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Detecting Freezing-of-Gait During Unscripted and Unconstrained Activity

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***Abstract*—We present a dynamic neural network (DNN) solution for detecting instances of freezing-of-gait (FoG) in Parkinson's disease (PD) patients while they perform unconstrained and unscripted activities. The input features to the DNN are derived from the outputs of three triaxial accelerometer (ACC) sensors and one surface electromyographic (EMG) sensor worn by the PD patient. The ACC sensors are placed on the shin and thigh of one leg and on one of the forearms while the EMG sensor is placed on the shin. Our FoG solution is architecturally distinct from the DNN solutions we have previously designed for detecting dyskinesia or tremor. However, all our DNN solutions utilize the same set of input features from each EMG or ACC sensor worn by the patient. When tested on experimental data from PD patients performing unconstrained and unscripted activities, our FoG detector exhibited 83% sensitivity and 97% specificity on a per-second basis.**

I. Introduction

FREEZING-of-gait (FoG) is a movement disorder common in patients with late-stage Parkinson's disease (PD) that can be described as a type of akinesia, or loss of movement [1]. FoG occurs during walking when the muscles in the leg are incorrectly activated by the brain; as a result, the patient is unable to initiate a step, and may momentarily "freeze" in place or even fall, leading to injury [2]. Thus the identification of FoG is of special interest to clinicians monitoring the health of PD patients. Currently, monitoring is primarily done through the use of self-report diaries completed by the patient. However, self-report diaries have been shown to be unreliable. As an example, Reimer et al. [3] report that the best agreements between self-report diaries of motor disorders and expert annotations range only between 0.49 and 0.78 using a kappa statistic.

The proliferation of wearable sensor technology and improvements in machine learning algorithms have created the possibility for development of a system that will allow clinicians to unobtrusively detect movement disorders (such as FoG) in sensor-wearing patients in their natural environment of daily living. This type of detection would offer a more accurate, objective, and reliable alternative to self-report diaries.

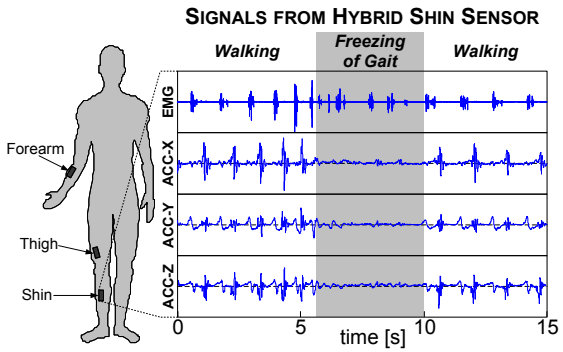

Fig. 1. Locations of the triaxial ACC and surface EMG sensors on the PD patients. Data from the ACC sensors on the forearm, thigh, and shin are used to determine whether or not the patient is upright, and data from the ACC and EMG sensors on the shin are used to detect FoG during intervals where the patient is upright. An example of the signals collected from the shin sensor of a PD patient is given. The patient is upright throughout and experiences FoG in the shaded region.

We have been developing exactly such an algorithm to detect FoG in PD patients. Our algorithm is applied to data from wireless wearable miniaturized sensors that are attached to parts of the body as illustrated in Fig. 1. Three triaxial accelerometer (ACC) sensors are placed on one forearm, thigh, and shin of the subject, while an additional surface electromyographic (EMG) sensor is placed on the shin. We have collected an extensive database from PD patients while they carried out unscripted and unconstrained activities of daily living in an apartment-like setting. Each patient was videotaped during the experiments and the resulting videotapes were annotated on a per second basis by individuals trained in identifying FoG. These annotations were then used to guide the development of a process for detecting the presence of FoG through the analysis of ACC and EMG data.

In order to understand the challenges of the FoG detection problem, consider the sample of ACC/EMG signals presented in Fig. 1. Here we see the signals for a 15-second region that includes both normal walking and FoG for a PD patient in our database. The region in which the patient experiences freezing is shaded, while the regions in which the patient is walking normally are unshaded.

During the walking regions, the patient correctly applies the force required to activate the appropriate leg muscles; this is captured in the periodic bursts of energy seen in the

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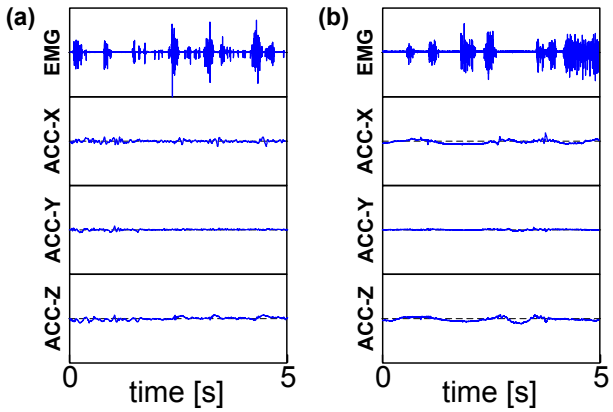

Fig. 2.Comparison of the ACC and EMG signals collected from the shin sensor of a PD patient while (a) standing still and (b) experiencing FoG. Both states show little movement in the ACC channels, and aperiodic bursts of energy in the EMG channel; this similarity makes it difficult to distinguish FoG from normal standing.

EMG signal. As this force is applied, the ACC channels register the swing of the leg as the patient takes a step, culminating in the large spike caused by the sudden deceleration due to the heel strike. These steps occur at approximately the rate of one per second.

In contrast, we see very little movement in the ACC channels as the patient experiences FoG; this is comparable to the ACC signals observed in regions where the patient is standing. However, we can still see some activation of the leg muscles in the EMG channel as the patient attempts to continue walking, though the applied activation is less periodic and contains less energy than during walking regions. It is this characteristic of the EMG signal, along with the relatively small movements seen in the ACC signals, that can be used to detect FoG. Detection is made difficult by the fact that EMG activity may be present even when the patient is standing. Fig. 2 offers a comparison of the signals seen in a PD patient while experiencing FoG and while standing normally.

II. Previous Work

There has been no previously published investigation into the detection of FoG during unscripted and unconstrained activity. However, there has been considerable effort expended in the development of algorithms for the detection of FOG during scripted activities.

Previous research by Moore et al. [4] has used a single uniaxial accelerometer placed on the shin to detect FoG in PD patients during a scripted walking and standing routine. Using a Bayesian classifier, they were able to achieve a 78% sensitivity and 80% specificity after subject-independent training. The authors admit their algorithm best detects FoG in episodes longer than 3 seconds, where an episode is defined as an interval over which FoG takes place continuously. However, our data shows that FoG frequently occurs over shorter intervals. Fig. 3 shows the distribution of FoG episode length in our testing database, which contained 87 FoG episodes across two hours of data taken from four PD patients. Of these 87 FoG episodes, 48 were 3 seconds long or less. In order to capture these shorter episodes, a more sensitive algorithm is required.

The work of Moore et al. [4] was expanded upon by Bächlin et al. [5], who used a single triaxial accelerometer placed on the knee to perform online detection of FoG in PD patients during a scripted walking and standing routine. Their algorithm incorporated additional features to distinguish standing from FoG, as well the application of a shortened window to improve detection of short duration FoG episodes. Using these modifications, they were able to create an online subject-independent Bayesian classifier with a sensitivity of 73% and a specificity of 82% on the data from the scripted walking activities.

In recent work [6], we have developed algorithms for the detection of other movement disorders during unconstrained and unscripted activities. Specifically, we have developed dynamic neural networks (DNNs) to detect time-varying occurrences of tremor and dyskinesia at one-second resolution from data acquired from triaxial ACC and surface EMG sensors worn by PD patients performing unscripted and unconstrained activities of daily living. Our DNNs were able to achieve a sensitivity and specificity of greater than 90% for both tremor and dyskinesia over an extensive 45-hour database containing both PD patients and healthy controls. However, as we will discuss, FoG detection presents a number of challenges not found in the detection of either tremor or dyskinesia; in order to meet these challenges, we needed to design a distinct FoG solution.

III. Algorithm Development

We have designed and implemented a two-stage FoG detection algorithm consisting of a linear classifier to detect when the subject is upright (i.e., standing or walking) and a DNN designed to detect FoG given that the subject is upright. This solution is architecturally distinct from our previously-designed tremor and dyskinesia solutions [6], as required by the unique challenges posed by FoG detection. For instance, while a patient may exhibit tremor and dyskinesia for minutes at a time, occurrences of FoG are

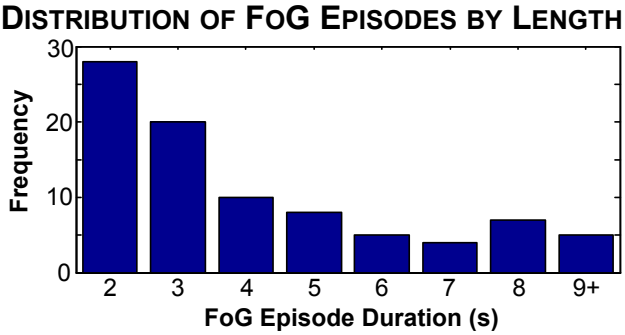

Fig. 3. Distribution of length of FoG episodes in testing database in seconds. Our testing database included 87 total FoG episodes with an average length of 4.3 seconds and a standard deviation of 2.8 seconds. The database included five episodes of length > 9 s: one of length 10s, one of length 11s, one of length 12s, one of length 14, and one of length 16s.

much more transient, and can last for only a few seconds. In addition, both tremor and dyskinesia can be detected separately in each limb, while FoG requires information from sensors on multiple limbs. As a result, we have developed a multi-sensor system to detect FoG, using the ACC and EMG sensors placed on the subject as seen in Fig. 1.

A. Detection of Upright Regions

FoG only occurs when the subject is either attempting to initiate walking while standing still or attempting to continue walking. Thus the first stage of our algorithm is the application of a linear classifier to determine when the patient is upright. The algorithm detects the upright state using the triaxial accelerometers placed on the forearm, thigh, and shin. Because the orientation of the ACCs is constant across subjects, we can use the acceleration due to gravity to measure the patient's mobility state. When the subject stands or walks, the acceleration due to gravity predominantly registers in the Y-channel of the thigh and shin ACC sensors. When the patient sits, the acceleration due to gravity registers in the Z-channel of the thigh ACC sensor while still registering in the Y-channel of the shin sensor. Furthermore, we can differentiate walking from standing regions using the energy of the ACC signals from the forearm and shin sensors.

Our linear classifier uses two input features calculated over a two-second window with one-second overlap. The algorithm calculates the percentage of samples over which the acceleration in the Y-channel has the greatest magnitude, and the percentage of samples over which the acceleration in the Z-channel has the greatest magnitude. The classifier declares the subject to be upright in those intervals where the percentage of samples where the Y-channel dominates is greater than the percentage of samples in which the Z-channel dominates.

B. DNN Architecture for FoG Detection

If our algorithm declares the subject to be upright for five or more consecutive seconds, the algorithm applies a dynamic neural network (DNN) over the interval in which the patient is upright to determine if FoG is present. We have chosen to use a DNN [7] to better capture the time-varying nature of FoG. Whereas a static neural network (SNN) can only learn time-independent weights to apply to the features of the underlying data, a DNN can learn and apply time-dependent weights. This allows DNNs to be trained to learn how features of FoG change over time. In contrast, SNNs are constrained to learning from single snapshots of the input features at particular times.

The DNN we have designed to detect FoG is a multi-layered neural network with an input layer of eleven nodes and a hidden layer of four nodes. The hidden nodes apply the weights of a 3-point FIR filter to time-delayed and time-advanced versions of the inputs, while the output node applies scalar weights to the outputs of the hidden nodes.

The eleven input nodes to the FoG DNN consist of various features designed to distinguish voluntary movements from involuntary movements, and shown to be useful in the detection of dyskinesia and tremor [6]. The algorithm extracts these features from 2-second windowed sections of the ACC and EMG sensor signals. The sensor signals are collected from customized hybrid ACC/EMG sensors that sample the signals at 1 KHz (with appropriate anti-aliasing filtering). In all, eight features are calculated from the two ACC sensors placed on the forearm and the shin, and three features are calculated from the EMG sensor placed on the shin.

IV. Results

To determine the efficacy of our algorithm, we next trained and tested our FoG classifier on ACC and EMG data collected from 10 different PD subjects and 2 control subjects. The data were collected from the sensors identified in Fig. 1 while the subject performed unscripted and unconstrained activities of daily living.

Our algorithm was trained using six minutes of data taken from six PD patients. The training data included 20 FoG episodes, each on the order of 2-3 seconds long. The training set was carefully chosen to be representative of the different manifestations of the disorder, including different FoG durations and severity levels. To improve our algorithm's specificity, our training set also included representative samples of FoG-free data from a variety of mobility states (e.g., walking, standing, and turning around), as well as intervals in which the PD patient exhibited other disorders, such as tremor and dyskinesia. This strategy allowed us to minimize the amount of training data required while still producing a classifier that generalized well over testing data.

We then created a dataset for testing which contained two hours of data (including 46 minutes of upright data) from 4 PD patients who exhibited FoG, and 12 minutes of upright data from 2 healthy controls. Our test set included 87 FoG episodes with an average duration of 4.3 +/- 2.8 seconds. The video data, the EMG data, and the ACC data within the testing database were visually inspected on a per-second basis to produce the "truth" as to when the subject was upright and, if so, whether the subject experienced FoG in the dominant leg. The trained DNN was tested on this dataset and the detection results were evaluated to determine the sensitivity and specificity of our DNN solution.

In total, we achieved a sensitivity of 83% over the 369 seconds included in the 87 FoG episodes, and a specificity of 97% over the 12 minutes of data collected from the two controls. This includes a sensitivity of 98% and specificity of 95% for our upright detection DNN. The results of testing are summarized in Table I. Fig. 4 gives examples of our algorithm's performance over two regions from our testing data: the first from a PD patient who experiences FoG, and the second from a healthy control.

These results imply that our algorithm would produce two false positive instances on average for each minute of data taken from a healthy control. Because of the risk of injury

TABLE I
TESTING RESULTS

Subject	FoG Episodes	Sens	Spec
P1	28	84.7%	---
P2	30	86.6%	---
P3	24	75.0%	---
P4	5	92.3%	---
C1	0	---	96.9%
C2	0	---	97.8%
TOTAL	87	82.9%	97.3%

Results of FoG algorithm testing on 4 PD patients (P1-P4) and 2 healthy controls (C1-C2). P2 and P4 were included in training, while P1, P3, C1, and C2 were not included in training.

due to falls [2], the presence of many FoG episodes may require adjustment of a patient's treatment, raising the cost associated with a false alarm. In order for our system to be truly useful, we must then ensure that our algorithm minimizes the false alarm rate (i.e., maximizes the specificity) even if some reduction in sensitivity may be necessary.

However, observation shows that the false positives produced by our algorithm are mostly of short duration and isolated from other regions of potential FoG. An example of this isolation can be seen in Fig. 4(b), in which three false declarations of FoG are made over a 165-second interval of data. All three potential FoG episodes have a duration of one second, and are several seconds removed from other potential FoG episodes. Given that FoG episodes frequently happen in the vicinity of other FoG episodes, and that episodes with a duration of one second are rare, a clinician can safely deduce that the examples in Fig. 4(b) do not represent instances of FoG. If we ignore as false alarms all FoG episodes of length 1s and more than 8 seconds away in each direction from another FoG episode, the algorithm's specificity improves to 99% over our testing database, while the algorithm's sensitivity becomes 82%.

V. CONCLUSION

In this paper, we have presented a DNN solution for detecting freezing-of-gait using EMG and ACC data from wireless miniaturized sensors that can be conveniently worn by PD patients. Our solution was found to detect FoG on a per-second basis at a level comparable to previous work [4,5] when tested on data from patients performing unconstrained and unscripted activities, in contrast to the scripted walking activity previously required. Furthermore, our algorithm achieved a similar sensitivity when tested on patients whose data was not used to train the algorithm, demonstrating that our algorithm can be used to detect FoG in additional subjects without the need for additional training. Thus, our algorithm is a practical solution to the problem of detecting FoG in PD patients during activities of daily living, and can be combined with previously developed algorithms for dyskinesia and tremor detection [6] as part of a holistic monitoring system to automatically and unobtrusively detect symptoms of PD in patients in their home environments.

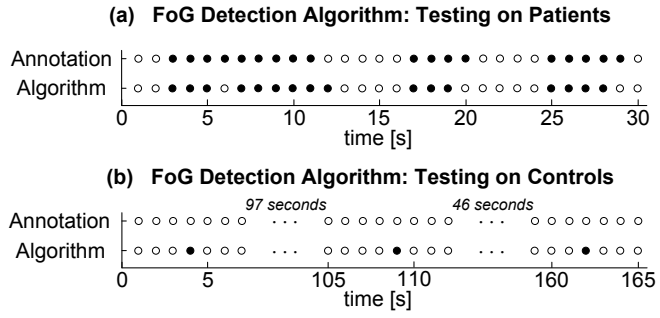

Fig. 4. Sample algorithm output for (a) a 30-second interval of data collected from a PD patient and (b) a 165-second interval of data collected from a healthy control. In both cases, the black dots represent instances where FoG is declared present.

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