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NEXT-GENERATION DECOMPOSITION OF MULTI-CHANNEL EMG SIGNALS

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Abstract- **We have developed a knowledge-based system for the improved decomposition of multi-channel EMG signals. This system incorporates streamlined and/or modified versions of the basic algorithms in the precision decomposition technique. In addition, it employs the IPUS framework from artificial intelligence to implement signal re-processing strategies for the detection and subsequent correction of decomposition errors arising from its initial signal processing stage. Experiments on real EMG data indicate that our new system has significant speed as well as accuracy advantages over previous generations of precision decomposition programs.**
Keywords - **EMG, decomposition, IPUS, multi-channel**

I. INTRODUCTION

Over the last two decades, the NeuroMuscular Research Center (NMRC) at Boston University has developed and refined a precision decomposition technique [1] as the basis of a system (DECOMP) that decomposes 3-channel EMG signals into their constituent trains of motor-unit action potentials. The application of DECOMP to experimental EMG data has led to significant physiological findings. However, progress has been slow because DECOMP often takes several hours to analyze even one minute of EMG data. Furthermore, extensive manual editing of the results is necessary to achieve reasonable accuracy rates. In order to overcome such limitations, we have developed and implemented a knowledge-based framework for EMG decomposition.

II. FRAMEWORK

A multi-channel EMG signal from an electrode inserted into a muscle may be modeled as a sum of N quasi-periodic pulse trains in each of the channels. Typically, $N \in [1,20]$. 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 [2], the IPUS paradigm is intended for "complex environments, which are characterized by variable signal-to-noise ratios unpredictable source behaviours, 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 signal processing that includes pulse detection and classification as well as the initiation and updating of prototype pulses corresponding to the different motor-units.

A. *The pulse detector*

The pulse detection process is complicated when there is a degree of overlap between pulses from different trains. The basic strategy from [1] is to first detect and classify the pulse with the highest amplitude peak and then to subtract the corresponding prototype pulse from the data before trying to detect any overlapping pulses. Since the subtraction process can introduce error energy, there is the potential for the system to erroneously detect this energy as another pulse. To avoid such errors, we have introduced the following innovation with respect to [1]: After subtraction of a prototype pulse, data values whose magnitudes are below the corresponding prototype pulse magnitude are ignored when attempting to detect another pulse. In other words, we model the subtraction process as introducing errors proportional to the values being subtracted.

B. *The MAP receiver*

The task of the MAP receiver is to associate a particular pulse train with a detected multi-channel pulse. Denoting the i'th pulse train by the symbol u_i, the MAP receiver selects a particular symbol, say u_k, such that:

$$P(u_k \mid \underline{\rho}) > P(u_i \mid \underline{\rho}), \quad 1 \le i \le M, \; i \ne k, \tag{1}$$

where $\underline{\rho}$ is the vector consisting of the concatenated data channels of the detected pulse. In the presence of white Gaussian noise with variance σ^2, the MAP decision criterion in (1) may be restated as:

$$|\underline{\rho} - \underline{s}_k|^2 - 2\sigma^2 \ln P(u_k) < |\underline{\rho} - \underline{s}_i|^2 - 2\sigma^2 \ln P(u_i), \quad 1 \le i \le M, \; i \ne k, \tag{2}$$

where $\underline{s}_i$ is the vector consisting of the concatenated data channels of the prototype pulse for the i'th train, and $P(u_i)$ is the a priori probability that the detected pulse belongs to the pulse train u_i. In the EMG application, the lengths of vector waveforms for each prototype pulse differ, and may vary over time for the same train. As a result, the MAP decision criterion in (2) may be modified [1] by normalizing the error signals as follows:

$$\frac{|\underline{\rho} - \underline{s}_k|^2}{|\underline{s}_k|^2} - 2\sigma^2 \ln P(u_k) < \frac{|\underline{\rho} - \underline{s}_i|^2}{|\underline{s}_i|^2} - 2\sigma^2 \ln P(u_i), \tag{3}$$

$$1 \le i \le M, i \ne k.$$

An innovation with respect to [1] is the manner in which $\underline{\rho}$ is aligned with $\underline{s}_i$ before computing their difference. Rather

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than simply basing the alignment on the locations of the highest peaks in each of the vectors, our alignment process also considers the second highest peak in $\underline{\rho}$ as well as the polarities (negative or positive) of the peaks whose locations are being aligned. To estimate the a priori probabilities $P(u_i)$ in (3), we assume that the first order inter-arrival times are Gaussian distributed and thus the corresponding hazard function is:

$$R_i(t) = f_{Ti}(t) \,/\, (1-F_{Ti}(t)), \tag{4}$$

where $f_{Ti}(t)$ is the density function for the inter-arrival time and $F_{Ti}(t)$ is the corresponding cumulative distribution function. There is always the possibility that some of the pulses may not be detected (e.g. due to overlap with pulses from other trains). Such missed detections may be accounted for in the hazard function calculation by modeling the missed detections as a Bernoulli process with probability of miss p. This results in the following expression for $f_{Ti}(t)$ in (4):

$$f_{T_i}(t) = \sum_{n=1}^{\infty} \frac{1}{\sqrt{2\pi n \sigma_i^2}} e^{-\left[\frac{(t-n\mu_i)^2}{2n\sigma_i^2}\right]} (1-p)p^{n-1}, \tag{5}$$

where μ_i is the mean and σ_i^2 is the variance of the inter-arrival time for the i'th train. Following [1], we estimate the a priori probability of occurrence of a pulse from the i'th train from among M trains at time t as:

$$P(u_i) = R_i(t) \Big/ \sum_{j=1}^{M} R_j(t). \tag{6}$$

where M is the total number of pulse trains at time t.

C. *Prototype pulses: initiation and updating*

When pulse train u_k is selected by the MAP receiver, we find the scalar A which minimizes the error $|\underline{\rho}-A\underline{s}_k|^2$. We then determine the degree of shape mismatch as $XN=|\underline{\rho}-A\underline{s}_k|$. If $|A-1|$ and/or XN are unacceptably large, we initiate a track representing a new pulse train. When neither $|A-1|$ nor XN are unacceptably large, the detected pulse is assigned to pulse train u_k selected by the MAP receiver. In this instance, the prototype pulse $\underline{s}_k$ is updated by a weighted average of $\underline{s}_k$ and the corresponding portion of $\underline{\rho}$.

D. *Resolution of pulse overlap*

We have found the pulse overlap resolution strategies in [1] to have unacceptably large error rates for the type of signal data reported in section 4. Furthermore, these strategies are computationally expensive because they search through all possible combinations of prototype pulses to account for the signal data. We have focused instead on ruling out the possibility of pulse-overlap by using heuristics involving pulse duration and pulse energy. By minimizing the number of times pulse-overlap resolution is performed, our system gains in accuracy and speed of execution.

E. *IPUS-Based Repair*

The results from the initial round of signal processing give rise to decomposition errors because of missed detections and uncertain classifications. We utilize the IPUS framework to control a process that seeks to repair such errors by examining the initial decomposition results for inconsistencies with constraints that typically govern the characteristics of EMG trains. The constraints used for this purpose are stored in the IPUS knowledge base. Detection of the inconsistencies leads to a hypothesize-and-test strategy for repairing the underlying errors.

III. RESULTS

We display our system's output in Fig. 1 where the input is a three-channel intramuscular EMG signal, approximately 65 seconds long and sampled at 50KHz. We use dots to represent inter-pulse intervals in milliseconds for each detected track. Also shown is the level of force applied by the subject, which initially ramps up to 50% maximum voluntary contraction (MVC) for approximately one second, then decreases to 20% MVC for approximately 50 seconds. At a 0.6% incorrect classification rate, our system detects and correctly classifies approximately 90% of the total number of pulses while DECOMP detects and correctly classifies only 70% of the pulses. The execution time is under a minute for the new system as opposed to several hours for DECOMP.

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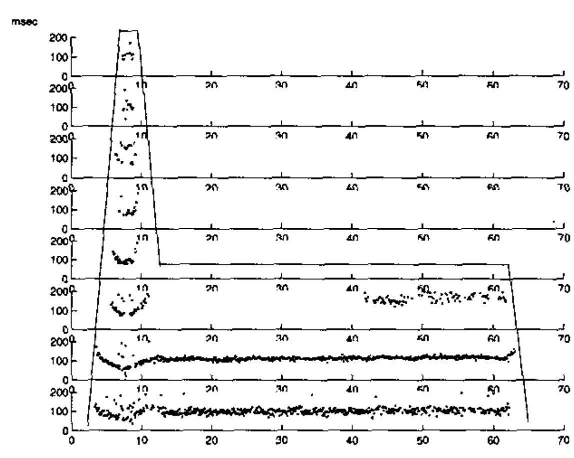

Fig. 1. Results from our system