# An Anomaly Detection Technique in Wearable Wireless Monitoring Systems for Studies of Gait Freezing in Parkinson's Disease

Thuy T. Pham*[1] Diep N. Nguyen [2] Eryk Dutkiewicz [2] Alistair L. McEwan[1] Philip H.W. Leong[1]

[1] Department of Electrical and Information Engineering, University of Sydney, NSW, Australia.
[2] School of Computing and Communications, University of Technology Sydney, NSW, Australia.

***Abstract*—Wearable monitoring systems have been in need for studies of gaits especially freezing of gait detection in patients with Parkinson's disease. The causality of gait freezing is still not fully understood. The histogram of gait freezing is the key assessment of the disease, thus monitoring them in patients' daily life is much appreciated. A real-time signal processing platform for wearable sensors can help record freezing time instances. However, current monitor systems are calibrated with offline training (patient-dependent) that is cumbersome and time-consuming. In this work, by using acceleration data and spectral analysis, we propose an online/real-time detection technique. Periods of low acceleration and low spectral coherence are identified and patient-independent parameters are then extracted. Using this set of new features, we validated our method by comparing it with clinicians' labels. The proposed approach achieved an overall mean (±SD) sensitivity (specificity) of $87 \pm 0.3\%$ ($94 \pm 0.3\%$). To our best knowledge, this is the best performance for automated subject-independent approaches.**

***Index Terms*—Pervasive computing, eHealth, anomaly detection, wearable sensor, aged care.**

## I. Introduction

Pervasive computing enables us to provide more effective aged care systems with real-time monitoring/aiding capability. For seniors suffering from advanced Parkinson's disease (PD), freezing of gait (FoG) is one of the most common symptoms. FoG is defined as a motor block of movement, especially before gait initiation, during turns or when meeting obstacles [1]. Reference [2] reported that 47% of PD patients had regular FoG events (28% every day). Moreover, there is a strong relationship between FoG and falls in people with PD [1], [3]. Current clinical assessment of FoG is commonly based on self-report diaries from patients (e.g. the Unified Parkinson's Disease Rating Scale-UPDRS). This method is subjective and has poor agreement with expert labels (e.g., reference [4] showed that the kappa statistic ranged from 0.49 to 0.78). An additional difficulty lies in invoking freezing in patients during routine clinical exams [5].

To help prevent FoG-associated falls in PD patients, several investigators [6], [7], [8], [9], [10] have recently proposed automatic FoG detection techniques using bioelectrical characteristics from acceleration and/or electromyographic (EMG) data. Although most state of the art detection techniques have been implemented in an offline manner, some online technologies (e.g. [8], [9], [10]) have also been proposed. Authors of works [8] and [10] used a power-threshold (P-TH) [6] and the freeze index threshold (FI-TH). While [8] utilized the Context Recognition Network (CRN) Toolbox [11], [10] used machine learning algorithms such as Random Forests (RF) and bagging with pruned C4.5 trees as base classifiers. These attempts, however, achieved moderate performance with subject-independent settings. Better results were obtained using patient-dependent thresholds (e.g. individual P-THs and FI-THs).

In order to develop a wearable device for FoG detection, subject-independent settings are highly desirable. As FoG can be considered as a departure from normal gait, we suggest that anomaly detection techniques can be used to detect FoG in real time. Frequency domain features which have been used successfully for discrimination (e.g. wavelet coefficients in [12] and spectral snapshots [13]) can be used to calculate anomaly score. In this work, we extracted spectral coherence features and applied a coherence threshold that are robust across patients to achieve a patient-independent technique. We believe our scheme is suitable for wearable wireless monitoring systems which can be used for real-time monitoring, and may become an attractive alternative to standard procedures such as diaries and expert annotations which are subjective and time-consuming.

The main contributions of this work are:

- This is the first reported gait sensor using spectral coherence, an unitless feature, for FoG detection with anomaly scores.
- We propose a novel detector for subject-independent settings using anomaly scores which, to the best of our knowledge, achieves the best reported performance.

## II. Methods

### A. Anomaly Detection

Anomaly detection refers to the identification of patterns in data that are not similar to previous behaviour. In medical applications, point anomalies are targeted to detect disease outbreaks in a specific area (e.g. anomalous records [14]) while collective anomalies are analyzed in applications of time-series data (e.g. EMG or electrocardiography data [15]). To detect freezing of gait events, we consider time periods of normal activities of the patient normal behaviour data and epochs of gait freezing anomalies. We have computed following *movement scores* as anomaly scores for the detection.

*correspondence: thuy.pham@sydney.edu.au. EIT Dept. The University of Sydney, 2006, NSW, Australia

Initially, the normal behaviour is learned from the first few windows of the unlabeled data, assuming that the subject is active and alert for at least a few seconds when data acquisition is started. In subsequent processing, the normal behaviours is updated in an online fashion. Hence, our method does not require any label in the detection process.

### B. Anomaly Scores

The standard deviation of accelerations was used as a measure of the smoothness of movement [16] [17]. Low acceleration is assumed to imply a FoG anomaly. These events are then confirmed by considering a spectral coherence measure of the epoch in question with an earlier period. We stored the previous data frame which contains no freezing event detected as the non-freezing data. Then, for every sliding window of test data, we calculate the spectral coherence between the current data and the training segment. Test data segments exhibiting low spectral coherence were then identified as putative anomalous events. Therefore, we define a set of binary movement scores which consists of an acceleration indicator $S_{Ac}$ and a spectral coherence score $S_{speco}$.

$$S_{AC} = sgn((X - (\overline{X} - \sigma))_+) \tag{1}$$

where $X$ is a set of acceleration data, $\overline{X}$ and $\sigma$ are the mean and the standard deviation of $X$, respectively, and $sgn(a)$ is a sign function of $a$ while $(a)_+$ is a function which returns $a$ only if $a \geq 0$ otherwise returns 0.

Let $C_{xy}$ be spectral coherence between discrete signals $x$ and $y$. $C_{xy}$ is defined by the Welch method [18] as:

$$C_{xy}(\omega) = \frac{P_{xy}(\omega)}{\sqrt{P_{xx}(\omega).P_{yy}(\omega)}} \tag{2}$$

where $\omega$ is frequency, $P_{xx}(\omega)$ is the power spectrum of signal $x$, $P_{yy}(\omega)$ is the power spectrum of signal $y$, and $P_{xy}(\omega)$ is the cross-power spectrum for signals $x$ and $y$. When $P_{xx}(\omega) = 0$ or $P_{yy}(\omega) = 0$, then also $P_{xy}(\omega) = 0$ and we assume that $C_{xy}(\omega)$ is zero. To estimate power and cross spectra, let $\mathfrak{F}_x(\omega)$ and $\overline{\mathfrak{F}_x(\omega)}$, denote the Fourier transform and its conjugate of signal $x$, respectively, i.e. $\mathfrak{F}_x(\omega) = \int_{-\infty}^{+\infty} x(t).e^{-j\omega t}dt$. The power spectrum is then: $P_{xx}(\omega) = \mathfrak{F}_x(\omega).\overline{\mathfrak{F}_x(\omega)}$; $P_{yy}(\omega) = \mathfrak{F}_y(\omega).\overline{\mathfrak{F}_y(\omega)}$; and $P_{xy}(\omega) = \mathfrak{F}_x(\omega).\overline{\mathfrak{F}_y(\omega)}$. Given a desired resolution of Fourier transformation $\Delta_f$ $(Hz/point)$ with a sampling frequency $f_s$, the window length should be $N_{FFT} \geq \frac{f_s}{\Delta_f}$. Furthermore, reference [8] suggested at least 10 frequency components between $0.5Hz$ and $3Hz$, therefore $N_{FFT}$ should be at least $4f_s$. For comparison purposes, we choose $N_{FFT} = 4f_s$.

Small coherence values $C_{xy}(\omega)$ indicate that the test and the non-freezing data segments are weakly correlated while large values indicate that the correlation is high. For a given window of data, the binary score $S_{speco}$ is calculated by (3).

$$S_{speco} = \begin{cases} 1, & \text{if } N_{peak} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $N_{peak}$ is the number of peaks in $C_{xy}(\omega)$ that are greater than a specified correlation threshold level $\Theta_{speco}$.

### C. Online FoG Detection Scheme

As the normal behavior of a freely moving patient changes through time, we need to dynamically update the *non-freezing event* profile. We assume that data segments with very low anomaly score (or zero value for a binary score) are examples of normal behaviour of the patient. Hence, the non-freezing profile is learned with the latest normal period.

Let $X$ represent a data segment recorded from an accelerometer attached to a subject. $S_{AC}$ is first computed from data (Fig. 1) and windows of data are cached for further calculation. Initially, the first few windows of data with zero $S_{AC}$ are considered to be normal behaviour data. The normal behaviour profile, *nom*, is updated with previous windows of data for with a positive flag ($autoflag = 1$) interpreted as "a non FoG event". To calculate $C_{xy}$ and $S_{speco}$ for every sliding window of $w$ second, *nom* is used as a reference. Observations of both low acceleration and low spectral coherence are used to find FoG events (Algorithm 1).

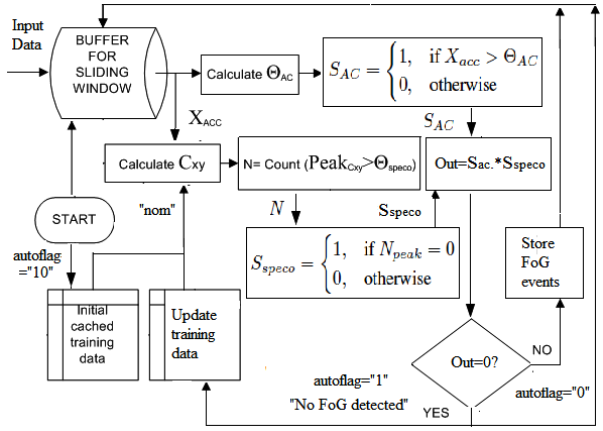


Fig. 1. Anomaly score calculation.

### D. Data Set

We tested our method on a recently published dataset from DAPHNet [8]. This dataset was recorded from experiments on 10 advanced PD patients who had regular FoG events. The patients undertook three walking tasks ($10-15$ minutes each task). As illustrated in Fig. 2, three tri-axial accelerometers were attached at the shank, thigh, and lower back using elasticized straps. Data was recorded at $64Hz$ and transmitted via a Bluetooth link. Annotation and simultaneous video taping were used by physiotherapists to determine the number and exact start/end times of FOG episodes [8]. According to these labels, 237 freezing events were recorded. The mean duration of freezing events was $7.3 \pm 6.7s$, and 50% of the FoGs lasted for less than $5.4s$; 93.2% were shorter than $20s$ (Fig. 2). These labels were used as references in evaluating our technique.

### E. Performance Metrics

Sensitivity represents the proportion of correct *"FoG"* windows detected (considering the clinician's labels as the "ground truth"). The specificity represents the proportion of

**Algorithm 1** FoG detection scheme

**Input:** $X$,$w$,$\Theta_{speco}$; % channel X, window, & threshold
**Output:** $Out$; % FoG detection outcome
**Begin**
  $k$=1; $buf$=$2*w$; $autoflag$=10;
  While $(k < length(X) - buf + 2)$
    If $autoflag$==10 then $nom \leftarrow X(w : 2*w-1)$;
    ElseIf $autoflag$==1 then $nom \leftarrow X(k-buf : k)$
    $X_{buf}$= $X(k : k+buf)$;
    $S_{Ac}$(k:k+buf)= $(X_{buf} < \overline{X_{buf}} - \mathrm{Std}(X_{buf}))$;
    i=1;  c=0;
    While $(i < length(X_{buf}))$
      $X_{win}$= $X_{buf}(i : i+w)$;
      $C_{xy}$= $\frac{P_{xy}(\omega)}{\sqrt{P_{xx}(\omega).P_{yy}(\omega)}}$
          where $x \leftarrow nom$ and $y \leftarrow X_{win}$;
      $N$= Count(Peak($C_{xy}$)> $\Theta_{speco}$);
      $S_{speco}(i : i+w)$= $(N == 0)$;
      $Out$(k+i:k+i+w)= $S_{speco}(i : i+w).*S_{Ac}(i : i+w)$;
      $i = i+w$;
    End;
    If $Out$(k:k+buf)==0 $autoflag$=1; Else $autoflag$=0;
    k=k+buf;
  End;
**End**;

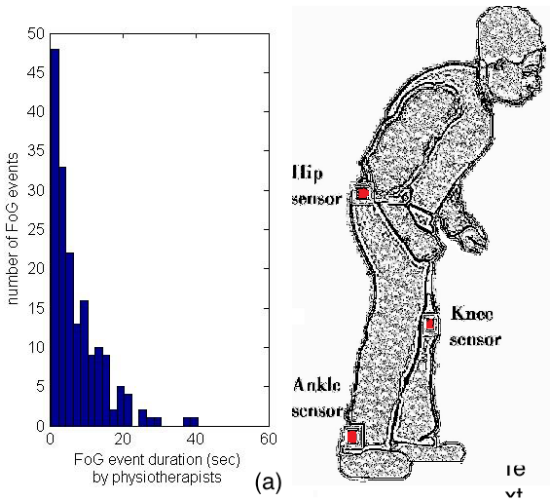


Fig. 2. a: Histogram of FoG episode durations by annotations. It has a mean of $7.5 \pm 7s$; range $0.5s$-$40.5s$. Most of events last less than $20s$. b: Three tri-axial accelerometers were attached at the shank, the thigh, and the lower back.

correct *"No-FoG"* windows. Windows which were labelled the same as the annotation were denoted as True Positives (TP), and windows labelled as FoG which did not agree with the ground truth were denoted as False Positives (FP). Windows that we failed to label as FoG but were annotated as such, were defined as False Negatives (FN). When our method and the annotation agreed that there was "No-FoG", the window was counted as a True Negative (TN). Because non-freezing events vastly outnumber freezing events, we use F1-score [19] which is the harmonic mean of precision and sensitivity for detection evaluation. F1-score is calculated as $\frac{2TP}{(2TP+FP+FN)}$ with best being 1 and worst 0.

## III. Results

### A. Parameter Settings

We analyzed the performance of our method for every data channel by varying two parameters $\Theta_{speco}$ from 0.1 to 1 and $w$ from $0.2s$ to $1s$. Fig. 3.a shows the receiver operating characteristic (ROC) versus $\Theta_{speco}$ and $w$. Each marked point in the figure represents the mean performance over all three sensor locations and all tested subjects. We have observed that when $\Theta_{speco}$ increases, the sensitivity increases dramatically from $0.28 \pm 0.25$ to $0.81 \pm 0.29$ while the specificity decreases slightly from $1.00 \pm 0.05$ to $0.81 \pm 0.06$. This suggests a high precision configuration for any subject with a $\Theta_{speco}$ range of $0.4 - 0.6$.

### B. FoG Detection Experiments

The set of $\Theta_{speco} = 0.4$ and $w = 0.6s$ gives excellent performance for all tested patients and their sensors, with F1-score in Fig. 3b. The performance of this configuration was best with windowing step range from $0.6s$ to $0.7s$. Hence, the settings of these global $\Theta_{speco}$ and global windowing step yield a high performance subject-independent configuration which is higher than other independent methods and is comparable to other dependent methods as in [8] (Table I).

TABLE I
FoG Detection Performance comparison with subject-independent settings.

| Features and techniques used | Sensitivity | Specificity |
|---|---|---|
| P-TH and FI-TH using Random Forests classifier (off-line training) [10] | 66.25% | 95.38% |
| P-TH and FI-TH using CRN Toolbox [8] | 73.1% | 81.6% |
| Spectral coherence threshold using an on-line anomaly detection technique (this work) | 87 ± 0.3% | 94 ± 0.3% |

With the aforementioned subject-independent settings, Fig. 4 illustrates an example of our anomaly detection method at the ankle of patient ID3. The first trace (top) is the acceleration data from channel *ChX* (anterior/posterior). The amplitude of the trace was normalized for presentation purposes. The middle trace is the expert's annotation *ChLabel*. The bottom trace is our detection result *ChOut*. In the last two traces "0" corresponds to no-freezing and "1" to freezing. In general, our technique detected most FoG events with small delays.

In terms of FoG episode durations, the mean (± SD) duration we estimated was $11 \pm 8$ seconds with a range from $3s$ to $60s$. These values are close to those identified from the annotations ($7.5 \pm 7s$; range $0.5s$-$40.5s$). Our method and the annotations agreed that most of FoG events last less than $20s$. In partial concordance with the clinical annotations described above, prediction of freezing fell to 86% for the data of the patient (ID1) with foot drop. Zero F1-score cases are also detected for patient ID10 and ID4 for which no freezing of gait events were recorded. Among three locations, sensors at the knee yielded a higher sensitivity than the others. The distribution of metrics for the entire datasetare presented in Table. II.

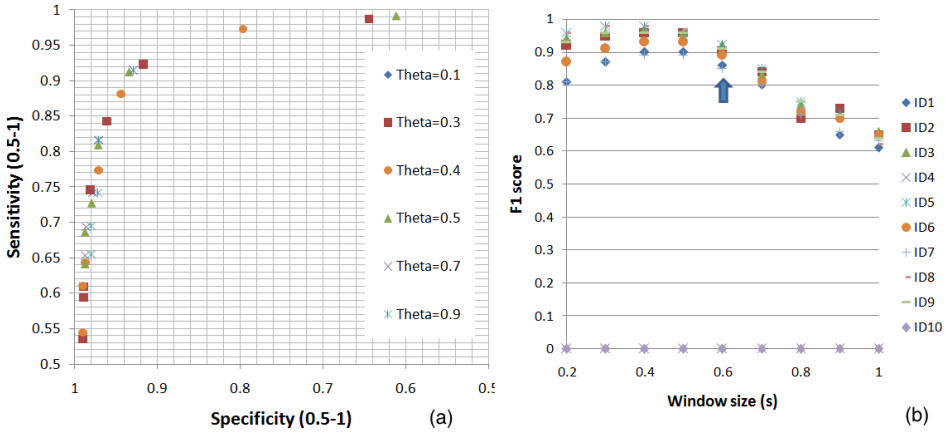


Fig. 3. a: Performance (ROC) of our method versus $\Theta_{speco}$ and window size $w$ in a range of interest $(0.5-1)$. b: F1-score was measured individually accross varied $w$ ($\Theta_{speco}=0.4$). The optimal $w=0.6s$ is suggested for a subject-independent setting.

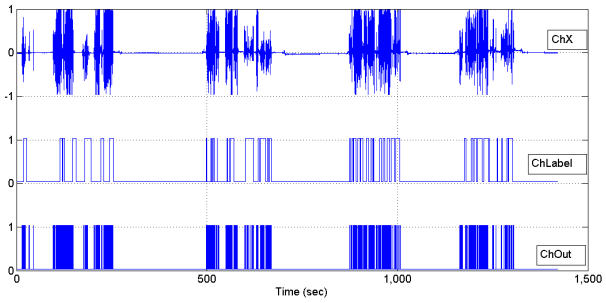


Fig. 4. Example of FoG detection by our method at ankle sensor of patient ID3. The top trace is the data from channel *ChX* (anterior/posterior). The next two traces are the expert's labels and our method ("0": *no-FoG* and "1": *FoG*).The amplitudes were normalized for presentation purposes.

TABLE II
PERFORMANCE DISTRIBUTION AMONG SENSOR PLACEMENTS.

| Sensor | Sensitivity | Specificity | Accuracy | F1-score |
|---|---|---|---|---|
| Ankle | $86\pm36\%$ | $94\pm1\%$ | $91\pm2\%$ | $71\pm38\%$ |
| Knee | $88\pm37\%$ | $94\pm1\%$ | $92\pm3\%$ | $72\pm38\%$ |
| Hip | $87\pm37\%$ | $94\pm1\%$ | $92\pm3\%$ | $72\pm38\%$ |

## IV. DISCUSSION

Comparing with the current 'gold standard' clinical method, time-frequency domain analysis offers an objective scheme and can be used in standardized protocols [20]. However, automatic FoG detection still has several difficulties. First, we need to find well-defined FoG features and a better understanding of FoG pathogenesis [21]. A recent review of FoG studies [22] concluded that gait pattern generation disturbances are central to FOG rather than a combined motor and cognitive de-automatization deficit. Therefore, our future work will also consider the cerebral basis of FOG. Finally, the large variability in motor performance due to different walking styles makes it hard to accurately detect FoG, especially with a limited data set as used in this study. In the future, we will extend this study to a larger group of advanced PD patients. We also will explore the effect of varying range of the frequency components in our $C_{xy}$ calculations.

## V. CONCLUSION

This study proposed a patient-independent FoG detection in Parkinson patients using anomaly detection algorithms. Such a subject-independent FoG detection method is a key enabler for a more effective eHealth system for seniors. For that purpose, we applied a time-frequency domain analysis and introduced a new feature based on spectral coherence. We validated our detection scheme by comparing its results with expert annotations made by physiotherapists. Over a set of 10 subjects with advanced Parkinson's disease, we achieved an overall mean ($\pm$SD) sensitivity (specificity) of $87\pm0.3\%$ ($94\pm0.3\%$). For the knee, ankle, and hip sensors, the accuracies were $92\pm3\%$, $91\pm2\%$, and $92\pm3\%$, respectively. The results showed a strong agreement with the diagnostic notes for four special patients among tested subjects. Furthermore, predicted durations of freezing were similar to those identified by clinicians.

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