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Multi-Receiver Precision Decomposition of Intramuscular EMG Signals

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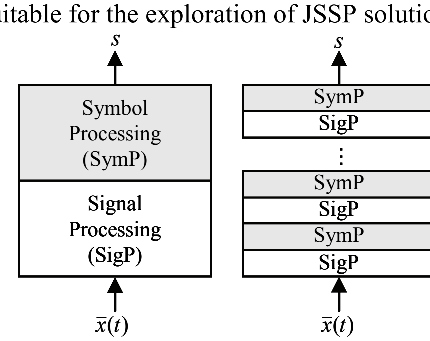
Abstract— **The Precision Decomposition technique can accurately identify a significant number of action potential trains within intramuscular electromyographic (EMG) signals. The original version of this technique (PD I) often requires extensive user-interactive editing to improve upon the results from a Maximum A-Posteriori Probability receiver (MAPR). We have used the Integrated Processing and Understanding of Signals methodology from artificial intelligence to formulate and implement a new multi-receiver solution that augments MAPR with two other receivers to gain greater accuracy. Specifically, each new receiver utilizes an interleaving of signal and symbol processing stages to address MAPR inadequacies in resolving cases of acute superposition and shape instability among motor unit trains. Prior to any user-interactive editing, our multi-receiver system achieves a classification accuracy of 85.1%, a significant improvement over the 66.0% accuracy of PD I on the same database of challenging EMG signals.**

I. Introduction

From an artificial intelligence perspective, EMG decomposition may be viewed as a challenging signal-to-symbol conversion (SSC) problem [1]. A symbol structure is used to represent information of interest about the *source* of the underlying signal. For example, in EMG decomposition, a symbol structure for any given signal has to represent detailed information (firing times and action potential shapes) about each active motor unit whose presence can be ascertained from the data. The classical solution to SSC problems is depicted in Fig. 1(a) as a signal processing stage followed by a symbol processing stage. If there are a finite number of possible symbol structure instances, the SSC problem is said to be of the *classification* type. In such cases, the symbol processing stage can typically be formulated as a conventional pattern classifier [2] whose input consists of signal features computed via the signal processing stage. In the case of EMG decomposition, there are an infinite number of possible classifications that could be attributed to a given signal because of the different possibilities for every active motor unit that may have contributed to it. This makes EMG decomposition fall squarely within the relatively more sophisticated *interpretation* class [3] of SSC problems. The symbol processing stage now becomes more complicated because one or more infinitely large subgroups of symbol structure instances must first be “pruned out” from consideration to create a finite set of alternatives to be considered by a conventional pattern classifier. The pruning process can be quite complicated and may end up even using signal processing in the course of achieving its goal. The resultant solution (depicted in Fig. 1(b)) employs interleaved stages of signal processing and symbol processing. Such Joint Signal and Symbol Processing (JSSP) solutions have previously been proposed and studied. Previous research also indicates that the most appropriate SSC domains for the formulation of JSSP solutions are those in which the input signal is generated by a superposition of temporally overlapping sources [4]. The complex superpositions encountered in EMG signals thus make EMG decomposition problems suitable for the exploration of JSSP solutions.



(a) Classical SSC (b) JSSC SSC

Fig. 1. SSC solutions

For the EMG Precision Decomposition problem we have formulated a JSSP solution that consists of three “receivers” as depicted in Fig. 2; they include a Maximum A-posteriori Probability Receiver (MAPR), an Integration Receiver (INTR), and a Superposition Receiver (SUPR). Each receiver 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.

II. MAP Receiver (MAPR)

The MAP receiver [5], [6] generates MUAPT classifications (represented via symbols $u_1, u_2, \cdots etc.$) that are supported by the underlying EMG signal. Upon detection of candidate MUAP data $\bar{\rho}$, MAPR assigns it to one of the

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MUAPT

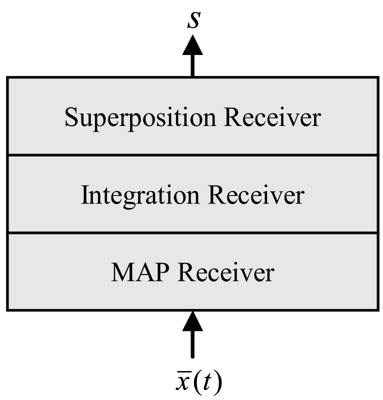


Fig. 2. The JSSP block diagram.

classifications, say u_j, provided the data meets certain classification criteria [5] involving an adaptively updated *recognition template* for the *j*th MUAPT. If MUAP data $\bar{\rho}$ does not support one of the prior symbols, MAPR declares data $\bar{\rho}$ as support for a new MUAPT classification. Once the entire EMG signal has been analyzed, a "symbol filtering" stage rejects MUAP classifications that are determined to be weakly supported by the signal data. The symbol filtering is primarily based upon results from extended criteria involving an adaptively updated *subtraction template* for each motor unit.

III. INTEGRATION RECEIVER (INTR)

The algorithm parameters associated with MAPR have their values assigned in a manner that makes the probability of false alarms extremely small. However, in avoiding false alarms, MAPR often produces different MUAPT classifications for different MUAP subgroups of the same underlying MUAPT. The INTR is designed to integrate different classifications corresponding to the same underlying MUAPT. Let's define a set S of MUAPT classifications produced by MAPR. The goal of INTR is to produce another set S' of MUAPT classifications such that any underlying MUAPT has at most one MUAPT classification corresponding to it in S'. Each element in S' is either an element of S or it is obtained via an "integration" operation, say $\oplus$, applied to a subgroup of S. We adopt the notation $u_{1,2} = u_1 \oplus u_2$ to represent a MUAPT classification that includes each MUAP of classification u_1 in S as well as each MUAP of classification u_2 in S but includes no MUAP of any of the other MUAPT classifications in S. More generally, assuming $S = \{u_1, u_2, \cdots u_N\}$, we can define an integration operation as resulting in $u_{i_1,i_2,\cdots,i_k} = u_{i_1} \oplus u_{i_2} \oplus u_{i_3} \oplus \cdots \oplus u_{i_k}$ where $i_j \neq i_k, \forall j \neq k$. The INTR can now be defined as a *greedy* algorithm [7] for similarity/dissimilarity pursuit that on each iteration seeks to place in S' an element $\hat{u} = u_{\hat{i}_1,\hat{i}_2,\cdots,\hat{i}_k}$ such that

$$c(u_{\hat{i}_1,\hat{i}_2,\cdots,\hat{i}_k}) = \min_{\substack{1\le k\le N\\ 1\le i_1\le N\\ \vdots\\ 1\le i_k\le N}} \left\{c(u_{i_1,i_2,\cdots,i_k})\right\}, \tag{1}$$

and to remove the elements $u_{\hat{i}_1,\hat{i}_2,\cdots,\hat{i}_k}$ from S. The function $c(u)$ is an estimated integration "cost" that is the sum of an *inclusion* measure and an *exclusion* measure. The inclusion measure relates to the degree of inter-element *dissimilarity* within u. The exclusion measure relates to the cross-element *similarity* between the elements of u and the elements of S not in u.

Each iteration of the greedy algorithm for dissimilarity / similarity pursuit has to carry out the cost minimization specified in (1). This cost-minimization problem can be viewed as a minimum-cost 1-path trellis traversal problem [8]. An efficient algorithm [9] is available for carrying out the trellis traversal for each iteration. Since trellis traversal is fundamentally a search problem, we have incorporated heuristic search methods of IPUS to obtain even greater efficiencies. Many of the paths can be simply eliminated either by simple comparisons of template energy and/or template duration or via the unrealistic IPI values that may be generated through the integration of certain MUAPT instances.

IV. THE SUPERPOSITION RECEIVER (SUPR)

The SUPR applies an "iterative correlation procedure" [10] to the *k*th candidate data $\bar{\rho}_k$ where one or more weak classifications were rejected by MAPR. This procedure is designed to estimate "likelihood" values for possible MUAP classifications. The SUPR then uses statistical utility maximization [11] for symbol processing to identify MUAP classifications it deems to be definitely supported by the *k*th candidate data $\bar{\rho}_k$. Denoting the template of the *i*th MUAPT by the vector $\bar{s}_i$, SUPR estimates the "likelihood" of the *i*th MUAPT to be supported by the *k*th candidate data $\hat{P}_{k,i}$. If $\hat{P}_{k,j} = \max_i \hat{P}_{k,i}$, and $\hat{P}_{k,j}$ is above a threshold, the SUPR subtracts $\bar{s}_j$ from $\bar{\rho}_k$ and iteratively repeats this process. If there have been m subtractions in $\bar{\rho}$, SUPR also adjusts the corresponding "likelihood" values by multiplying them with $f(m)$ in order to compensate for subtraction noise. Since multiple "likelihood" values may be calculated for each MUAPT, the SUPR uses the maximum value among them when using utility maximization to identify the MUAP classifications it deems to be definitely supported by the data, $\bar{\rho}_k$.

V. SYSTEM CONTROL

The JSSP decomposition accuracy is empirically found to be significantly influenced by *variations* in these parameters and estimates. This influence arises from complex and highly nonlinear interactions among algorithm and signal characteristics. It therefore becomes necessary to develop a sophisticated system control capability that can conduct a signal-dependent search for an appropriate JSSP operating point in the space of all possible parameter settings and estimates. In view of the combinatorial explosion associated with such a search, we decided to employ heuristic search methods [12] from the field of Artificial Intelligence (AI). In particular, we utilize the IPUS methods for "Integrated Processing and Understanding of Signals" [4]. These methods were specifically designed for providing the control regime associated with the heuristic adaptation of parameter settings and estimates in complex signal and symbol processing applications.

VI. SYSTEM IMPLEMENTATION

To implement the JSSP framework we have used a software environment known as the IPUS C++ Platform or simply ICP [13]. The final JSSP system has on the order of 61,000 lines of C++ code. This does not include the 6200 lines of C++ code of the ICP platform used to build the JSSP application. The control system components take up a total of 34,924 lines of code while the signal and symbol processing algorithms for the three receivers take up 25616 lines of code. In other words, the control component takes up a significant (about 60%) share of the system's code. This is primarily because the control component is dominated by the heuristic search for the values of algorithm parameters and signal parameter estimates. In contrast, the signal and symbol processing algorithms in JSSP are principle-based and thus can be programmed into relatively compact modules.

The large size of the C++ code also translates into a large executable (1,100 Kbytes) along with a requirement for a large amount of memory (350 Mbytes) as the program is executed. However, these numbers are within the bounds of what is achievable with many modern laptops computers. We have implemented our JSSP system on a Dell Inspiron 9300 laptop with a 2GHz Pentium M processor and with 512 Mbytes of RAM.

VII. PERFORMANCE EVALUATION

The EMG signal database we used for evaluating Precision Decomposition algorithms was obtained from five different experiments in which subjects were asked to perform various types of muscle contractions. Three of the experiments involved contractions of the Vastus Lateralis (VL) muscle, while the other two involved contractions of the Tibialis Anterior (TA) and First Dorsal Interosseous (FDI) muscles. The contraction durations ranged from 21 s to 60 s. The "% MVC" value in each case expresses the largest contraction level the subject attains during the experiment and is expressed as a percentage of the maximum voluntary contraction level he/she is able to attain prior to the experiment but in the same experimental set up. In each experiment, the three-channel EMG signal from the electrode was sampled at 20 KHz, using an analog anti-aliasing 4^{th} order Butterworth filter with a 3 dB cutoff at 9.5 KHz. Subsequently, a 1-pole high pass filter with a 3 dB cutoff at 1 KHz was applied to the digital EMG signal in order to keep individual action potential durations as short as possible while retaining the information that experimentally has been found to provide a sufficient discrimination capability.

All signals in the database had previously been analyzed via PD I and had undergone user-interactive editing in accordance with the Mambrito & De Luca procedure [14]. When PD I was applied to the database, the number of motor units whose action potentials were decomposable ranged from 5 to 11 per experiment. The resulting decompositions were used as the standard against which the accuracy of JSSP decompositions was compared.

Suppose that a "benchmark" of firing times of any given MUAPT within an EMG signal is known a-priori. In our case, this benchmark is assumed to come via user-interactive editing of PD I results by an experienced human operator following the Mambrito and De Luca procedure [14]. When a decomposition algorithm produces its estimates for the firing times of that MUAPT, two types of errors can occur: false negatives and false positives. A false negative occurs

TABLE 1
JSSP ACCURACY IMPROVEMENT OVER PD I

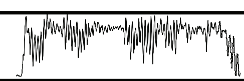
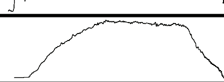
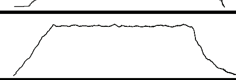
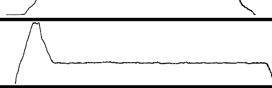
Expt. #	Muscle	Contraction Time	# MUs via PD I	Force	% MVC	PD I Acc.	JSSP Acc.	Improvement Factor
1	First Dorsal Interosseous	23 s	5		25%	56.4%	74.1%	1.31
2	Tibialis Anterior	21 s	6		45%	64.5%	89.9%	1.39
3	Vastus Lateralis	30 s	8		50%	75.1%	96.6%	1.29
4	Vastus Lateralis	32 s	10		50%	74.3%	87.4%	1.18
5	Vastus Lateralis	60 s	11		50%	59.7%	77.5%	1.30
				Average →		66.0%	85.1%	1.29

TABLE II
CONTRIBUTIONS TO ACCURACY BY EACH RECEIVER

Expt. #	MAPR Accuracy	INTR Accuracy	SUPR Accuracy
1	45.6%	52.9%	74.1%
2	61.7%	69.5%	89.9%
3	75.3%	75.9%	96.6%
4	74.1%	75.2%	87.4%
5	60.1%	71.5%	77.5%
Avg.	63.4%	69.0%	85.1%

when the algorithm fails to find a particular firing of the MUAPT. A false positive occurs when the algorithm declares a firing to have occurred where no firing of that MUAPT actually took place. Assuming that each type of error carries equal weight, it is reasonable to define the accuracy $A(i)$ of the algorithm on the *i*th MUAPT as:

$$A(i) = \frac{N_{FIR}(i) - N_{FN}(i) - N_{FP}(i)}{N_{FIR}(i)} \times 100\%$$

where $N_{FIR}(i)$, $N_{FN}(i)$, and $N_{FP}(i)$ are the number of firings, false negatives and false positives for the *i*th MUAPT.

On our database of challenging EMG signals, the JSSP algorithms yielded an improvement by a factor of 1.3 over the decomposition accuracy of PD I algorithms. In Table I, we present a comparison of decomposition accuracies achieved by the two systems on different signals within our database. The average decomposition accuracy of JSSP algorithms is 85.1% over the entire database in comparison to 66.0% for PD I algorithms. The improvement factor for different signals ranges from 1.18 to 1.39 with an average of 1.3. The improvement factor of 1.18 was on a signal (experiment 4) in which the dynamic range of decomposed MUAP amplitudes was 19.6 dB in comparison to dynamic ranges of 8.0 dB (experiment 2), 11.0 dB (experiment 1), 12.5 db (experiment 3), and 18.4 dB (experiment 5) with respective improvement factors of 1.39, 1.31, 1.29, and 1.30. Given that the improvement factor is fairly stable, it appears that the final JSSP accuracy is mostly dependent on the initial MAPR accuracy of PD I. In any given experiment, the initial MAPR accuracy is influenced by a multitude of factors; these include but are not limited to factors such as the force profile of the muscle contraction, the stability of electrode position throughout the contraction, and the number of MUAP trains that give rise to strong signals at that particular electrode position.

Table II shows the accuracy values attained after the final application (by the JSSP control system) of each of the three JSSP receivers. The MAPR in JSSP is on the average found to produce an accuracy of 63.4% on this database. This is lower than the accuracy achieved via PD I (that has its own version of MAPR) because the MAPR in JSSP includes symbol processing for rejecting weak classifications. Subsequent receivers replace those weak classifications by more accurate classifications. First, the INTR takes the accuracy to 69.0%. Secondly, SUPR further boosts the accuracy to 85.1%.

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