RESOLVING EMG PULSE SUPERPOSITIONS VIA UTILITY MAXIMIZATION

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ABSTRACT

A major task in the decomposition of multi-channel Electromyographic (EMG) signals into their uni-source pulse train (UPT) components is to resolve pulse superpositions. Even optimal *segmental analysis* that fits linear combinations of temporally aligned UPT pulses to short data segments gives rise to errors because of pulse evolution and the presence of non-stationary noise. To address such shortcomings, we use the results of segmental analysis to estimate the probability of occurrence of each UPT in every segment. These probabilities, in conjunction with validity constraints on UPT 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 under 75% to well over 95% on real EMG data.

1. INTRODUCTION

The processes by which the brain causes muscles to produce force are not yet fully understood by researchers. These processes are mediated by the motor control system, a complex network of interconnected neurons. There are a large number of research areas that depend on the study of the motor control system, ranging from the study of muscular disorders and diseases such as (potentially fatal) spasmodic dysphonia to the effects of microgravity on the human body.

Muscle fibers are stimulated by neurons whose cell bodies are located in the spinal cord. These muscle fibers together with the motor neuron are referred to as a motor unit. To study the firing patterns of motor units, a multi-channel electrode is inserted into the muscle, which records an intramuscular EMG signal. When the muscle fibers near the electrode detection surface contract, the electrode records a pulse, widely known as a motor unit action potential, on each channel.

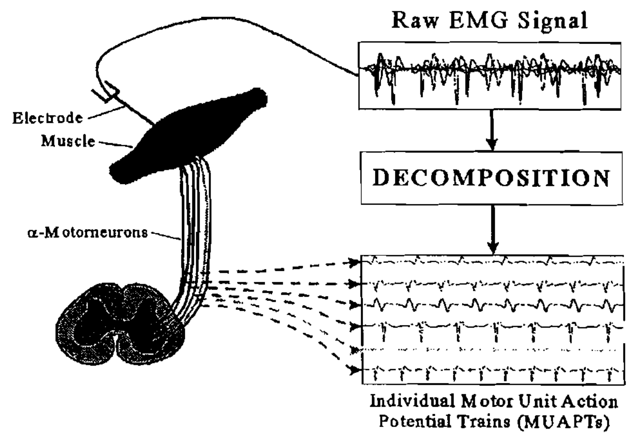

Fig. 1. EMG Measurement & Decomposition

Throughout a muscle contraction each motor unit fires repetitively, generating a uni-source pulse train (UPT), commonly referred to as a motor unit action potential train in the physiological literature. The recorded EMG signal is thus a summation of multi-channel UPT contributions from all of the motor units which have fibers near the electrode.

To study the firing patterns of the motor units during a muscle contraction, it is desirable to decompose the multi-channel EMG signal into its UPT components. However, since the detected pulse shapes can interfere with each other when they are superimposed in time, and since pulse shapes and amplitudes evolve over time, such decomposition is a very challenging task.

A central theme in solutions to the EMG decomposition task is to divide the multi-channel EMG signal into segments that are individually constrained not to contain pulse repetitions from any particular UPT. This permits segmental analysis to be conducted for modeling the data in each segment as a linear combination of temporally aligned UPT pulses. We have extended this approach to include a stage of suprasegmental analysis in

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order to counter the shortcomings (largely due to pulse evolution and non-stationary noise) in the results obtained from segmental analysis, regardless of whether segmental analysis is optimal or not.

2. 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 UPT contributions in those segments was originally proposed by LeFever and De Luca in 1982 [1] and elaborated by Broman [2]. This framework includes:

(1) Criteria for initiating a "template" for the pulse shape of a UPT encountered for the first time.
(2) Strategy for updating templates to account for pulse evolution within each UPT.
(3) Criteria for comparing segment data against UPT 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 [3] devised a computationally expensive continuous-time optimization method for the *simultaneous* recognition of UPT contributions by minimizing the squared error over the entire duration of a segment. McGill [4] 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 [5] and Neural Networks [6].

3. SUPRASEGMENTAL ANALYSIS

The need for suprasegmental analysis arises because of the shortcomings of segmental analysis for resolving pulse superpositions in practical situations. The difficulties encountered there are due to significant pulse evolution within each UPT 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 UPT 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 UPT pulse actually occurred in the given segment as:

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

where $\beta = a$ if $0 = a = 1$, $\beta = 1/a$ if $a > 1$, and $\beta = 0$ if $a < 0$, and a is the scale factor that minimizes the value of $|e|^2$ when $e = (d - \alpha\ p)$. Conceptually, α 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 kth UPT in the nth segment is assigned as the final estimate $\hat{P}_{n,k}$ and incorporated within a utility maximization process for selecting among the various UPT 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 kth UPT has a pulse in the nth segment. We denote the set of all N data segments of the EMG signal by S and we define the jth valid subset $S^{(j)}$ of S as one whose segments are such that if a UPT 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 kth UPT in $S^{(j)}$ may be represented as:

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

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

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

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 kth UPT and the data for the nth 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:

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

4. 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 UPT's. The application of this system to experimental EMG data has led to significant physiological findings [7]. 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 [8] 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) [9].

5. 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 two examples to illustrate the accuracy improvement obtained via suprasegmental analysis. In each 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 [1]. Replacing the sequential strategy by an optimal segmental analysis such as that of McGill [4] 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 first example, the level of force applied by the subject initially ramps up to 50% maximum voluntary contraction (MVC) and stays there for approximately 20 seconds, and then ramps down. Figures 2 and 3 illustrate the pulse detection times for the ten most significant UPT's found in the EMG data. The accuracy improves from 73.3% to 95.6% with respect to a decomposition obtained via a proven human-operator interactive technique [10].

In the second example, the level of force applied by the subject initially ramps up to 50% MVC for one second and then ramps down to 20% MVC and stays there for 50 seconds. Figures 4 and 5 illustrate the pulse detection times for the 9 most significant UPT's found in the EMG data. The accuracy improves from 63.4% to 97.3%. The accuracy in the most difficult peak-force region improves from 39.2% to 92.7%.

6. REFERENCES

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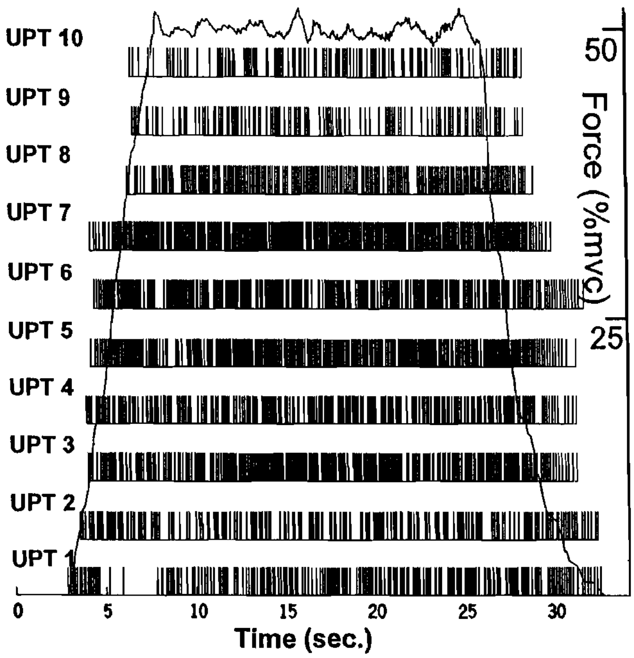

Fig. 2. First Example – UPT detection times BEFORE Suprasegmental Analysis.
(Solid curve shows force profile.)
Accuracy: 73.3%; Sensitivity: 73.3%; Specificity: 99.9%.

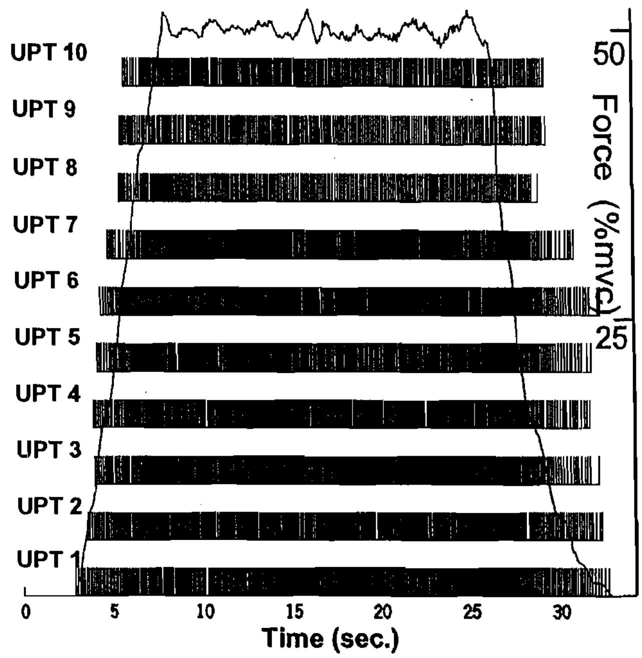

Fig. 3. First Example – UPT detection times AFTER Suprasegmental Analysis.
Accuracy: 95.6%; Sensitivity: 96.0%; Specificity: 99.6%.

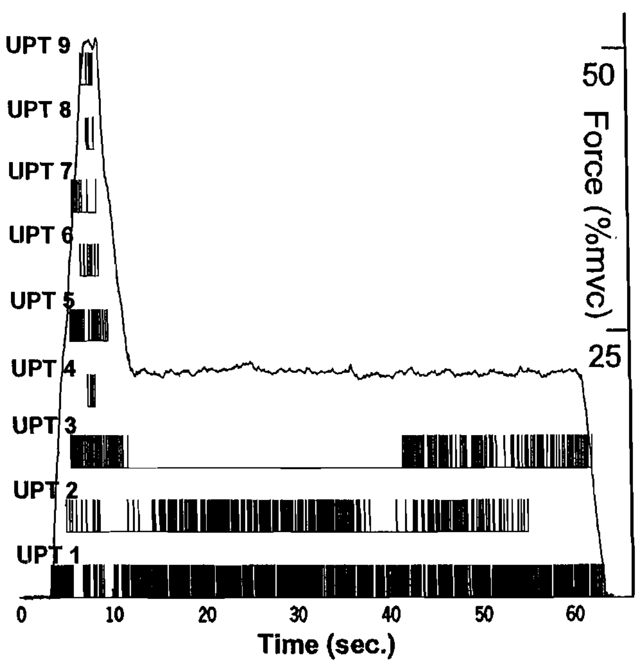

Fig 4. Second Example – UPT detection times BEFORE Suprasegmental Analysis.
Accuracy: 63.4%; Sensitivity: 63.5%; Specificity: 99.8%.
Within the force peak we get:
Accuracy: 39.2%; Sensitivity: 39.3%; Specificity: 99.6%.

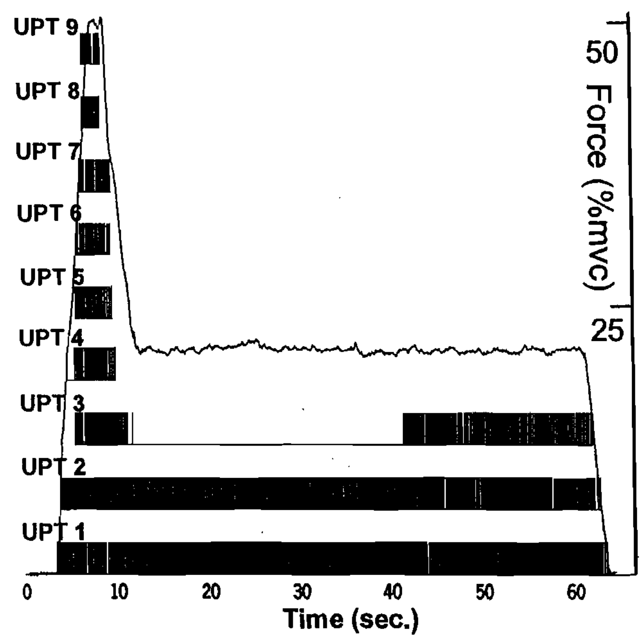

Fig. 5. Second Example – UPT detection times AFTER Suprasegmental Analysis.
Accuracy: 97.3%; Sensitivity: 97.6%; Specificity: 99.7%.
Within the force peak we get:
Accuracy: 92.7%; Sensitivity: 93.3%; Specificity: 99.4%.