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Functional Activity Monitoring From Wearable Sensor Data

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Abstract—**A novel approach is presented for the interpretation and use of EMG and accelerometer data to monitor, identify, and categorize functional motor activities in individuals whose movements are unscripted, unrestrained, and take place in the "real world". Our proposed solution provides a novel and practical way of conceptualizing physical activities that facilitates the deployment of modern signal processing and interpretation techniques to carry out activity monitoring. A hierarchical approach is adopted that is based upon: 1) Blackboard and Rule-Based technology from Artificial Intelligence to support a process in which coarse-grained activity partitioning forms the context for finer-grained activity partitioning; 2) Neural Network technology to support initial activity classification; and 3) Integrated Processing and Understanding of Signals (IPUS) technology for revising the initial classifications to account for the high degrees of anticipated signal variability and overlap during freeform activity.**

Keywords—**Accelerometers, activity monitoring, blackboard systems, EMG, IPUS, neural networks, wearable sensors**

I. Introduction

Each year approximately one million Americans are struck with a debilitating motor disorder or are afflicted with a disease which impairs their ability to move, carry out normal activities of daily living, or in various ways, degrades their quality of life [1]. The national cost for treating such patients has been estimated at $82 billion. It is therefore remarkable that the tools available to the researcher and clinician to monitor functional capability in these patients are either qualitative (e.g. questionnaires and patient diaries) or are impractical for the home or clinic (e.g. motion analysis systems and force platforms). The objectivity and comprehensiveness of a patient's performance record could be improved with a system that automatically identifies and assesses the activities carried out by the individual throughout the day, particularly in remote locations such as the home. Only a few reports in the literature describe the use of portable activity monitors for measuring functional activities [2, 3, 4]. For the most part, these systems do not produce a monitoring capability beyond distinguishing between different postures or various forms of ambulation.

In contrast to previous work, we envisage an activity monitoring system that is able to identify the functional activities when they are performed in a "real-world" environment (that is, when they are unscripted, freeform, and unrestrained). Under such conditions, activity monitoring is confounded by the presence of extraneous activities, noise, inherent variability of the person's environment, or fluctuations in their physical state (e.g. from neuromuscular or other disorders). We have decided to address the totality of these confounding factors by adopting a knowledge-based framework for integrating signal processing, pattern recognition, and artificial intelligence techniques. These algorithms can then be placed in a portable data-logger to make up a device we call a Personal Status Monitor (PSM). Such a device could provide an effective basis for home or long-term care planning, or as a means of evaluating the effectiveness of therapeutic interventions. The system monitors functional activities using data from small "hybrid" sensors placed on the body that detect both Electromyographic (EMG) and Accelerometer (ACC) signals. EMG signals represent the electrical activity that emanates from contracting muscles and is proportional to the force being generated by the muscle. ACC signals represent the displacement of the body segment to which the sensors are attached. The use of hybrid sensors is new to the problem of monitoring functional activities.

II. Hierarchical Activity Partitioning

The central technical challenge addressed by our approach is the development of a system that can process EMG and ACC signals (see Fig.1) from body-worn sensors in order to monitor (to within a specified degree of resolution) the freeform functional activities of individuals. The end product of such monitoring is a partitioning of the sensor signals into intervals corresponding to distinct functional activity states. The question naturally arises as to what resolution to adopt in defining the activity states. Rather than arbitrarily selecting a particular scale, we consider the more general problem of performing the activity partitioning at multiple *hierarchically related* scales. This concept, which is a novel way of looking at physical activity, is illustrated in Fig. 2, where the top-level nodes represent four mutually exclusive *"Principal Activities"* – Sit, Stand, Walk and Lie – and lower level nodes represent

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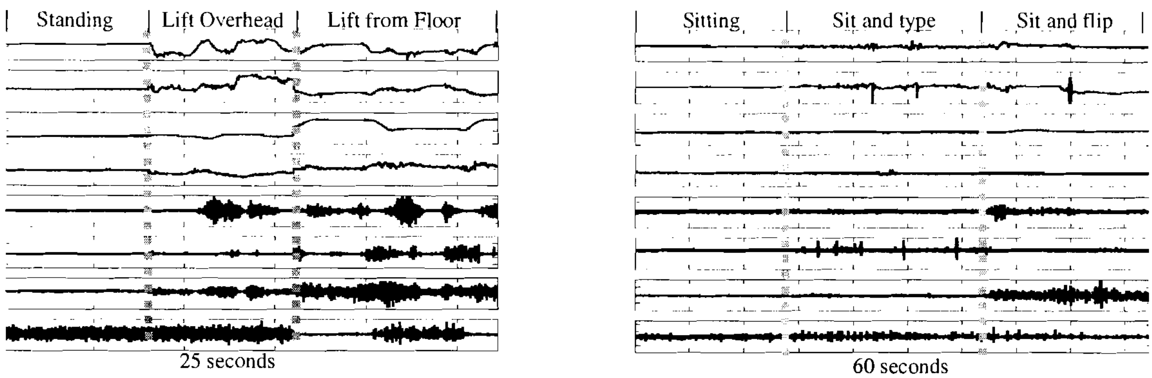

Fig. 1. Sample of EMG and ACC data acquired continuously from an unimpaired subject while performing a sequence of freeform standing activities, such as quiet standing, lifting a box overhead, and lifting a box from floor to waist (left); and sitting activities such as quiet sitting, sitting and typing on a keyboard, and sitting flipping pages in a book (right).

finer resolution activity classifications. Here we have adopted the perspective that all physical activity of an individual may be broadly classified at any time as being in one of several Principal Activity states or in a transition between these states. These "*Transitional Activity*" states, such as Sit-to-Stand, are represented in Fig. 2 by the smaller dark-shaded nodes with dashed arrows indicating the "input" state at the beginning of the transition and the "output" state at the end of the transition. Finer resolution activity classifications are represented in the figure as "*Co-activities*", when a specified functional activity takes place during one of the Principal Activities (e.g.; sitting and typing on a keyboard; walking and carrying an object; etc.). To help obtain an operational definition for the various activity states we propose the use of a visual inspection protocol in which (say) 20 volunteers are asked to perform the activity partitioning by viewing videotapes of the freeform activity. Thus, for example, an activity interval may be classified as "Walk 100%," denoting the fact that there is unanimous agreement between the volunteers that the Walk activity is taking place. In the absence of unanimity we may obtain classifications such as "Stand 85%, Stand-to-Walk 15%," representing the fact that 17 of the volunteers classified the interval as Stand while the remaining 3 classified it as Stand-to-Walk. Ideally, for each interval classified through the visual inspection protocol we would like to design sensor-based classification algorithms whose results are in complete agreement with the activity classification picked by the largest percentage of volunteers. The classification challenge in carrying out the partitioning suggested by the top level in Fig. 2 may thus be posed as follows:

Broad Classification Challenge: *Develop algorithms for the time-dependent classification of EMG and ACC sensor signals from freeform activity into Principal Activities and Transitional Activities with the objective of emulating the performance obtained through visual inspection of freeform activity.*

Moving down the partitioning hierarchy in Fig. 2, each principal activity may be further partitioned in accordance with whether or not a co-activity is taking place. The presence of co-activity is represented in Fig. 2 by the "*Co-activity*" state and its absence by the "*Uni-activity*" state. Regardless of the precise nature of the co-activity, at this level we would like to be able to detect it whenever it takes place. Thus, the detection challenge in carrying out second-level partitioning in accordance with Fig. 2 may be posed as follows:

Co-Activity Detection Challenge: *Develop algorithms for detecting co-activity in principal activity segments of the sensor signal with the objective of emulating the performance obtained through visual inspection of freeform activity.*

While the Broad Classification and Co-Activity Detection challenges are formidable, our previous work on the sensor-based classification of scripted functional activities indicates that the judicious use of signal processing and neural network technology has significant potential of successfully accomplishing these challenges for freeform activity. The more speculative aspect of our research arises as we proceed to the third level in Fig. 2 where we seek to classify the co-activity as belonging to one of a finite number of pre-determined categories of interest. For this purpose we have chosen a few categories that are representative of the types of activities one might want to monitor to evaluate functional independence. For example, in Fig. 2 we have indicated that in the context of Sit we will seek to determine whether the co-activity can be categorized as that of reading a book or magazine ("flipping pages"), feeding oneself, operating a computer keyboard, or "other" to denote that it is none of the other three activities. Similarly, in the context of Stand we will seek to determine whether the co-activity can be categorized as that of opening a door, lifting an object from the floor, lowering an object from overhead, or "other". In this classification context, principal activity signals may be viewed as masking noise

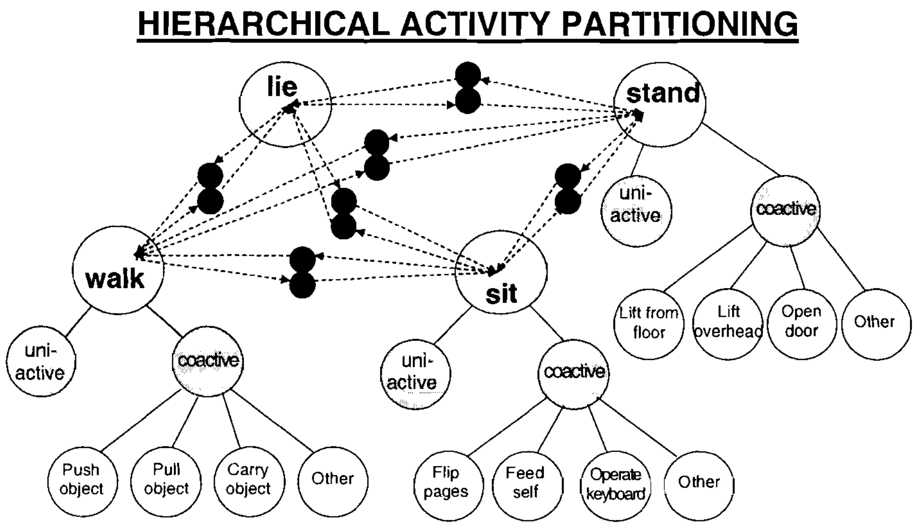

Fig 2. The hierarchical activity classification. The larger circles indicate the 4 Primary Activities. Each can be further partitioned into coactive or uni-active activities. The coactive activities are further resolved into specific functional activities.

for co-activity signals. The co-activity classification challenge may thus be summed up as:

Co-Activity Classification Challenge: *Develop algorithms for co-activity classification in the context of masking by a pre-classified principal activity with the objective of emulating the performance obtained through visual inspection of freeform activity.*

We advocate a knowledge-based approach to the development of these algorithms. In particular, the IPUS technology addresses many of the issues that arise from the presence of complex signal masking phenomena. Such an approach would also be needed if we were to seek finer resolution of partitioning beyond the third level in Fig. 2. An example of a finer resolution activity would be in determining whether stroke patients walked with or without the assistance of a cane, or the degree to which they used their hemi paretic limb when feeding themselves.

III. Technical Infrastructure Development

Our approach to addressing the challenges associated with hierarchical partitioning of freeform activity is illustrated in Fig. 3. A sequence of three pairs of processing stages is applied to the input sensor signals. Each pair of stages involves the application of Time-Dependent Neural Network (TDNN) technology followed by knowledge-based revision of the TDNN output using IPUS technology. While the first pair of stages is aimed at addressing the broad classification challenge, the second and third stage pairs are aimed at addressing the co-activity detection and co-activity classification challenges, respectively. The integration of these signal processing and AI technologies into an overall system would be accomplished by utilizing Blackboard and Rule-Based technology.

A. Blackboard and Rule-Based Technology

Our approach uses a variation of the Blackboard architectural model [5] to integrate diverse AI techniques into a single system. Blackboard architectures cast the process of generating the output associated with a given input signal as a series of transformations between multiple data representation levels on a global, hierarchical blackboard data structure.

The Blackboard infrastructure will play a dual role in our project. Firstly, it will serve as a development platform for the various algorithms (TDNN, IPUS, etc.) for hierarchical activity partitioning. Secondly, it will serve as the backbone of the final system with all the algorithms integrated within it. In developing the Blackboard infrastructure for our project we will make use of a C++ software environment [6] for implementing Blackboard mechanisms. The environment contains generic Blackboard mechanisms (the Blackboard database, the Planner, and templates for Control Plans) and the tools needed to tailor these mechanisms for specific applications.

B. Neural Network Technology

Some activity categories, such as walk, sit-to-stand, and stand-to-sit have a significant non-stationary temporal dimension to their defining characteristics. That is, each category involves its own dynamic evolution of the various short-term features of the EMG and ACC signals. It stands to reason, therefore, that classification performance may potentially be improved by using pattern recognition approaches that explicitly incorporate the temporal dimension inside the classification process. Time-Dependent Neural Networks, also known as FIR Neural Networks, can be designed to provide this very capability. For example,

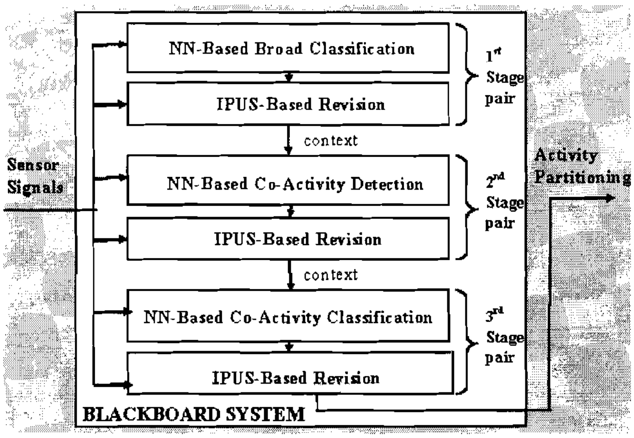

Fig. 3. Diagram illustrating our approach to hierarchical partitioning of freeform activities using Time-Dependent Neural Networks (TDNN) technology followed by knowledge-based revision using IPUS technology.

Haselsteiner and Pfurtscheller [7] and Englehart et. al. [8] have demonstrated the advantages of TDNN classification for EEG and EMG tasks, respectively. A TDNN is obtained by replacing each static weight of a standard (static) NN by an FIR filter. This allows the TDNN to linearly combine each current input of a neuron with past values of that input for previous frames. The TDNN input dimensionality is thus the same as that of the static NN for a single input frame.

C. (IPUS) Integrated Processing and Understanding of Signals

IPUS technology [9,10] may be used to implement the process of revising the initial TDNN detection and classification results, particularly in the presence of co-activity. When a co-activity is being performed, we anticipate that the TDNN process would not assign a high likelihood to any particular category; the overlapping imprints of the simultaneous activities will tend to distort each other's features. In such cases, IPUS-based mechanisms [10] may be used to propose and test hypotheses about different combinations of simultaneous activities as we have done successfully in the case of an intramuscular EMG system application [11] and a musical decomposition system [12]. This approach is based on the following observations about our application:

(1) Even though the activities are overlapped, each activity would dominate a few of the time steps and the TDNN process would thereby successfully classify at those particular time steps (i.e. with a high associated likelihood of being correct). These successful classifications could then be used to hypothesize the presence of overlapping signal contributions for regions that have classifications with greater uncertainty during the initial processing.

(2) Using an iterative decomposition technique for separating signal features that was successfully deployed in the Intramuscular EMG system for an analogous task, we would determine whether or not the hypothesized overlaps are consistent with the sensor data for the other time steps.

In terms of software implementation, a key feature of the IPUS-related blackboard architecture [10] is that it provides a generic mechanism (the *IPUS Loop*) for supporting iterative *hypothesize-and-test* strategies such as the one described above. In particular, the C++ software environment [6] for implementing Blackboard systems facilitates implementation of the *IPUS Loop*.

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