Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004



# Improved Resolution of Pulse Superpositions in a Knowledge-Based System for EMG Decomposition

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*Abstract*—**We have improved the accuracy (sensitivity x specificity) of a knowledge-based system from 90% to well above 95% in decomposing complex EMG 3-channel data into its constituent Motor Unit Action Potential (MUAP) trains. The key to achieving this improvement is our use of a probabilistic framework for resolving pulse superpositions through the application of *utility maximization* at the suprasegmental level.**

*Keywords*—**Decomposition, EMG, IPUS, multi-channel, utility maximization**

## I. Introduction

The challenge of EMG signal decomposition is to determine the firing times of individual motor units whose pulse shapes evolve over time (primarily due to electrode movements during signal acquisition). A further complicating factor is that different motor units may have pulses with similar shapes, making it difficult to distinguish between the motor units. Also, when two or more motor units fire at about the same time, the measured pulse in each channel is a superposition of the individual motor-unit pulses, making the detection task more difficult. To address such problems, we have undertaken a knowledge-based approach from the field of artificial intelligence. Specifically, we are using the IPUS framework for Integrated Processing and Understanding of Signals. As stated in [1], the IPUS paradigm is intended for "complex environments, which are characterized by variable signal-to-noise ratios unpredictable source behaviors, and the simultaneous occurrence of objects whose signal signatures can distort each other." We use the IPUS framework to repair the results from an initial round of segmental analysis that includes pulse detection and classification as well as the initiation and updating of prototype pulses corresponding to the different motor units.

In our latest improvements to the knowledge-based system, we have used the results of segmental analysis to estimate the probability of occurrence of each MUAP train in every segment. These probabilities, in conjunction with validity constraints on MUAPT inter-pulse intervals, are then used in a *utility maximization* process to revise the initial hypotheses. Inclusion of such *suprasegmental analysis* in a second generation EMG decomposition system has increased the system's accuracy from around 90% to well over 95% on complex EMG data.

This work was supported by a NIH Bioengineering Research Partnership Grant #1R24HD38585 from the National Center for Medical Rehabilitation Research of the NICHD.

## II. Background

The basic framework for dividing an EMG signal into a sequence of segments and using cross-correlation concepts to initiate and sustain the recognition of MUAPT contributions in those segments was originally proposed by LeFever and De Luca in 1982 [2] and elaborated by Broman [3] and Nawab et. al.[4]. This framework includes:

(1) Criteria for initiating a "template" for the pulse shape of a MUAPT encountered for the first time.
(2) Strategy for updating templates to account for pulse evolution within each MUAPT.
(3) Criteria for comparing segment data against MUAPT templates.
(4) Criteria for initiating the process of resolving pulse superpositions in segment data.
(5) Strategy for resolving pulse superpositions within a segment.

Extensions and alternatives to this framework have been proposed and investigated by various researchers over the past two decades. For example, in addressing pulse superpositions within a segment, LeFever and De Luca had utilized a *sequential* strategy that upon finding a match for a template in the segment data, subtracts that template's contribution in the segment before proceeding to find the next match in the same segment. While computationally efficient, their approach is definitely sub-optimal. In contrast, De Figueiredo and Gerber [5] later devised a computationally expensive continuous-time optimization method for the *simultaneous* recognition of MUAPT contributions by minimizing the squared error over the entire duration of a segment. McGill [6] refined this approach by using a mixture of continuous-time and discrete-time optimization to reduce the cost of the search for the minimum error. Other alternatives that have been explored for resolving pulse superpositions within individual segments include methods based upon wavelet spectrum matching [7] and Neural Networks [8].

## III. Suprasegmental Analysis

The need for suprasegmental analysis arises because of the shortcomings of segmental analysis for resolving pulse

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superpositions in practical situations. The difficulties encountered there are due to significant pulse evolution within each MUAPT and the non-stationary noise from distant motor units.

Let us assume that segmental analysis has already been carried out to identify each segment's candidate MUAPT pulses along with their respective locations and gain factors. Denoting the template for one of the candidate pulses by the vector $p$ and the corresponding segment data by the vector $d$, we initially estimate the probability that the MUAP actually occurred in the given segment as:

$$\hat{P} = \beta\left(\sqrt{1-|e|^2/|d|^2}\right)$$

where $\beta = \alpha$ if $0 \le \alpha \le 1$, $\beta = 1/\alpha$ if $\alpha > 1$, and $\beta = 0$ if $\alpha < 0$, and $\alpha$ is the scale factor that minimizes the value of $|e|^2$ when $e = (d - \alpha\ p)$. Conceptually, $\alpha$ represents the degree to which $d$ and $p$ are collinear, and $e$ represents the orthogonal component of the modeling error. We then proceed to obtain alternative probability estimates, each time replacing $d$ by a modified version to include the effect of subtracting one or more of the other templates hypothesized to be in the same segment. If there have been $m$ subtractions in $d$, we also adjust the corresponding probability estimate by multiplying it with $(0.5)^m$ in order to account for subtraction noise. The maximum of these different probability estimates for the $k$th MUAPT in the $n$th segment is assigned as the final estimate $\hat{P}_{n,k}$ and incorporated within a utility maximization process for selecting among the various MUAPT hypotheses in each segment.

To establish the framework for utility maximization, we define a Boolean random variable $x_{k,n}$ which is equal to 1 when the $k$th MUAPT has a pulse in the $n$th segment. We denote the set of all $N$ data segments of the EMG signal by $S$ and we define the $j$th valid subset $S^{(j)}$ of $S$ as one whose segments are such that if a MUAPT had a pulse in each segment, the resulting inter-pulse intervals would not be less than a specified minimum. The total number of pulses of the $k$th MUAPT in $S^{(j)}$ may be represented as:

$$y_k^{(j)} = \sum_{n \in \mathbf{S}^{(j)}} x_{k,n}\,.$$

The "utility" of $S^{(j)}$ as the subset that contains all pulses of the $k$th MUAPT is then obtained as:

$$E(y_k^{(j)}) = \sum_{n \in \mathbf{S}^{(j)}} E(x_{k,n}) = \sum_{n \in \mathbf{S}^{(j)}} P_{k,n}$$

where each probability $P_{k,n}$ may be estimated (as described earlier in this section) on the basis of a cross-correlation analysis between the template for the $k$th MUAPT and the data for the $n$th segment. Finally, we search the subsets $S^{(j)}$ for the one that has the maximum "utility." Formally, we find a value $j_0$ for $j$ in $S^{(j)}$ such that:

$$E(y_k^{(j_0)}) = \max_j\{E(y_k^{(j)})\}\,.$$

## IV. Implementation

Over the last two decades, the NeuroMuscular Research Center (NMRC) at Boston University has developed and refined a Precision Decomposition technique as the basis of a system that decomposes 3-channel EMG signals into their constituent MUAPTs. The application of this system to experimental EMG data has led to significant physiological findings [9]. However, progress has been slow because that system often takes several hours to analyze even one minute of EMG data. Furthermore, extensive manual editing of the results is necessary to achieve reasonable (above 95%) accuracy rates.

In order to overcome the speed and accuracy limitations of the original system, we have been developing [4] over the last couple of years a second-generation EMG decomposition system. We have utilized the IPUS architecture (for Integrated Processing and Understanding of Signals) for flexibly coordinating the actions of various phases of operation of the system: filtering, segmentation, pulse detection, segmental analysis, and suprasegmental analysis. The implementation of our system is within an object-oriented framework in C++, and we have made extensive use of the IPUS C++ Platform (ICP) [10].

## V. Results

With the incorporation of suprasegmental analysis, our new EMG decomposition system is on the average providing over 95% accuracy (taken as the product of *sensitivity* and *specificity*) in decomposing experimental EMG data. We present an example to illustrate the accuracy improvement obtained via suprasegmental analysis. In this example the input is a three-channel intramuscular EMG signal sampled at 20KHz and segmental analysis is carried out using a computationally efficient sequential strategy adapted from LeFever and De Luca [2]. Replacing the sequential strategy by an optimal segmental analysis such as that of McGill [6] offers only marginal accuracy improvements since those techniques do not address the errors that arise due to factors such as pulse evolution and the presence of non-stationary noise from distant motor units. Since our suprasegmental analysis framework has been empirically observed to overcome these factors, we anticipate it will do the same in conjunction with optimal segmental analysis.

In the example, the level of force applied by the subject initially ramps up to 50% maximum voluntary contraction (MVC) and remains there for approximately 20 seconds, and then ramps down. Figs. 1 and 2 respectively illustrate the pulse detection times for the eight most significant MUAPTs found before and after suprasegmental analysis. The accuracy improves from 67.1% to 98.0% with respect to a decomposition obtained via a proven human-operator interactive technique [11]. The inter-pulse intervals and mean firing rates after suprasegmental analysis are shown in Figs. 3 and 4 respectively.

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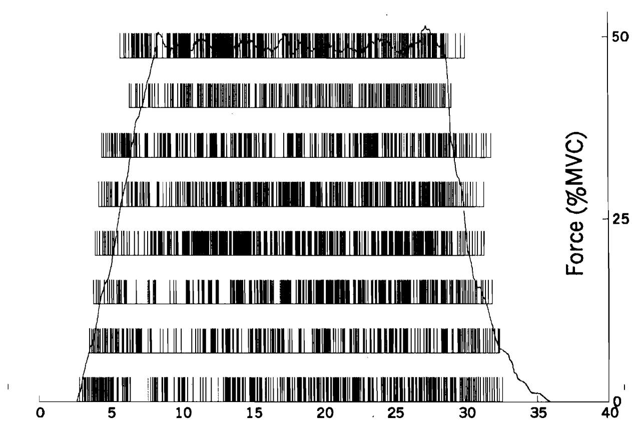


**Fig. 1.** MUAPT detection times BEFORE Suprasegmental Analysis. (Solid curve shows force profile.)
Accuracy: 67.1%; Sensitivity: 67.1%;Specificity: 100.0%.

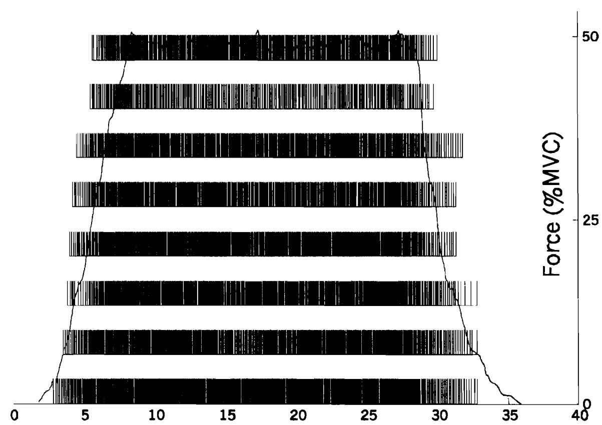


**Fig. 2.** MUAPT detection times AFTER Suprasegmental Analysis.
Accuracy: 98.0%; Sensitivity: 98.2%; Specificity: 99.8%.

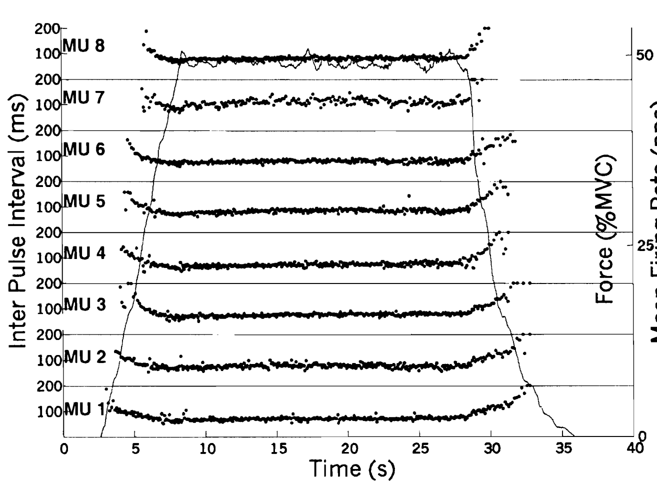


**Fig. 3.** MUAPT inter-pulse intervals AFTER Suprasegmental Analysis.

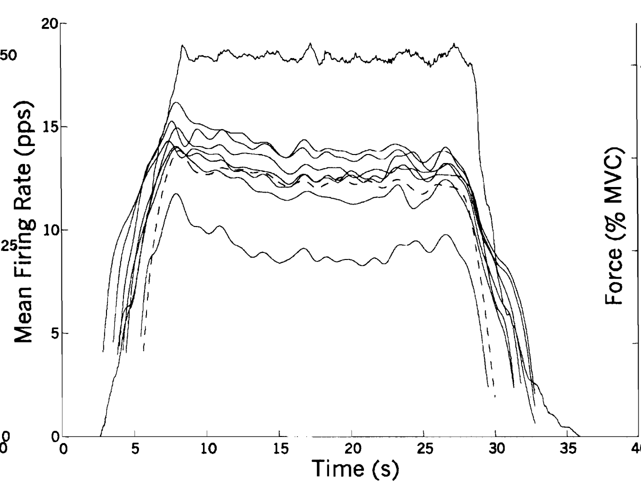


**Fig. 4.** MUAPT mean firing rates AFTER Suprasegmental Analysis