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Surface EMG Signal Decomposition Using Empirically Sustainable BioSignal Separation Principles

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Abstract—**We introduce the concept of empirically sustainable principles for biosignal separation as a means of addressing the complexities that are practically encountered in the decomposition of surface electromyographic (sEMG) signals. Recently, we have identified two new principles of this type. The first principle places upper bounds on the inter-firing intervals and residual signal energies of the separated components. The second principle seeks a local minimum in the coefficient of variation of inter-firing intervals of each separated component. Upon incorporation of these principles into our latest Precision Decomposition system for sEMG signals, 20 to 30 motor unit action potential trains (MUAPTs) were decomposed per experimental sEMG signal from isometric contractions with trapezoidal force profiles. Our new system performs well even as the force generated by a muscle approaches maximum voluntary levels.**

I. Introduction

DECOMPOSITION of the surface electromyographic (sEMG) signal into its constituent motor unit action potential trains (MUAPTs) is a challenging signal separation problem that has received considerable attention [1,2,3] over the last decade. Broadly speaking, two basic approaches can be taken to address such problems. In the "applied mathematics" approach, a formulation is found for the signal decomposition problem that enables the application of a pre-existing optimized mathematical solution (e.g. blind signal separation [4]) to the problem as a whole. In the "empirically sustainable" approach, the signal decomposition problem is divided into (possibly inter-dependent) sub problems, each of which can be solved using a separate mathematical framework. However, instead of there being a mathematical optimality requirement for the solution as a whole, there is the requirement that the solution undergo extensive empirical testing to determine the fidelity with which it carries out the sEMG signal decomposition task.

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The empirically sustainable approach is exemplified by our Precision Decomposition approach for indwelling EMG signals and, more recently, surface EMG signals. The original version of the system [5] was designed by dividing the overall problem into sub problems involving template formation, template matching, and template updating. Empirical testing of the decomposition results was conducted by trained human operators and by comparing decompositions of the same MUAPT on different sensors [6]. Further subdividing the decomposition problem and formulating new solutions for them addressed the identified shortcomings of the system. As the number of sub problems kept increasing, it became clear that significant consideration would be warranted on how the (usually parameterized) solutions for the sub problems interact with each other and how that affects the overall solution. To address this new level of complexity, we imbued subsequent implementations of the Precision Decomposition system with the IPUS architecture [7,8] for Integrated Processing and Understanding of Signals. This architecture enables the system designer to conveniently specify and test principles that can be utilized by the overall system to adaptively decide upon what values to assign to the various parameters of its sub systems. The formulation of such principles requires extensive trial-and-error procedures to ensure that the overall signal separation task is empirically sustainable.

In this paper, we present examples of two biosignal separation principles that we have recently incorporated into our Precision Decomposition system for surface EMG signals. Experimental results from the resulting decomposition system for real sEMG signals are used to illustrate the effectiveness of these principles.

II. Methods

The current version of our Precision Decomposition system can be conceptualized as consisting of two stages (Stage I and Stage II). Stage I consists of the algorithms described in [3] and its primary purpose in the current version of the system is to identify the evolving action potential templates of as many MUAPT constituents of the input signal as possible. Stage II utilizes those action potential templates to estimate the firing times of as many of the identified MUAPTs as possible.

As indicated in Figure 1, Stage II begins by applying a shape-matching procedure to the sEMG signal and produces shape-evidence signals for the various PD-IPUS identified MUAPT constituents. Conceptually, a shape-evidence signal

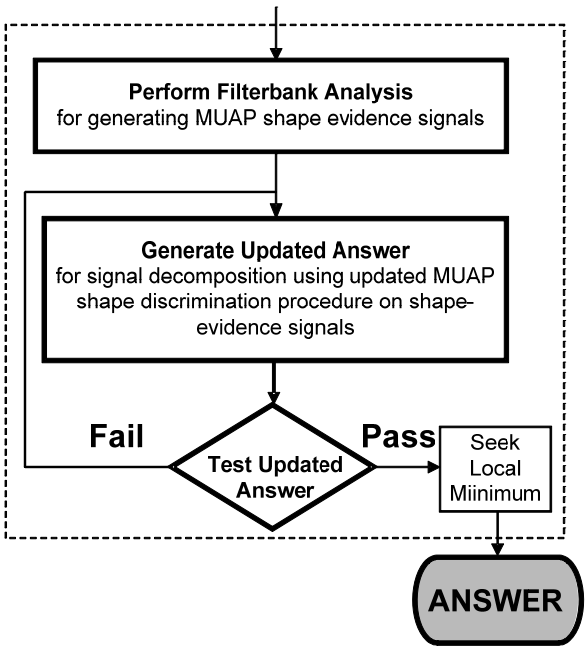

Fig. 1: Stage II diagram.

$s_m(n)$ at any time *n* represents a measure of shape similarity between the *m*th motor unit's template vector $\vec{h}_{mn}$ and a data vector $\vec{d}_{mn}$ representing the shape of the input sEMG signal in the vicinity of time *n*. More specifically, the definition of $s_m(n)$ is based upon the normalized cross-correlation (C) of $\vec{d}_{mn}$ and $\vec{h}_{mn}$:

$$\mathrm{C}(\vec{d}_n, \vec{h}_{mn}) = \frac{\langle \vec{d}_{mn}, \vec{h}_{mn} \rangle}{|\vec{d}_{mn}| \cdot |\vec{h}_{mn}|} \quad . \tag{1}$$

Taking a parameter α_m as the ratio of the largest magnitude in $\vec{h}_{mn}$ to that of the largest magnitude among all MUAPT templates, the intermediate signal $g_m(n)$ is obtained from C as:

$$g_m(n) = \begin{cases} \mathrm{C}(\vec{d}_{mn}, \vec{h}_{mn}) \cdot \dfrac{\langle \vec{d}_{mn}, \vec{h}_{mn} \rangle}{|\vec{h}_{mn}|^2} & \text{if } \dfrac{\langle \vec{d}_{mn}, \vec{h}_{mn} \rangle}{|\vec{h}_{mn}|^2} \le 1 - \alpha_m \\ \mathrm{C}(\vec{d}_{mn}, \vec{h}_{mn}) \cdot \dfrac{|\vec{h}_{mn}|^2}{\langle \vec{d}_{mn}, \vec{h}_{mn} \rangle} & \text{if } \dfrac{\langle \vec{d}_{mn}, \vec{h}_{mn} \rangle}{|\vec{h}_{mn}|^2} > 1 + \alpha_m \\ 1.0 & \text{otherwise} \end{cases} \tag{2}$$

The weighting factor on C in equation (2) serves to penalize the shape-correlation score where the amplitude of the signal data is significantly higher or lower than that of the template. The values of $g_m(n)$ can be seen to range between -1.0 and 1.0 with larger values representing greater degrees of shape match between the signal data and the template. The next step is to modify each $g_m(n)$ to form $g'_m(n)$ by retaining the values of $g_m(n)$ at local maxima and setting the rest of the values of $g'_m(n)$ to zero. Finally, the shape-evidence signals $s_m(n)$ are obtained by setting them equal to the corresponding $g'_m(n)$ values and performing an aliasing-rejection analysis [9] that sets some additional values of each $s_m(n)$ to zero.

The aliasing-rejection process basically limits the number of MUAPT constituents that can share any single data peak in the sEMG signal; it allows only the largest subset of the MUAPT constituents that can adequately account for the height of the data peak. Whenever aliasing rejection excludes a MUAPT at any particular time, n_0 , the corresponding value of $s_m(n_0)$ is set to zero.

The shape-evidence signals then undergo iterative MUAPT discrimination analysis to resolve the high degrees of MUAP superimposition that were not adequately handled by the Stage I. Each of the iterations of the MUAPT discrimination analysis is controlled by the values assigned to a set of 3*M* decision variables, where *M* is the number of MUAPT constituents identified by the Stage I.

Stage II then proceeds to conduct a principled iterative search for the values of the 3*M* decision variables of the MUAPT discrimination procedure. The underlying ***biosignal separation principle*** requires each MUAPT to simultaneously satisfy the following two criteria:

(1) *The mean energy of the residual signal (the difference between the original signal and all the identified MUAPT constituents) at the firing locations of a MUAPT must be a relatively small fraction of the mean energy in all the MUAPT constituents at those locations.*

(2) *The mean inter-firing interval of a MUAPT must not be greater than* τ *s. We use* $\tau = 0.35$ *s in our current implementation of the algorithm.*

The above principle was arrived at using extensive experimentation on a database of real sEMG signals and user

inspection of the results. At all times, care was taken to make sure that the principle is general enough to apply to all sEMG signals of interest.

Any MUAPT for which Stage II is not able to satisfy the previously described principle by the end of the iterations is rejected. The MUAPT constituents that remain then undergo another principled search. The underlying ***biosignal separation principle*** that we have empirically derived for this search is given below:

The coefficient of variation of the inter-firing intervals of each MUAPT should be a local minimum as a function of the three decision variables per MUAPT of the MUAPT discrimination procedure.

The rationale behind this search principle of Stage II is that random placements of false positives and/or false negatives amongst the firings of a MUAPT always tend to increase MUAPT inter-firing irregularity. The true firings would therefore be expected to cause a local minimum in inter-firing irregularity.

III. Results

Upon incorporation of the biosignal separation principles described in this paper, the current version of our Precision decomposition system is typically able to decompose 20 to 30 MUAPTs per sEMG signal. In some cases, it can decompose more than 30 MUAPTs. This is a much higher yield of MUAPTs decomposed per signal when compared to previously published techniques [3,4]. The surface EMG sensor produced 4 channels of data, which were band pass filtered between 50 Hz and 2500 Hz before being decomposed by the latest version of our Precision Decomposition system for surface EMG signals.

The inter-firing intervals of the 28 MUAPTs obtained by decomposing an sEMG signal from an 80% MVC of the Tibialis Anterior (TA) muscle are shown in Figure 2 for the most current version of our Precision Decomposition system for surface EMG signals.

In Figure 2, the "dot" plot of each MUAPT's inter-firing intervals consists of a series of dots. The horizontal and vertical coordinates of each dot respectively represent a specific firing time and the time elapsed since the immediately preceding firing of the same motor unit. In the plot, the maximum height of any dot is restricted to 200 ms. We have also superimposed on the bar plot a solid line that represents the force profile generated during the muscle contraction. The vertical axis on the left represents the recruitment order of MUAPT constituents while the vertical axis on the right represents force level as a percentage of MVC.

It is seen in Figure 2 that earlier recruited motor units typically have smaller mean inter-firing intervals than later recruited motor units. Later recruited motor units are also seen to have greater variance in inter-firing intervals than earlier recruited motor units.

The dot plot of each MUAPT in Figure 2 can also be seen to exhibit "canoe like" characteristic. For further evaluation of the empirical sustainability of our sEMG signal decomposition, we have been applying our system on a large database of real and synthetic EMG signals. We are also in the process of carrying out two-source tests to quantify the signal decomposition accuracy of the system.

IV. Conclusions

We have presented the concept of empirically sustainable biosignal separation and how it has proved useful in the design of the latest version of our surface EMG signal decomposition system. Initial experiments indicate that with the incorporation of two new biosignal separation principles our decomposition system is able to decompose 20 to 30 MUAPTs per signal and in some cases even more.

The accuracy of our sEMG signal decomposition technique is being actively investigated but appears to be comparable to the accuracies attained by the best indwelling sEMG signal decomposition techniques.

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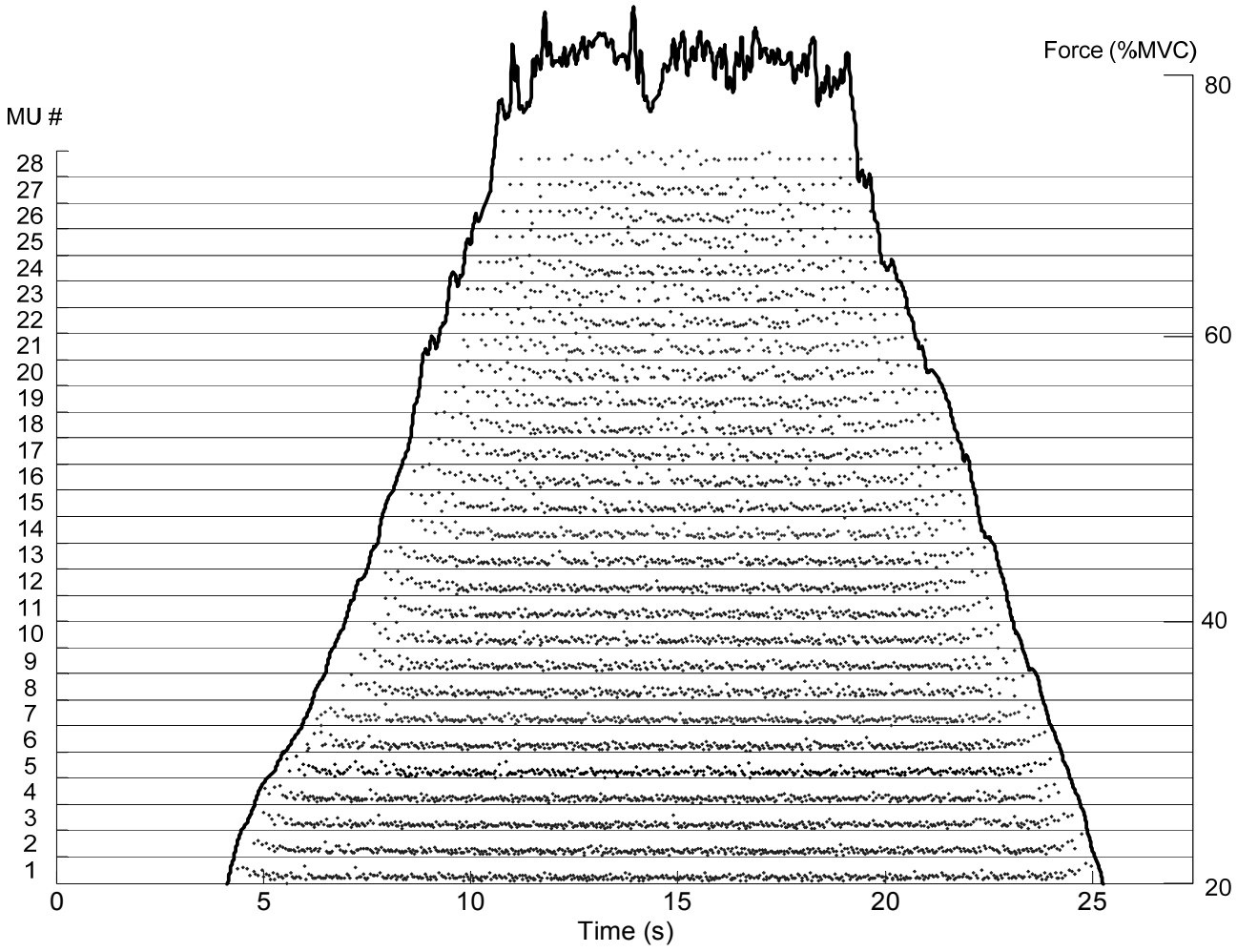

Fig. 2: Dot plot of 28 MUAPTs decomposed from 4-channel sEMG signal of 80% MVC of TA muscle.