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What is IPUS and How Does It Help Resolve BioSignal Complexity?

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Abstract—**Integrated Processing and Understanding of Signals (IPUS) combines signal processing and artificial intelligence approaches to develop algorithms for resolving signal complexity. It has also led to development over the last decade and a half of software tools for supporting the algorithm design process. The signals to be analyzed are the superposition of temporally localized and temporally overlapping signal components from broadly defined signal classes pertinent to the given application. Resolving a signal's complexity thus amounts to "decoding" it to reveal details of the specific signal components that are present at each point of a dense temporal grid defined on the signal. IPUS uses artificial intelligence techniques such as rule-based inference in conjunction with parameterized signal processing transformations to combat the combinatorial explosion encountered in any exhaustive search among the possible decoding answers for a given signal. Originally developed in the mid 1990's for auditory scene analysis, the IPUS approach has since been refined and extended in the context of various applications. In this paper, we present an overview of IPUS and discuss why its latest developments significantly impact biosignal analysis in diverse rehabilitation applications.**

I. Introduction

THERE is a tremendous need in various rehabilitation applications to develop algorithms that can resolve the complexities that arise from non-trivial superposition among temporally localized signal components belonging to broadly defined signal classes of natural origin. Important examples of such applications include the automatic detection of movement disorders from signal data acquired through wearable sensors [1], and the non-invasive assessment of neural mechanisms of motor control using surface electromyographic (sEMG) sensors [2,3]. It is critical in such applications for the algorithm to not "hallucinate" signal components by trying to "fit" the answer to an anticipated model (either deterministic or probabilistic) in opposition to the signal evidence. For example, an algorithm for analyzing sEMG signals should not declare a firing of a motor unit to have taken place at a particular time *just* because that would make the firings of the motor unit conform to a more uniform firing rate; the algorithm must require that signal data is actually present that conforms to the action potential characteristics of the concerned motor unit, although it may be in superposition with data from other motor units. It is precisely such insistence on "model-free" decoding of complex superposition that makes biosignal analysis fertile ground for applying and refining the IPUS approach [4] to algorithm development.

In the IPUS approach, our primary concern is with the combinatorial complexity that can arise when a large number of classification problems have to be solved along a dense temporal grid defined on the signal under analysis. More specifically, the IPUS approach is designed to address situations where the classification problems are (1) *mutually independent* and (2) *individually complex*. Here, mutual independence of the classification problems means that solving any subset of them has no bearing on the potential solutions for the remaining ones (i.e., there is no model for interpolating between solved grid points). The complexity of each classification problem arises out of the fact that its corresponding signal data typically are comprised of a superposition of non-orthogonal signal classes. It follows that the computational cost of any algorithm for correctly (i.e., without error) solving such a classification problem is necessarily exponential in the number of signal classes. In IPUS, we combat such exponential complexity by allowing for a limited classification error rate over the entire set of grid points but strictly disallowing any interpolation between solved grid points. This permits computational cost per classification solution to be carried out in polynomial rather than exponential time while avoiding any hallucination implied by interpolation processes.

In Section II we illustrate the IPUS temporal grid used for biosignal analysis in two different applications. In Section III, we discuss how IPUS has been used to reduce the search combinatorics in those applications. In Section IV, we describe the important role played in IPUS system implementations by "rules" for the controlled application of parametric signal processing transformations. In Section V, we discuss a software environment for designing IPUS systems. The practical impact of IPUS in the field of biosignal analysis is reported in Section VI. We conclude the paper in Section VII.

II. The Grid

Consider a sEMG signal analysis application in which a surface EMG sensor with K contact surfaces is placed on the

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surface of the skin over a muscle of interest. The K-channel signal thus obtained may be expressed as:

$$\bar{x}(t) = [x_1(t), x_2(t), \ldots, x_K(t)]^T. \quad (1)$$

Here each signal $x_k(t)$ is the sum of contributions from N motor units:

$$x_k(t) = \sum_{i=0}^{N-1} f_{i,k}(t). \quad (2)$$

The contribution $f_{i,k}(t)$ of the ith motor unit to the kth input signal channel is in turn given as:

$$f_{i,k}(t) = \int_{-\infty}^{\infty} a_{i,k}(\tau, t) p_i(\tau) d\tau. \quad (3)$$

Here $a_{i,k}(\tau, t)$ represents the ith motor unit's action potential shape (as a function of t) on the kth channel if the ith motor unit is said to have "fired" at time τ, and $p_i(\tau)$ is a non-uniform impulse train representing the F_i firing times ($\theta_i(m); 0 \le m \le F_i - 1$) of the ith motor unit:

$$p_i(\tau) = \sum_{m=0}^{F_i-1} \delta(\tau - \theta_i(m)). \quad (4)$$

Combining (3) and (4), it follows that:

$$f_{i,k}(t) = \sum_{m=0}^{F_i-1} a_{i,k}(\theta_i(m), t) \quad (5)$$

The signal analysis objective is to determine for the ith motor unit ($0 \le i \le N-1$), all of its firing times, $\theta_i(m)$, and the corresponding action potential shapes, $a_{i,k}(\theta_i(m), t)$. Each action potential shape is typically 5 to 10 ms long and there are typically well over 500 action potentials in superposition in every second of data.

To illustrate the use of the grid concept for the above sEMG signal analysis application, consider the 1 ms grid defined in Fig. 1 with respect to one of the K channels of the acquired sEMG signal. This grid helps divide the signal into 1ms intervals. The 9ms interval around the grid point at n_0 ms is shaded in Fig. 1. Given the density of action potentials in the signal, *on the average* only one action potential's major peak would fall in that interval. However, *on the average* it would be in non-trivial superposition with 8 other action potentials. We thus define the classification problem at grid point n_0 as that of determining which action potentials have their major peak in the gray interval while being in superposition with a number of other action potentials. The shape of each action potential constitutes a "signal class" and is to be determined directly from the sEMG signal by finding partially isolated instances of each class. When solving the overall classification problem, every action potential class is allowed to occur at every grid point, thus not imposing any temporal model on the firing pattern of any of the concerned motor units.

Another illustration of the IPUS grid concept is given in Fig. 2 for a wearable sensor application where the sensor is an accelerometer. Here the grid points are 1s apart. Each grid point represents a 1s interval during which signal classes corresponding to different types of movement disorders (tremor, dyskinesia, bradykinesia, etc.) are in superposition with voluntary movements. The classification problem is to determine the movement disorders present in the interval for each grid point while not allowing the answer at any grid point to constrain the answer at any other grid point.

III. The Combinatorics

Let us first consider the search combinatorics involved in the sEMG signal application. Assume that the 1ms interval of any particular grid point contains the central portion of the major peak of just one action potential out of N that actually contribute to that interval. To correctly classify the motor unit centered in that interval, any algorithm would have to exhaustively consider the 2^N possibilities for different combinations of motor units. Given that the signal classes are very similar to each other [2] and therefore non-orthogonal, there is no hope of solving the classification problem in less than exponential time without incurring error. However, using the IPUS approach, we have recently [3] reduced the search space to a linear function of N but sacrificed the error rate to an average of 5% per motor unit. We have been able to accomplish this for N as large as 60 and typically in the range from 20 to 40. The key to our IPUS solution is to employ heuristics ("rules") for

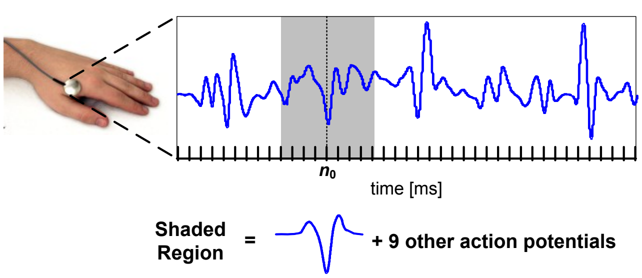

Fig. 1. Illustration of the grid concept used in the sEMG signal analysis application. At a given point n_0 on the grid, the system must determine which action potentials have their major peak in the shaded interval while being in superposition with a number of other action potentials.

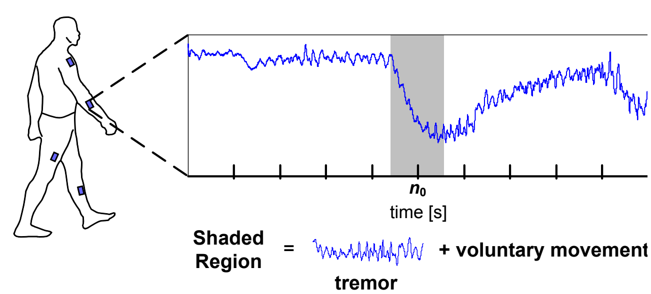

Fig. 2. Illustration of the grid concept used in the wearable sensor application. Each grid point represents a 1s interval (shaded) during which over 100 categories of signal classes corresponding to different types of movement disorders (tremor, dyskinesia, bradykinesia, etc.) and voluntary movements may be in superposition.

controlling parametric signal processing methods with the aim of (1) keeping the least squares error per motor unit firing below an adaptive threshold and (2) ensuring that the answer at each grid point does not depend in any way on the answer for any other grid point.

In the wearable sensor application, we have to deal with over 100 categories of signal classes corresponding to different limb movements and movement disorders found in Parkinson's disease patients. In this case, our IPUS solutions [1] avoid exponential search by employing dynamic neural network (DNN) classifiers that are explicitly trained to allow for limited error rates. These DNN classifiers are in turn controlled by rule-based mechanisms that also ensure that no interpolation is employed in determining the answers at any of the grid points.

IV. THE RULES

A critical aspect of IPUS systems is a rule-based controller for context-specific invocation of parametric signal processing transformations. An example of the role played by the rule-based controller is shown in Fig. 3 for the wearable sensor application [1]. Raw signals from the sensors worn by the patient are windowed and processed to create features, which in turn are fed as inputs to parameterized DNN classifiers designed to determine the movement disorders and voluntary movements exhibited by the patient. The rule-based IPUS controller adjusts the parameters that drive the DNNs, and activates other DNNs as needed to adapt to changes in patient activity. The rules are crafted to ensure that no interpolation takes place in between different grid points.

The parameters of the DNN are the analysis interval durations in time or frequency of various signal features. For instance, we have developed rules to shorten the time window used to calculate the input features for dyskinesia detection if the patient is walking. This is because the superposition of walking tends to obscure the sporadic movements that characterize dyskinesia. Additional rules are in place to adjust the cutoff of a highpass filter to separate involuntary from voluntary movement. This enables disorders such as tremor to be more accurately detected when voluntary movements are superimposed on them.

V. THE SOFTWARE

Over the years, we have developed a software environment for rapid IPUS system development. This software, based on an original design [5], offers a unique combination of features with respect to currently available design tools such as Matlab [6]. The environment presents a unified platform in which embedded signal processing applications which require sophisticated rule-based control can be designed, prototyped, tested, and implemented. In particular, this can be accomplished without the need for the labor intensive and error prone steps of manual format conversion and design reentry which are inevitable when incompatible tools are required for different stages of a system's design cycle. An object-oriented design philosophy is employed throughout the environment, enabling applications to be constructed and tested in an incremental manner.

The basic system model employed within the environment is that of a collection of independent signal processing algorithms which are invoked according to algorithmically defined rules. In addition to supporting standard signal processing architectures, this paradigm allows the development of systems which may alter their processing activities in response to conditions such as fluctuating system resources, requests from other system components, or the results of their own calculations. This flexibility is provided through the use of a control mechanism (or planner) based on the RESUN control paradigm [7]. The planner allows for both strategic (plan-based) and opportunistic (reactive) control to be applied. The strategic component is based on an application specific goal/plan/subgoal hierarchy (referred to collectively as control plans) in which all system goals are explicitly submitted to the planner and may be addressed by either a single algorithm or decomposed into an algorithmically defined sequence of further subgoals.

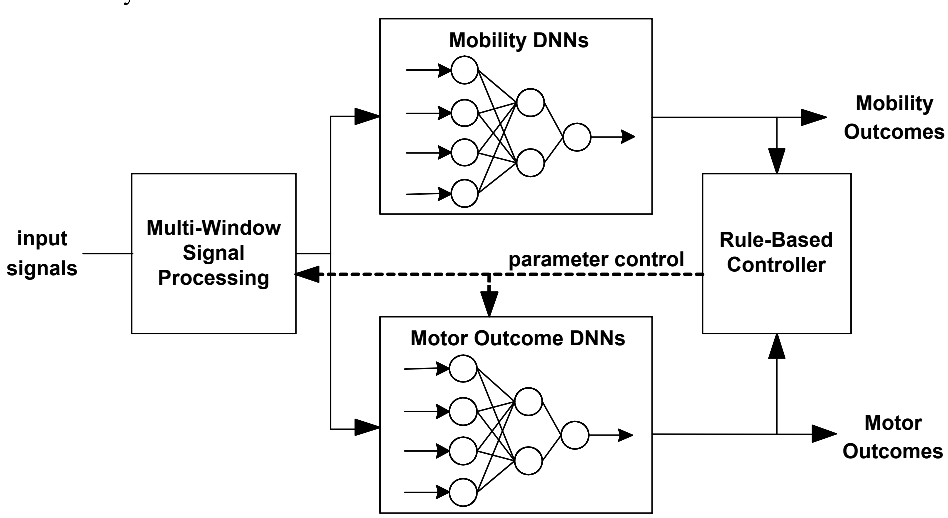

Fig. 3. Block diagram of the system designed for the wearable sensor application, providing an example of the role of the rule-based IPUS controller. In this system, the controller adjusts the parameters that drive the DNN classifiers, and activates other DNNs as needed to adapt to changes in patient activity.

VI. Latest Achievements

Table I shows the progression of IPUS applications in the period from 1995 to 2011. We want to emphasize that over this decade and a half not only did the applications become more sophisticated but IPUS itself evolved as a signal analysis approach and as a set of tools and techniques. The earliest applications to the analysis of sound signals [4] and music signals [8] were limited to synthetic signals because at that time IPUS technology had not matured enough to deal with the complexities of real-life operating conditions. As indicated in Table I, the algorithms could deal with only 20 to 30 signal classes and worked only in the total absence of noise. Furthermore, the conditions under which the systems operated were highly constrained. For example, the music analysis system assumed that the music is played on a specific instrument (violin) and is used to play only in accordance with the Classical Western scale.

More recent applications of IPUS in the biosignals area have yielded considerable practical success, particularly when it comes to dealing with the analysis of real-life signals. In 2008, Nawab et al. [9] showed that the decomposition of indwelling EMG signals acquired under isometric force conditions from human subjects could be carried out with greater accuracy and greater motor unit yield than previously published systems. In particular, our IPUS-based decomposition of indwelling EMG signals is found to typically yield 10 to 15 motor units with an average accuracy of over 90% per motor unit firing pattern. The system performed at this level across a wide range of human subjects and muscle types.

Similarly, in 2010, Nawab et al. [3] developed another IPUS-based system that can decompose EMG signals acquired from the surface of the skin during isometric muscle contractions to yield the firing patterns of as many as 60 motor units per contraction with average accuracy around 95%. Previous systems for surface EMG signal decomposition never succeeded in producing a yield of more than a few motor units. The higher yield allows a decomposition algorithm to be used to carry out much more sophisticated physiological studies, as exemplified by the recent work of De Luca and Hostage[10].

The most recent IPUS application reported by Cole et al. [1] is found to operate reliably in even more unconstrained conditions. In particular, movement disorders of Parkinson's disease are classified on a per second basis with an error rate below 10% while the patient carries out unscripted and unconstrained activities of daily living. The signal to noise ratio tolerable by this system can be as low as 0.1.

TABLE I

Progression of IPUS Applications

Date	IPUS System	# Signal Classes	Signal Origin	SNR Floor	Operating Conditions
1995	Sound	20+	Synthetic	∞	Highly Constrained
1999	Music	30+	Synthetic	∞	Highly Constrained
2008	iEMG	15+	**Real-Life**	**10**	Moderately Unconstrained
2010	sEMG	**60+**	**Real-Life**	**1**	Moderately Unconstrained
2010	PSM	**45+**	**Real-Life**	**0.1**	**Highly Unconstrained**

Since 1995, as the IPUS approach has evolved, IPUS systems of increasing complexity have been developed; they can now handle real-life signals representing highly unconstrained situations with signal to noise ratio (SNR) as low as 0.1 and handle signal classes in the upper 10's.

VII. Conclusion

The analysis of complex biosignals often has to take two important factors into consideration. The first factor is that biosignals often result from the complex superposition of multiple underlying phenomena that are difficult to resolve without incurring exponential cost. The second factor is that in physiological and clinical applications a strong premium is placed on ensuring that the algorithm for resolving different components does not "impose" any model on the data; the algorithm has to avoid seeing in the data simply what it is programmed to see regardless of the data evidence. The IPUS approach and its associated tools and techniques have in the last few years had a major impact on this type of biosignal analysis in several rehabilitation related applications.

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