2, 1997 Chicago, IL. USA

# DECOMPOSITION OF EMG SIGNAL BY WAVELET SPECTRUM MATCHING

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**Abstract:** We have developed a technique using wavelet transform to classify single motor unit (SMU) potentials and to decompose EMG signals into their constituent SMU potentials. The distinction between this technique and previous techniques is that it measures waveform similarity of SMU potentials from wavelet domain, which gives this technique many advantages over other techniques. Separation of compound motor unit potentials, on the other hand, is based on a sequence of waveform differential correlation processes. Our technique also utilizes the information on discharge regularities of SMUs. This technique had been tested using actual EMG recordings that were composed of more than 10 different motor unit potentials. The results were satisfactory.

## Introduction

Study of control mechanism of SMUs and the underlying physiological functions of human motor system is of significant importance for both clinicians and basic researchers. The activities of SMUs can be easily recorded by a needle electrode placed inside a muscle. However, it is inevitable that more than one SMU potentials will be registered at same time overlapping with each other, especially during a strong muscle contraction. Therefore, a successful study of SMU discharge properties relies on correctly decomposing multi-unit EMG signals into their constituent SMU potential trains. Over the years, many techniques have been developed, such as window discriminator technique, matched filter technique, feature extraction technique, and neural network technique [1,2,3].

In our study, we developed a different decomposition technique based on spectrum matching in wavelet domain. Spectrum matching technique is sometimes considered to be more effective than waveform matching techniques, especially when the interference is induced by low frequency baseline drift or by high frequency noise. In both cases, the interference only affects two marginal portions of the frequency spectrum. However, the previously described spectrum matching techniques [4] are based on Fourier spectrum, which normally requires additional windowing to eliminate truncation errors because of the rectangular data window for each action potential. With time-frequency analysis like wavelet transform, the window filtering becomes unnecessary. Moreover, the interference of white noise, which affects entire spectrum and makes Fourier transform vulnerable, can be easily de-noised with soft-threshold method. It has been shown that wavelet transform method achieves maximum number of vanishing moments; therefore, a substantial degree of separation between signals and noise can be obtained in wavelet domain.

## Methods

Our technique for multi-unit EMG signal decomposition consists of four separate procedures: signal de-noising procedure, spike detection procedure, spike classification procedure, and spike separation procedure.

1. Signal de-noising: The de-noising procedure is applied to reduce the interference of white noise. It is assumed that the recorded EMG data *r(t)* is a linear summation of an unknown, noise-free EMG signal *s(t)* and a Gaussian white noise process *n(t)*, i.e.,

$$r(t) = s(t) + n(t),$$

where $n(t) \in N(0,\sigma^2)$. Therefore, the wavelet coefficients of *r(t)* can be expressed as:

$$r_k^m = s_k^m + n_k^m,$$

where $r_k^m$, $s_k^m$, and $n_k^m$ are the wavelet coefficients of *r(t)*, *s(t)*, and *n(t)*, respectively, at scale *m*, and time index *k*. The de-noising process is based on the soft-thresholding technique [5]:

$$\hat{r}_k^m = \begin{cases} r_k^m, & if\ r_k^m > \sigma_z \\ 0, & if\ r_k^m < \sigma_z \end{cases} \qquad \sigma_z = \sigma\sqrt{\frac{2\log(L)}{L}},$$

where *L* is the total samples of *r(t)*. It has been shown [5] that the inverse wavelet transform, $\hat{r}$ (t), based on the $\hat{r}_k^m$, achieves the optimal estimation of the unknown, noise-free EMG signal *s(t)*.

2. Spike detection: The detection of spikes is based on an amplitude detection scheme. A horizontal cursor is set at a level to distinguish spike potentials from background noise. Upon detection of a spike, a segment of spike waveform with its peak aligned at the center will be collected. The sample size of segmented waveform is currently set to 64 sample points. At the sampling rate of 12 kHz, the size of 64 samples corresponds to a duration of 5.33 msec, which is wide enough to include the major portion of most SMU potentials. All the spike segments detected will then be assembled together to form a two-dimensional matrix with



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64 columns and N rows.

$$\begin{bmatrix} spike(1) \\ spike(2) \\ \vdots \\ spike(N) \end{bmatrix} = \begin{bmatrix} x_{1,0} & x_{1,1} & \cdots & x_{1,63} \\ x_{2,0} & x_{2,1} & \cdots & x_{2,63} \\ \vdots & \vdots & \cdots & \vdots \\ x_{N,0} & x_{N,1} & \cdots & x_{N,63} \end{bmatrix}$$

where $N$ is the total number of spikes detected. The discharge time of each spike will also be recorded in a separated one-dimensional array $\mathbf{T}_{spike}$:

$$T_{spike} = [t_1, t_2, ..., t_N]^T$$

3. Spike classification: The detected spikes will then be sorted into different groups based on the similarities between the spikes. The similarity between spikes j and k, denoted as $J_{j,k}$, is measured in the wavelet domain as:

$$J_{j,k} = \max_n \{| w_{j,n} - w_{k,n} |\}, \; n>4$$

where $\mathbf{w}(i) = [w_{i,0}, w_{i,1}, \ldots, w_{i,63}]$, which is the wavelet transform of spike $i$ by Daubechies wavelet. The spike sorting process is based on the nearest neighbor algorithm. It is a recursive procedure to group the spike with the smallest similarity measure at each step until all the detected spikes are encountered.

4. Spike separation: Separation of a compound motor unit potential is achieved by searching for a set of template potentials, $C$, that the corresponding the squared error

$$E_{j,C} = \sum_{k=1}^{64} \left( S_j(k) - \sum_{i \in C} T_i(k - \tau_i) \right)^2$$

has minimum value [6]. The searching process accomplishes two objectives. The first is to identify the correct combination of template potentials for a give compound motor unit potentials, and the second is to locate the proper time delay for each corresponding template potential. In our technique, we use a procedure referred to as sequential differential correlation technique. It consists of $M$ steps of correlations, where $M$ is the number of template potentials. In each of these $M$ steps, a compound potential is sequentially subtracted by the unused templates potential that results in the minimal squared waveform error at that step. Each waveform differentiation takes place at the waveform translation that yields the maximum correlation. If we denote the order of the waveform differentiation as

$$\{i_1, i_2, ..., i_M\},$$

then there will be a number $v$, where $1 \le v \le M$, such that $C'=\{i_1, ..., i_v\}$, and

$$E_{j,C'} = \min_C (E_{j,C})$$

## Results

Our technique was used routinely in the study of SMU discharge patterns. Figure 2A shows a segment of an actual EMG recording, which was 7.7 seconds long. Interference of white noise for this segment of EMG signal was minimal so that the de-noising procedure was not necessary. For this particular example, a total of 502 spikes were detected. The results of the grouping process is demonstrated in figure 1, where 502 vertical lines formed a one-dimensional ordered list; the spikes associated with the consecutive lines in the list were of the closest similarity. Thus, by introducing a threshold at the level indicated in figure 1, the spikes between two threshold crossings were grouped together. For this particular recording, 252 groups resulted from 502 detected spikes. Among the 252 groups, 9 groups were recognized as template potentials (Fig. 2B). The determination of template potentials were based on the number of spikes in each group as well as the shape of the averaged waveform in the group. The final result of multi-unit decomposition for this example is shown in figure 2C. Our results revealed that this segment of EMG signals was comprised of 9 SMU potentials. They were recruited in an orderly fashion.

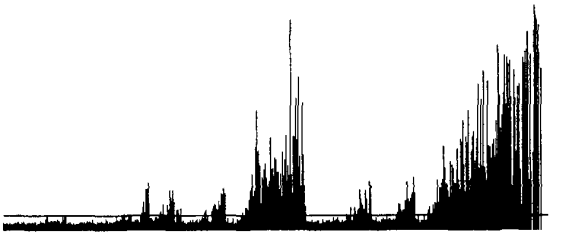

Fig. 1 The sorted similarity measures from an EMG recording.

## Discussion

Our technique is designed for decomposition of multi-unit EMG signals with serious waveform superimposition. Therefore, it is not suitable for on-line analysis. The entire process of multi-unit decomposition is conducted automatically under the control of a computer program we developed in C language. However, due to the complicated nature of waveform superimposition, human decision becomes necessary in reduction of the decomposition error. In our technique, the final decomposition results achieved by the computer program will be verified by an operator based on the comparison between the actual EMG signal and the signal reconstructed (Fig. 3). In general, the degree of human involvement depends on the number of active SMU potentials recorded in EMG signals.

Another factor that may affect the decomposition process is the peak-to-peak amplitude ratios among the different SMU potentials. In most cases, the small SMU potentials are often lost when they are superimposed with a much larger SMU potentials. In order to demonstrate our point, we plot



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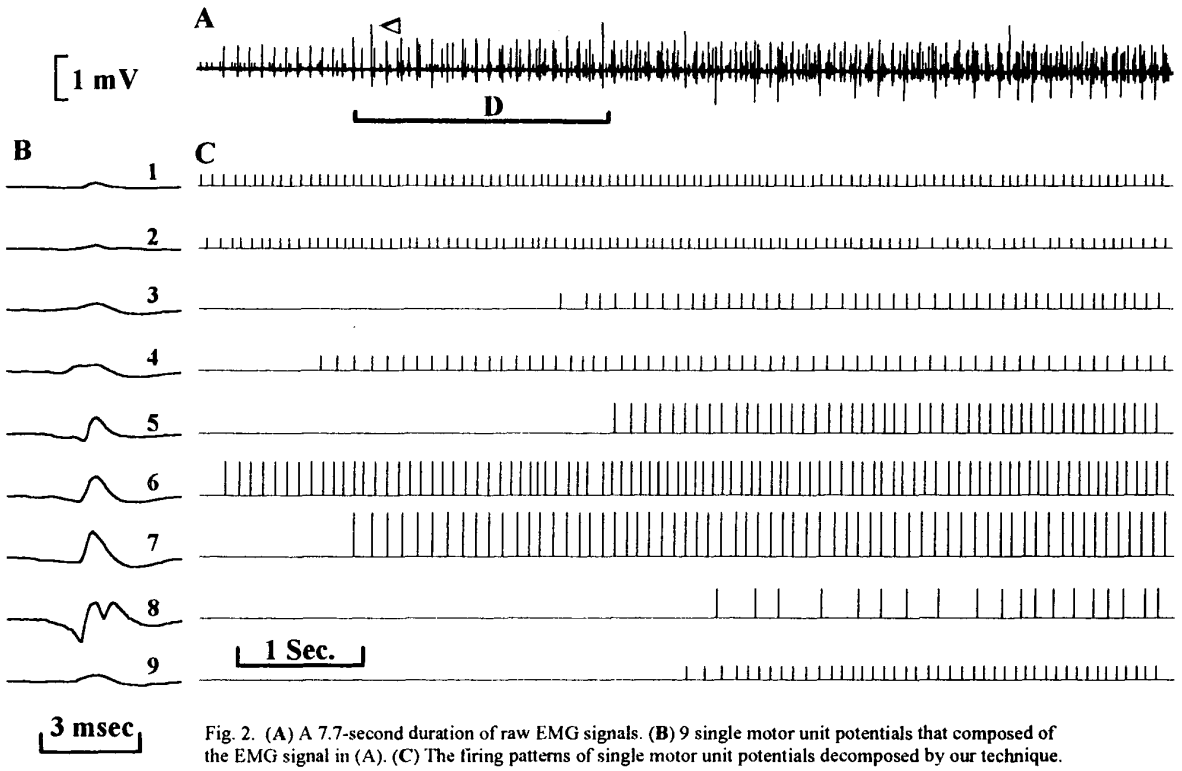


Fig. 2. (A) A 7.7-second duration of raw EMG signals. (B) 9 single motor unit potentials that composed of the EMG signal in (A). (C) The firing patterns of single motor unit potentials decomposed by our technique.

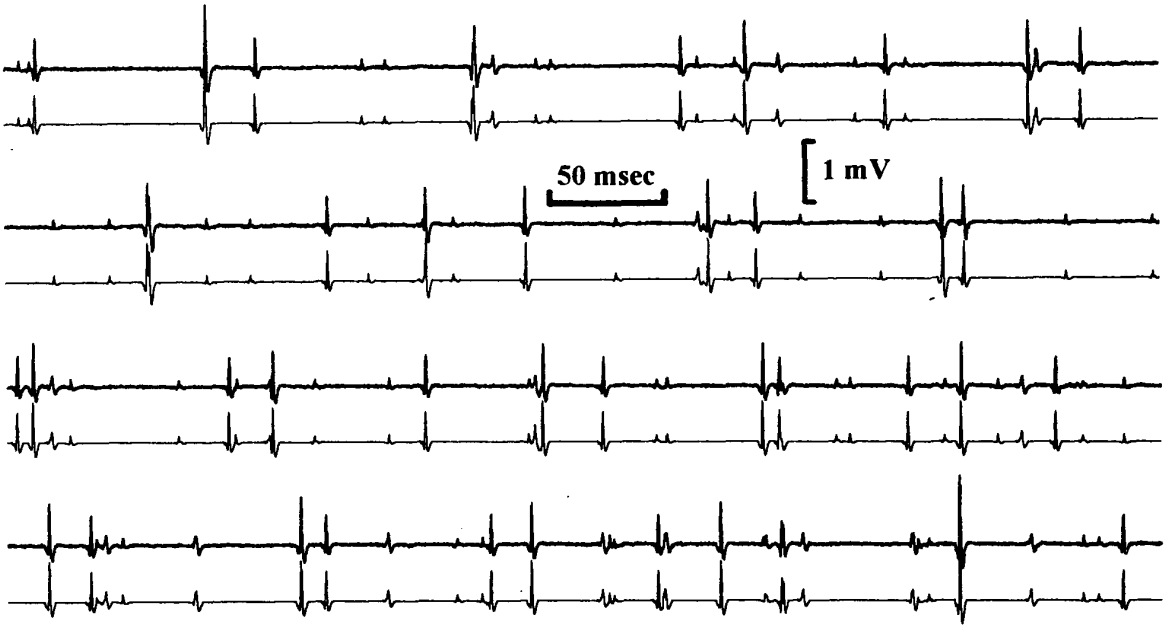


Fig. 3 Comparison of a portion of actual EMG signal (upper trace of the pair) with the reconstructed EMG signal (lower trace of the pair). This portion of EMG data is 2 seconds long and indicated by D in Fig. 2. The segment shown here is broken down into 4 cascade traces.



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a segment of EMG signal in a larger scale in figure 4. This segment of signal is mark by a triangular symbol in figure 2A. For this example, the compound motor unit potential was resulted from superimposition of four SMU potentials 1, 2, 3, and 7. However, the potential of SMU 1 could be easily missed due to its much smaller peak-to-peak amplitude comparing to that of other SMU potentials, for instance, SMU 7. Therefore, the identification of small SMU potentials within compound potentials will normally rely on the information of their discharge regularities.

Waveform variation of SMU potentials during the recording may also be the problems that one encounters in multi-unit EMG signal decomposition. It is believed that the variation is caused by the movement of the electrode. Based on our experience, waveforms of SMU potentials may not alter in a continuous manner. Instead, it mutates in a stepwise fashion and maintains the same configuration between steps. Therefore, an adaptive method to track the waveform variation may not work well in this case. With our technique, a mutated waveform will usually be classified into separated groups. However, they can easily be merged later on based on the discharge regularities during the final verification procedure.

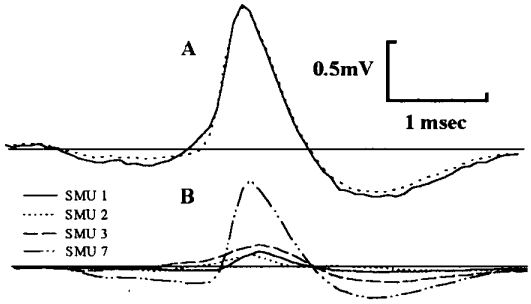


Fig. 4 (A) The waveform in solid line represents a compound motor unit potential recorded. The waveform in the dotted line represents the reconstructed potential resulted from superimposition of 4 SMU potentials. (B) Four SMU potentials that composed the compound motor unit potential in A.

## Conclusion

Our new technique has been successfully used for multi-unit EMG signal decomposition. It has been shown that this technique is accurate, reliable, and fast. We believe that it is a very useful technique in study of motor control mechanisms at SMU level.

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