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Resolving Signal Complexities for Ambulatory Monitoring of Motor Function in Parkinson's Disease

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***Abstract*—Automatic tracking of movement disorders in patients with Parkinson's disease (PD) is dependent on the ability of machine learning algorithms to resolve the complex and unpredictable characteristics of wearable sensor data. The challenge reflects the variety of movement disorders that fluctuate throughout the day which can be confounded by voluntary activities of daily life. Our approach is the development of multiple dynamic neural network (DNN) classifiers whose application are governed by a rule-based controller within the Integrated Processing and Understanding of Signals (IPUS) framework. Solutions are described for time-varying occurrences of tremor and dyskinesia, classified at 1 s resolution from surface electromyographic (sEMG) and tri-axial accelerometer (ACC) data acquired from patients with PD. The networks were trained and tested on separate datasets, respectively, while subjects performed unscripted and unconstrained activities in a home-like setting. Performance of the classifiers achieved an overall global error rate of less than 10%.**

I. Introduction

Attempts at developing a wearable device that can automatically track changes in the presence and severity of involuntary movement disorders have focused primarily on Parkinson's disease (PD). The relatively wide variety of motor disorders associated with the disease fluctuate throughout the day, making monitoring by paper-based instruments, such as motor diaries [1], difficult and ineffective. For effective therapeutic management, the clinician must determine the evolving temporal pattern of the patient's motor status and relate it to their use of anti-Parkinson's medication or deep brain stimulation (DBS) settings. Acquiring this information from a wearable sensor device is particularly challenging in these patients because the type of motor disorder may not only change rapidly over time, but may also fluctuate in intensity and body location throughout the day [2,3]. A wearable sensor solution must be non-intrusive (e.g., not interrupt daily activities), non-cumbersome (e.g., use a minimal number of sensors), sensitive to change (e.g., report occurrence and severity of multiple disorders on a per-second basis), and accurate (e.g., provide results that are consistent with observations by movement disorder experts). Our goal is to achieve these aims using classifiers that do not require training data from the patient being tested.

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II. Previous Work

Given the proliferation of wearable sensor technology and improvements in machine learning algorithms [4], the potential exists to develop systems that allow clinicians to detect movement disorders in sensor-wearing patients remotely and without intrusion. Despite this prospect, no currently available technology has produced a comprehensive system to monitor PD movement disorders with the desired time resolution and accuracy. Nevertheless, several research groups have proposed solutions to monitor individual disorders relying in part on the patient's performance of scripted activities or standardized tests. Such tests interfere with the patient's ability to carry out activities of daily living, and place an undue burden for timely administration on the patient. Accordingly, they do little to improve upon paper-based instruments. Our proposed system, by entirely avoiding the use of scripted activities and standardized tests, would thus represent an important improvement over the existing state of the art.

The detection of dyskinesia from ACC sensors worn by PD patients carrying out scripted activities in a randomized order was considered by Keijsers et al. [6] using static neural networks, however the activities were scripted, did not include tremor or other disorders, and the temporal resolution was limited to 1 minute.

In previous work by Salarian et al. [5], the detection of tremor was considered on a per-second basis using triaxial gyroscope signals from subjects performing a scripted sequence of activities such as tooth-brushing while standing and eating while sitting. Their algorithm yielded 99.5% sensitivity on tremor-only data and 94.2% specificity on tremor-free data, based on video annotation. This algorithm, however, was not designed to discriminate between tremor and dyskinesia and was therefore not tested on datasets containing instances of dyskinesia.

III. Approach

Novel data acquisition and signal processing technologies for resolving time-sensitive signal complexities were developed to achieve our aims. The following list summarizes the key components of the approach:

- Hybrid sensor technology was developed to provide both sEMG and tri-axial ACC data from a single, wireless, miniaturized sensor (Trigno™, Delsys Inc). The combined use of these measurement modalities is unique in this application.
- A single hybrid sensor is located at the distal portion of each symptomatic limb, to track motor disorders specific to that limb. This approach minimizes the overall number of sensors required and provides a mechanism for adapting the number of sensors to the patient's clinical signs and capabilities.
- Machine learning algorithms, implemented in the form of dynamic neural networks (DNNs) are assigned to each sensor and separately designed and trained to identify specific movement disorders or mobility states (e.g. sitting, standing, walking). We used dynamic (as opposed to static) neural networks, which have served as the *de facto* standard to date for this application [7], to learn how features of the movement disorders change over time.
- Multi-window signal processing is used to efficiently compute input features of the DNNs.
- Parameterized Machine Learning algorithms are incorporated into the framework of a rule-based controller within the Integrated Processing and Understanding of Signals (IPUS) framework [8].
- Features from the sEMG and ACC signals are calculated to provide inputs to the DNNs, as summarized in Table I [9].

A pictorial overview of the approach is summarized in Fig. 1. Raw signals from the ACC and sEMG sensors are processed using a multi-window approach to create features of these signals, which in turn are fed as inputs to the initial mobility and motor sign DNNs. These DNNs produce preliminary estimations of the motor outcomes and mobility states. Based on these results, the rule-based IPUS controller adjusts the parameters that drive the DNNs, and activate other DNNs as needed to adapt to changes in mobility state.

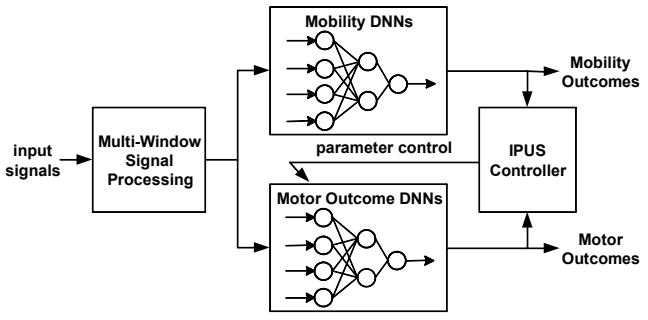

Fig. 1. Block diagram of the technology framework of the proposed system. Features are calculated across multiple time and frequency windows of the ACC and sEMG signals. These features are then fed into DNNs trained to detect the patient's mobility and motor states. The parameters controlling these DNNs are set by a rule-based IPUS controller, and adjusted according to the system outputs.

TABLE I
Input Features from sEMG and ACC Signals

Feature	Derivation	Description
ACC lowpass energy	Energy of ACC signal after application of 2.5 Hz lowpass filter	Amount of energy attributable to voluntary movement
ACC highpass energy	Energy of ACC signal after application of 2.5 Hz highpass filter	Amount of energy attributable to involuntary movements
ACC lag	Lag of first peak (not at origin) of the autocorrelation of ACC corrected signal	Dominant frequency of the involuntary movement
ACC ratio	Ratio of height of first peak (not at origin) to heigh of peak at origin in autocorrelation of ACC corrected signal	Percentage of energy due to involuntary movement that is within the range of the dominant frequency
sEMG RMS	RMS energy of the sEMG signal	Amount of muscle activity
sEMG lag	Lag of the first peak (not at origin) compute as an absolute value from the autocorrelation of the sEMG signal	Dominant frequency of the periodic components of the muscle activation
sEMG ratio	Ratio of height of first peak (not at origin) to height of peak at origin in the autocorrelation of the sEMG signal	Amount of energy present within the dominant frequency of the sEMG signal

IV. Methods

Two groups of subjects were tested: one (n=11 patients) provided a data set for algorithm development (Training Set) and the other (n=4 Controls; n= 8 patients) provided data for testing the algorithms (Test Set). Separation of the databases was implemented to develop and test classification algorithms that do not require *a priori* training from the patient being monitored. Patients were referred with mild to moderately severe categories of Parkinson's disease [Hoehn-Yahr stage II – III while On, and Hoehn-Yahr stage III to IV while off] and a mean disease duration = 13.2 years. All were taking levodopa medication and presented with mild to severe ratings of tremor (based on Unified Parkinson's Disease Rating Scale (UPDRS) [10] and dyskinesia complicated by motor fluctuations (based on the modified Abnormal Involuntary Movement Scale (m-AIMS) [11]).

Three channels of tri-axial ACC signals, and one channel of sEMG signals were recorded from each of four hybrid sensors placed on the distal portions of the upper and lower extremities. Sensor and video data were recorded continuously for 4 hours (sufficient to capture a complete On-Off medication cycle) while the subject carried out *unscripted and unconstrained* activities in a 100 meter^2 laboratory furnished to simulate a studio apartment. The

resulting videotapes were annotated by individuals trained in identifying PD motor signs using standardized methods. Tremor severity was scored based on Items 20, 21 of the Motor Examination section of the UPDRS [10] and dyskinesia severity was scored based on the m-AIMS scale (m-AIMS) [11]. Ratings were recorded for each second of videotaped data and were recorded separately for each of the four limbs.

V. Results

The DNN for detecting tremor was designed using a multi-layered neural network with a hidden layer of 4 nodes. The DNN for detecting dyskinesia was designed using a multi-layered neural network with a hidden layer of 2 nodes. The hidden nodes and the output node for both these DNNs use the weights of a 5-point FIR filter applied to time-delayed and time-advanced versions of their respective input data. The input nodes for the DNNs are features extracted from 2-second windowed sections of the sEMG and ACC sensor signals. Details of these DNNs can be found in [9].

In total, the training set for tremor and dyskinesia was 25 minutes long, including 100 instances of tremor and 100 instances of dyskinesia. The training set was carefully chosen to be representative of the different manifestations of the disorder; for instance, samples chosen to represent tremor included samples with different amounts of movement, different frequencies, and different severity levels of tremor. The following results are from the test database of approximately 29.5 hours of data from the eight PD patients, and 15.5 hours of data from the four controls. The testing was accomplished without subject-specific training; that is, no additional training data was required to accommodate the addition of new patients or controls in the testing database.

Table II summarizes the sensitivity, specificity, and global error rate results of testing the DNNs to detect tremor and dyskinesia in the test sample, based on data from a single hybrid sensor from a symptomatic limb.

TABLE II
DNN Testing Results

Disorder/ Site	Tested On	Sens	Spec	GER	Net Duration
Tre/Arm	8 Patients	93.8%	91.9%	7.2%	29:13
Tre/Leg	8 Patients	88.6%	94.6%	8.4%	29:13
Tre/Arm	4 Controls	---	93.7%	6.3%	15:18
Dys/Arm	8 Patients	90.0%	91.3%	9.4%	29:13
Dys/Arm	4 Controls	---	95.5%	4.5%	15:18

Mean sensitivity (Sens), specificity (Spec), and global error rate (GER) for identification of tremor (Trem) and dyskinesia (Dys) from DNN algorithms that processed summary sEMG and ACC data recorded from PD patients and control subjects.

The table differentiates between upper and lower limb results to demonstrate that the algorithms work with similar effectiveness regardless of which limb is symptomatic.

The DNNs were also able to identify the different severity levels of tremor and dyskinesia from this same data set, at sensitivity and specificity levels well above 90%, respectively (Table III). Severity levels varied across subjects, with severe levels of tremor and dyskinesia less prevalent in these subjects than mild and moderate severity levels.

TABLE III
Severity Detection Results

Category	Sens	Spec	Hours of Data	Number of Subjects
Mild Trem	97.2%	97.8%	1:56	5
Mod Trem	95.2%	97.1%	1:14	4
Sev Trem	96.3%	99.3%	0:26	3
Mild Dys	93.9%	95.5%	0:52	5
Mod Dys	91.9%	94.6%	0:46	5
Sev Dys	95.0%	98.6%	0:13	4

Mean sensitivity (Sens) and specificity (Spec) are shown from summary data for identifying mild, moderate (Mod), and severe (Sev) levels of tremor (Trem) and dyskinesia (Dys).

The results described above were from the Motor Outcome DNNs directly and did not include automatic mechanisms for adaptively invoking different signal processing algorithms and different DNNs in a situation-dependent manner, as was depicted in Fig. 1. There are instances, however, when such complexities warrant these procedures, as demonstrated in Fig. 2. Three ACC signals from a patient with tremor, one in a region with rapid voluntary movement, one in a region with gradual movement, and one in a region with no movement are shown. When the signals are unfiltered, as seen in the first row, the autocorrelation-based features have difficulty locating the tremor in the two regions with movement, whereas in the region with no movement, tremor is identified. When a high pass filter with a cutoff frequency (f_ℓ) of 1 Hz is applied (second row), we can virtually eliminate the gradual movement while leaving intact the slow-moving tremor seen in the region without movement. However, little

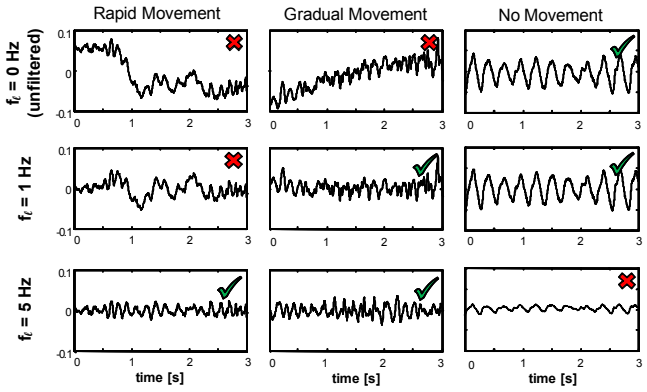

Fig. 2. Examples of ACC signals, before and after high pass filtering at different cutoff frequencies (f_ℓ) from a patient with tremor during different levels of movement. The segments with checkmarks are those in which the autocorrelation function will produce evidence of tremor; segments marked with X's produce no evidence of tremor due to the residual movement artifacts (left two columns) or elimination of slow tremors (bottom right). Therefore segments with different amounts of movement require different filters for optimal motor sign detection.

of the rapid movement has been eliminated, and the underlying tremor remains hidden. To correct this, we applied a highpass filter with a higher cutoff of 5 Hz (as seen in the third row). Though tremor is now clearly visible in the rapid movement and gradual movement regions, the slow-moving tremor present in the region without movement has begun to deteriorate, suggesting that this cutoff is too high for the autocorrelation features to continue detecting tremor in this region. We can see, then, that movement disorders occurring during different amounts of voluntary movement (e.g., during different mobility states) will necessitate the use of multiple window sizes when computing the autocorrelation. This is a novel approach in that no previous research has been done in applying different window sizes to movement disorders based on the signal environment. Because our problem is a complex and highly unpredictable one, we will be unable to predict which window size will be needed at any given second, and therefore would require features to be calculated from the autocorrelation over one of several different time and frequency windows. To compute all of the features for all possible windows would of course be prohibitively computationally expensive. Thus, we are currently investigating the use of approximate signal processing to estimate the desired features of the autocorrelation [12]. Approximate signal processing seeks to increase the computational efficiency of an algorithm by sacrificing the quality of the algorithm's output.

Multi-window signal processing will require the continuous switching between classifiers so that movement disorders can be detected with respect to various signal conditions. This switching will require a rule-based system in order to efficiently meet our stated goal of improving the local error rate in these transitional regions. To achieve this, we are integrating the IPUS framework into our signal processing scheme. The IPUS framework consists of a blackboard structure for storage, and a control architecture which uses the information stored on the blackboard [8]. It is this control architecture that will select which classifiers to apply based not only on the present signals but also, thanks to the discrepancy detection capabilities of IPUS, past classifier outputs that suggest a change in mobility state or disagreement between multiple classifiers.

We are currently developing, encoding, and testing the rules that will be used by the IPUS framework within our system to adaptively invoke the various classifiers needed. Our results to date indicate that in long, stable regions (e.g., when the patient is sitting with no change in disorder state) the rules will be relatively simple to describe and implement. Conversely, more complex rules will be required in regions with transitions or discrepancies between classifier outputs.

VI. Conclusions

In this paper, we have presented a DNN solution for detecting two motor signs (tremor and dyskinesia) of Parkinson's disease using sEMG and ACC data from wireless miniaturized sensors that can be conveniently worn by PD patients. The DNN solution was found to have high sensitivity and specificity levels for second by second analysis of tremor, dyskinesia, and normal movement from test data of subjects who were not included in the training of the DNNs. We are in the process of combining these DNN solutions with a larger artificial intelligence framework to support adaptively-invoked signal processing solutions to resolve localized signal complexities. In our on-going research, we are also developing and evaluating these solutions for tracking other PD motor signs (such as bradykinesia, akinesia, freezing of gait) from sEMG and ACC wearable-sensor data.

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