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Aliasing Rejection in Precision Decomposition of EMG Signals

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Abstract—**The use of Artificial Intelligence (AI) methods in Precision Decomposition (PD) of indwelling and surface electromyographic (EMG) signals has led to the recent development of systems that can automatically resolve most instances of complex superposition among action potentials. The remaining errors have to be corrected by a user-interactive editing process. Typically, 25% to 50% of such errors involve action-potential aliasing, whereby the action potential of a motor unit is incorrectly identified in signal data that actually supports the action potential of another motor unit. To drastically reduce this class of errors, we have added a new aliasing-rejection mechanism in PD algorithms. Experimental results on real EMG signals show that aliasing-related errors of the Precision Decomposition technique are thereby reduced by 80% to 90%.**

I. Introduction

PRECISION Decomposition (PD) of EMG signals into their constituent motor units has been significantly improved through Artificial Intelligence (AI) innovations over the last decade [1,2,3]. Prior to any user-interactive editing, the latest generation of PD systems with artificial intelligence architectures and algorithms have been reported to decompose indwelling EMG signals with 75% to 96% accuracy [3] and surface EMG signals with 75% to 91% accuracy [4]. Many of the decomposition errors of these PD systems can be detected and corrected via user-interactive editing to achieve clinically acceptable accuracy levels of 95% or greater. A major goal of our current research is to alleviate as much as possible the burden placed on user-interactive editing for achieving the desired accuracy levels.

A significant source of PD errors for indwelling as well as surface EMG signals is an aliasing phenomenon that essentially causes PD systems to “hallucinate” the presence of a motor unit action potential where it is actually not present. As an illustration, consider the two action potentials, AP1 and AP2, of Figure 1. The shape of AP2 is similar to a temporal portion (indicated by the shaded region in Figure 1) of AP1. When only AP1 is present, it can sometimes appear to a PD system that AP2 is also present; the problem is further exacerbated when other motor unit action potentials are also in superposition with AP1. Furthermore, there is always the chance that AP2 may actually be in superposition with the grayed portion of AP1. In this paper, we address how in such instances a PD system can be made to more effectively distinguish between actual superposition and the occurrence of aliasing.

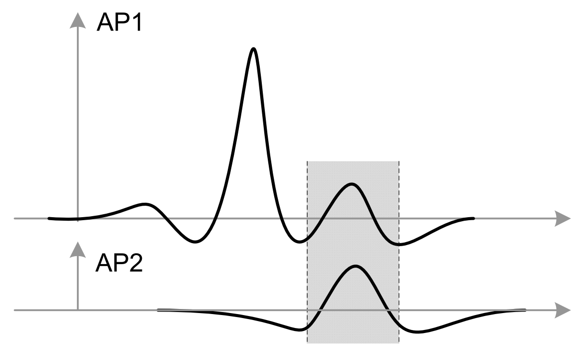

Fig. 1: Two action potentials with possible aliasing in shaded region.

II. Background

The Precision Decomposition solutions in [3] and [4] consist of a cascade combination of three basic classifiers (depicted in Fig. 2) embedded within an artificial intelligence architecture known as IPUS [5,6]; we therefore refer to this class of PD solutions as PD-IPUS. The Maximum A-posteriori Probability (MAP) classifier in PD-IPUS is adapted from the original Precision Decomposition solution proposed by LeFever and De Luca [7]. Each of the three basic classifiers in PD-IPUS consists of *signal processing* algorithms that operate directly on raw or filtered EMG signals and *symbol processing* algorithms that are applied to symbol structures containing classification results from previous rounds of signal processing and/or symbol processing.

The classifiers used in PD-IPUS have many *tunable* parameters associated with them. The tuning is performed by the IPUS elements of the decomposition system itself and it is entirely signal dependent rather than requiring any input from the user regarding the signal source (e.g. identification of the source muscle). The IPUS architecture permits the system designer to conveniently define specialized rules (the entire

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collection of these rules constitute a "knowledge base") that are used at run-time to decide how to tune the algorithm parameters in response to various statistics computed from the signal. For example, one of the rules associated with the MAP classifier in PD-IPUS continuously updates a statistic for how many MUAPT candidates per detection are being generated for application of the MAP criterion; if the statistic takes on a value less than an established threshold, the rule causes an increase in the value of one of the classifier parameters so as to relax the criterion for candidate generation. Two new IPUS rules are proposed in Section III (Methods) to introduce an aliasing-rejection mechanism into PD-IPUS.

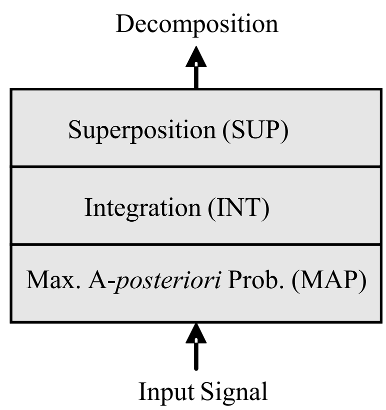

Fig. 2: The PD-IPUS Classifiers

The new aliasing rejection rules are designed into the signal and symbol processing associated with the Superposition (SUP) classifier of PD-IPUS. The SUP begins by applying an "iterative correlation procedure" [2] to the kth candidate data $\bar{\rho}_k$ in order to obtain an Absolute Shape Rating (ASR) for each possible action potential classification. Specifically, if h_{mn} denotes the hypothesis that the mth motor unit has an action potential whose main lobe is centered at time n, then the corresponding ASR is computed as:

$$\mathrm{ASR}(h_{mn}) = \begin{cases} \mathrm{NCC}(\vec{d}_{mn}, \vec{t}_{mn}) \cdot \dfrac{\langle \vec{d}_{mn}, \vec{t}_{mn} \rangle}{|\vec{t}_{mn}|^2} & \text{if } \dfrac{\langle \vec{d}_{mn}, \vec{t}_{mn} \rangle}{|\vec{t}_{mn}|^2} \le 1 \\ \mathrm{NCC}(\vec{d}_{mn}, \vec{t}_{mn}) \cdot \dfrac{|\vec{t}_{mn}|^2}{\langle \vec{d}_{mn}, \vec{t}_{mn} \rangle} & \text{if } \dfrac{\langle \vec{d}_{mn}, \vec{t}_{mn} \rangle}{|\vec{t}_{mn}|^2} > 1 \end{cases} \quad (1)$$

where $\vec{t}_{mn}$ is the waveform template corresponding to h_{mn} and $\vec{d}_{mn}$ is the portion of the signal data at location n that best "matches" the waveform template in accordance with a normalized cross-correlation (NCC) measure specified as:

$$\mathrm{NCC}(\vec{d}_{mn}, \vec{t}_{mn}) = \frac{\langle \vec{d}_{mn}, \vec{t}_{mn} \rangle}{|\vec{d}_{mn}| \cdot |\vec{t}_{mn}|} \quad (2).$$

The SUP, under the supervision of IPUS controlled symbol processing, then carries out statistical utility maximization to determine which of the hypothesized detections have sufficient data evidence to support them.

III. Methods

Even before the incorporation of the IPUS aliasing-rejection rules described in this section, the decomposition results from the SUP classifier of PD-IPUS were superior to those of previously reported methods. The new rules were specifically motivated by the desire to significantly reduce the burden on user-interactive editing for reaching clinically acceptable accuracy levels. One of the rules pertains to the rejection of possible aliasing of the main lobes of two different action potentials. The other rule pertains to the rejection of possible aliasing of the main lobe of one action potential and the side lobe of another.

<u>*Main Lobe to Main Lobe Aliasing Rule*</u>: This rule is applicable to the type of situation illustrated in Figure 3. The top plot in the figure represents the observed EMG data whose main lobe has peak height D. The second and third plots respectively represent the action potentials (AP1 and AP2) of two different motor units. The peak heights of AP1 and AP2 are A_1 and A_2 respectively. Without loss of generality, assume $A_2 < A_1$. The IPUS rule for aliasing rejection in such situations is given below [The fractional parameters p_1 and p_2 are IPUS controlled]:

If $(1-p_2)D \le p_1(A_1+A_2) \le (1+p_2)D$, **then** neither AP1 nor AP2 is rejected as a case of aliasing; **else**

- **If** $(1-p_2)D \le p_1 A_1 \le (1+p_2)D$, **then** AP2 is rejected as a case of aliasing; **else**
  - **If** $(1-p_2)D \le p_1 A_2 \le (1+p_2)D$, **then** AP1 is rejected as a case of aliasing; **else**
    - the action potential with lower ASR is rejected as a case of aliasing.

The IPUS parameters, p_1 and p_2 typically converge to the values around 0.5 and 0.1, respectively.

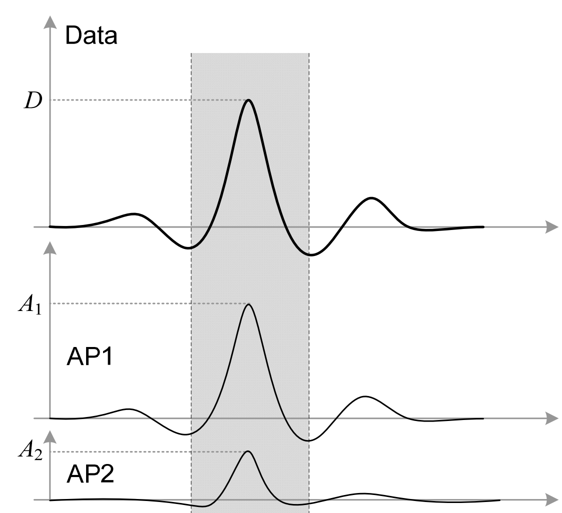

Fig. 3: EMG data with possible "main lobe to main lobe" aliasing of two action potentials, AP1 and AP2.

Main Lobe to Side Lobe Aliasing Rule: This rule is applicable to the type of situation illustrated in Figure 4. The top plot in the figure represents the observed EMG data whose main lobe has peak height D. The second and third plots respectively represent the action potentials (AP1 and AP2) of two different motor units. The side lobe height for AP1 is A_1 and the main lobe height for AP2 is A_2. The IPUS rule we have formulated for this type of situation is given below [The *fractional* parameters p_3 and p_4 are IPUS controlled]:

If $(1\text{-}p_4)D \leq p_3(A_1+A_2) \leq (1+p_4)D$, **then** AP2 is not rejected as a case of aliasing; **else**
AP2 is rejected as a case of aliasing.

The IPUS controlled parameters, p_3 and p_4, typically converge to the values around 0.2 and 0.5, respectively.

IV. Results

New versions of PD-IPUS have been implemented that incorporate the IPUS aliasing-rejection rules described in the previous section. Initial experimental results confirm the expectation that 80% to 90% of aliasing errors of the SUP classifier are eliminated. For example, we considered a 4-channel challenging surface EMG signal (see [4] for acquisition details) from the *First Dorsal Interosseous* (FDI) muscle with a 50% MVC trapezoidal force profile of 30s duration. Without the aliasing-rejection mechanisms, our fully automatic PD-IPUS system for surface EMG signals decomposed 6 action potential trains with approximately 75% accuracy. The same system with the addition of aliasing-rejection mechanisms described in this paper decomposed the 6 action potential trains with nearly 83% accuracy. Furthermore, a detailed inspection (via user-interactive editing) of the decomposition results indicated that the number of decomposition errors attributable to aliasing rejection had been reduced by approximately 85%. About two-thirds of the eliminated errors were due to the Main Lobe to Side Lobe Aliasing Rule, and the rest were due to the Main Lobe to Main Lobe Aliasing Rule. Similar results have been obtained so far with other surface EMG signals as well. We are currently conducting a detailed experimental evaluation for other surface EMG signals as well as for indwelling EMG signals. The trend that appears from our initial results is that roughly 25% to 50% of the decomposition errors prior to incorporation of aliasing-rejection mechanisms can be attributed to aliasing phenomena. Furthermore, 80% to 90% of those errors can effectively be eliminated via the aliasing rejection rules described in this paper.

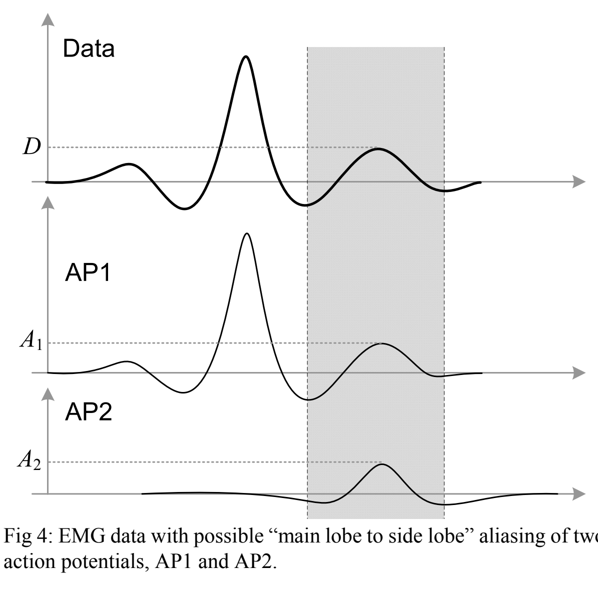

Fig 4: EMG data with possible "main lobe to side lobe" aliasing of two action potentials, AP1 and AP2.

We now present some examples of actual data illustrating the effectiveness of aliasing rejection on the surface EMG signal (50% MVC, FDI) that was decomposed into 6 motor units. In the figures for these examples, we show only the 3 dominant channels from among the four channels of the data; the energy in the fourth channel turned out to be much smaller than that of each of the other channels.

Example 1:
In this example, both motor unit 2 and 3 are classified as belonging to a single data-peak (See Figure 5), indicating that the Main Lobe to Main Lobe Aliasing Rule did not reject either motor unit as being an alias. The same rule rejected motor unit 6 for the data peak where only motor unit 5 is classified as being present (See Figure 5). Finally, the first positive side lobe to the right of the data peak for motor unit 5 had motor unit 4 rejected as a match for it because of the Main Lobe to Side Lobe Aliasing Rule. The correctness of the answers can be seen in Figure 5 from the flatness of the "residue" obtained by subtracting the hypothesized templates from the EMG data.

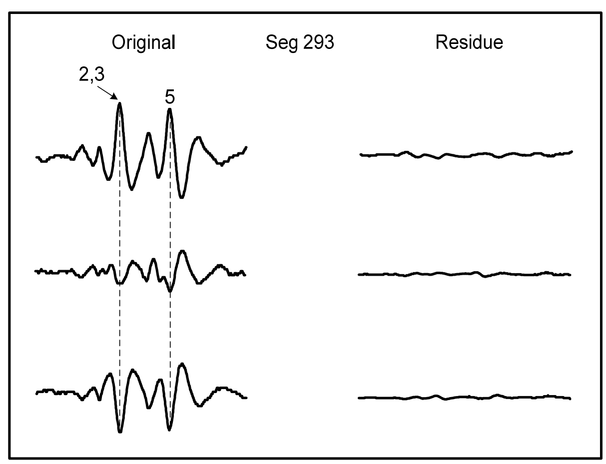

Fig. 5: EMG data and residue after subtraction of templates 2, 3, and 5.

Example 2:

In the example presented in Figure 6, all 6 motor units were found in the vicinity of the same data segment. The Main Lobe to Main Lobe Aliasing Rule rejected neither motor unit

4 nor motor unit 5. Similarly, the Main Lobe to Side Lobe Aliasing Rule rejected neither motor unit 3 nor motor unit 6. As in Example 1, the flatness of the residue after subtracting the six hypothesized motor units verifies the proper functioning of our aliasing-rejection mechanism.

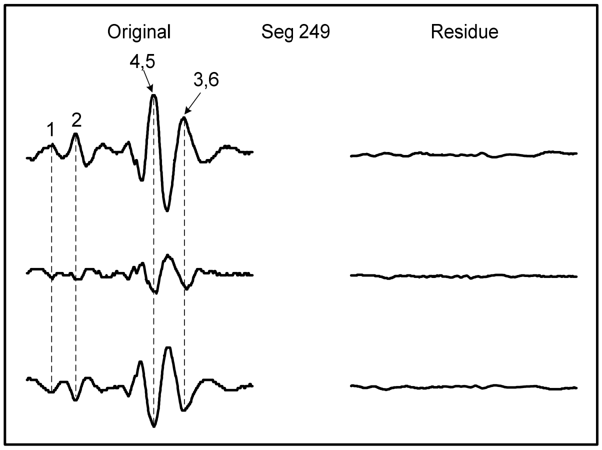

Fig. 6: EMG data and residue after subtraction of all 6 templates.

V. Conclusion

The impressive results we have obtained thus far with our IPUS-based aliasing-rejection mechanism are a small but important first step toward the achievement of *guaranteed* accuracy via fully automatic PD-IPUS. We are confident that the power of artificial intelligence mechanisms of IPUS will help achieve the ultimate goal, aided by the careful derivation of specialized rules such as the ones reported in this paper.

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