Wearable Healthcare Systems: A Single Channel Accelerometer Based Anomaly Detector for Studies of Gait Freezing in Parkinson's Disease

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***Abstract*—The causality of gait freezing in patients with advanced Parkinson's disease is still not fully understood. Clinicians are interested in investigating the freezing of gait (FoG) histogram of patients in their daily life. To that end, one needs a real-time signal processing platform that can help record freezing information (e.g., timing and the duration of every gait freezing occurrences). Wearable wireless sensors have been proposed to monitor FoG epochs. Existing automated methods using accelerometers have been introduced with high accuracy performance only for subject-dependent settings (e.g., an individual offline training process). This is a troublesome for large scale out-of-lab deployment and time-consuming. In this work, we used spectral coherence analysis for accelerometer data to apply an anomaly detection approach. Conventional features such as energy and freezing index are introduced to help refine normal epochs while the anomaly scores from spectral coherence measures define FoG epochs. Using this new set of features, our new FoG detector for subject-independent settings achieves the mean $\pm$SD sensitivity (specificity) of $89.2 \pm 0.3\%$ ($95.6 \pm 0.3\%$). To our best knowledge, this is the best performance for automated subject-independent approaches in literature of freezing of gait detection.**

***Index Terms*—Anomaly detection, wearable sensor, aged care.**

I. Introduction

Real-time monitoring systems using pervasive computing have been providing more effective aged care systems. One of the most common symptoms in patients with advanced Parkinson's disease (PD) is freezing of gait (FoG) that associate with falls [1], [2], [3]. FoG is described as a motor block of movement (e.g., before gait initiation, during turns, or when meeting obstacles) [1]. Self-report diaries from patients (e.g. the Unified Parkinson's Disease Rating Scale-UPDRS), that is commonly used as current clinical assessment of FoG, is subjective and has poor agreement with expert labels [4]. Freezing of Gait Questionnaire [5]) and manual video analysis of walking [6], [7] have been introduced to improve UPDRS but they are unfortunately also subjective [8]. The intra-rater reliability of existing manual video assessments was low and not robust (within or between patient sites) [8]. Hence, objective FoG detection is much desirable [9][10]. Moreover, it is difficult to invoke freezing status in participants during routine clinical exams [11], thus out-of-lab deployment is also of interest.

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Recently, small wearable devices that were designed to detect FoG events have been proposed [12], [9], [13], [14], [15], [16], [17], [18], [19], [10]. Most of these works used data from accelerometers and a few used electromyographic (EMG) data. There have been works proposed for online operation mode (e.g., [15], [16], [17]); others have been implemented in an offline methods. In terms of feature extraction, frequency analysis techniques for energy (P) [12][15] and freezing index (FI) [9] have been most used. Regarding detection algorithms, the Context Recognition Network (CRN) Toolbox [20] was utilized in [15] or machine learning based Random Forests (RF) used in [17]. Most of other works have utilized simple thresholding methods [12], [9], [13], [14], [18], [19], [10]. Nevertheless, only moderate performance was achieved in subject-independent settings (better results were obtained using subject-dependent thresholds).

When deploying as a wearable healthcare assistant in out-of-lab environment, subject-independent settings are highly desirable. Avability of a specialist and training the machine for each user is not practical for a massive deployment. In one of our prelimitary works [21], we have intensively reviewed existing and our novel feature extraction methods towards the subject-independent settings. From a large pool of 244 feature candidates, we found 33 most relevant and discriminative ones by three saliency criteria (after two rounds of selection). During the third round of process, we consider FoG as a departure from normal gait therefore suggested to use anomaly detection techniques for FoG monitoring in real time. Using a simple thresholding filter to detect FoGs, the so-called anomaly score detector (*ASD*) [21] limited this list to seven features that have had high accuracy metrics. All of them were freezing index features. One of them is extracted from multi-channel and the rest are single channel. Though the vertical axis input at ankle sensor was often used in literature works has been also included in our final list of selection, several other single channels at other sensor locations have been showed comparable.

In this work, we aim to evaluate further the third round of feature selection in [21] in which the outcome most depends on a given detection model. Our previous model used a threshold calculated from the average values with the unity scaling factor. In this model, we investigate incorporating findings of freezing index's relevancy in a novel threshold calculation. In the previous result of feature ranking using correlation and clusterability metrics, spectral coherence of snapshots have been highly ranked. We are interested in the coherence feature as it is unitless and intiutively ranges from 0 to 1 for the

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similarity metrics. Unitless features are often the best choice for subject-independent measurements as it can tolerate amplitude distortion due to artefacts during acquiring data especially for daily activities monitoring. Hence, we propose to use spectral coherence measurement for anomaly scores and incoporate abnormal freezing index for internal estimation of *normal* epochs.

The main contributions of this work are:

- A feature evaluation for combination of energy and spectral coherence features to refine the normal gait instances for FoG detector using anomaly scores is first reported .
- A novel model of FoG detection is proposed which, to the best of our knowledge, achieves the best reported performance for subject-independent settings.

II. Methods

A. Data Set

We developed and tested our method on a recently published dataset from DAPHNet [15]. There were 10 patients with advanced Parkinson's disease (i.e., had regular freezing event). Note that the proposed method uses an unitless correlation measurement that may not suffer from amplitude-related subject variablity and the inherent scheme of dynamic threholds learned within the recording make the size of development dataset not need to be large.

Participants attached three tri-axial (x - anterior/posterior, y - medial/lateral, z - vertical) accelerometers at three locations: the shank, thigh,and lower back. Each subject implemented three walking tasks (about $10-15$ minutes). Data from sensors were recorded at $64Hz$ and wirelessly transmitted (via a Bluetooth link). Labels/annotation were created by physiotherapists using video taping analysis to determine the timing of FoG events. According to the labels, FoG events last for $7.3\pm6.7s$ (50% less than $5.4s$; 93.2% were shorter than $20s$). We use this manual annotation as reference in performance evaluation for the proposed automated method.

B. Feature Extraction

1) Freezing index: Freezing gait has been found in the work [12] containing high frequency components ($6\rightarrow 8Hz$) compared with normal gait ($2Hz$) . A freezing index (FI) is defined as the power in the *freeze* band ($3\rightarrow 8Hz$), P_H, divided by the power in the *locomotor* band ($0.5\rightarrow 3Hz$), P_L [9]. The power, P, and freeze index FI values are computed as in Eq.1 and Eq. 2.

$$P = P_H + P_L \tag{1}$$

$$FI = \frac{P_H}{P_L} \tag{2}$$

where

$$P_H = \frac{\sum_{i=H_1+1}^{H_2}[P_{XX}(i)] + \sum_{i=H_1}^{H_2-1}[P_{XX}(i)]}{2fs} \tag{3}$$

$$P_L = \frac{\sum_{i=L+1}^{H_1}[P_{XX}(i)] + \sum_{i=L}^{H_1-1}[P_{XX}(i)]}{2fs} \tag{4}$$

and $H_1 = \frac{3N_{FFT}}{fs}$, $H_2 = \frac{8N_{FFT}}{fs}$, $L = \frac{0.5N_{FFT}}{f_s}$. $P_{XX}(\omega) = \mathfrak{F}_x(\omega).\overline{\mathfrak{F}_x(\omega)}$.

2) Spectral Coherence: Let x and y be two consecutive data windows. The correlation in frequency between x and y, called spectral coherence C_{XY}, is measured using the Welch method [22] as $C_{XY}(\omega) = \frac{P_{XY}(\omega)}{\sqrt{P_{XX}(\omega).P_{YY}(\omega)}}$where ω 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 $P_{XY}(\omega)=0$ and we assume that $C_{XY}(\omega)$ is zero. Note that when $C_{xy}(\omega)$ is small, x and y are weakly correlated in frequency domain.

C. Anomaly Detector

To detect freezing of gait events, we consider time periods of normal activities *normal behaviour* data and freezing epochs anomalies.

1) Normals and Anomalies: Normal epochs are predicted using the smoothness of activities and the dominated at low-band of the power distribution. This hypothesis has been demonstrated in our prelimitary work [21] when examining salient features from a large exploratory feature pool. Accumulating these *normal* epochs, we estimated continously the average of *normal* power features. Specifically in this work, the power and freezing index values P_x and FI_x have the average values μ_P and μ_{FI} respectively. If the current tested data epoch has abnormal P_x and FI_x (i.e., getting over the current thresholds) and has a failure test of the spectral coherence with the latest *normal* epoch, the current epoch is considered an anomaly. Otherwise, the theshold values are updated with this epoch. Note that our μ_P and μ_{FI} are only averaged continously from estimated normals thus are different from the fixed thresholds found in the literature (e.g., [9] [15] [17]) that are averaged from entire several measurements.

2) FoG Detection with μ_P and μ_{FI} : Let X represent a data segment recorded from a channel of an accelerometer attached to a subject. We compute a set of binary movement scores which consists of a low acceleration S_{AC} and a spectral coherence S_{speco} indicators. $S_{AC} = sgn((X-(\overline{X}-\sigma))_+)$ where $\overline{X}$ and σ are the mean and standard deviation of X and $sgn(x)$ is a sign function of x while $(x)_+$ is a function which returns x only if $x\geq 0$ otherwise it returns 0. $S_{speco}=1$ if the number of peaks in $C_{xy}(\omega)$ that are greater than a specified correlation threshold level Θ_{speco} otherwise $S_{speco}=0$.

From the learned information of *Normal*, dynamic thresholds μ_P and μ_{FI} are updated when a flag is asserted (Algorithm 1). Note that the flag is initialized at 10 to differentiate the beginning stage of the process from later stages of detection in which the flag changes between 1 and 0 (depending on if a FoG event is detected or not).

D. Performance Metrics

To evaluate accuracy performance of the proposed method, we note following measures. Windows which were labelled the same as annotation are True Positives (TP). Windows labelled as FoG which did not agree with the ground truth are False

Algorithm 1 FoG Detection Algorithm with μ_P and μ_{FI}.

Input:
X is from channel X
Output:
Out is FoG detection outcome
Parameters:
w is window size
Θ is minimum coherence level
Main
k=1; *buff*=2*w;
flag=10;
Ω Ψ are empty;
While $(k < length(X) - buff)$

$$Normal = \begin{cases} X(1:w), & \text{if } flag = 10 \\ X(last:last+w), & \text{if } flag = 1 \end{cases}$$

$[P_{Normal}, FI_{Normal}]$= *ComputePFI*(*Normal*)
$\Omega \supseteq P_{Normal}$;
$\Psi \supseteq FI_{Normal}$;
μ_P = mean(Ω);
μ_{FI} = mean(Ψ);
$[P_x, FI_x]$= *ComputePFI*(x)
S_{freeze}=$((P_x > \mu_P)\&(FI_x > \mu_{FI}))$;
$S_{Ac}(k:k+buff)$ is computed from Eq.**??**
S_{speco}=*ComputeCxy*(X_{buff}, *Normal*, w, Θ);
If $(S_{freeze}(k:k+buff) = 1)\&$
$((S_{freeze}(k-buff:k-buff+w) = 0)\&$
$((S_{Ac}(k-buff:k-buff+w)$=0)
$\|(S_{speco}(k-buff:k-buff+w)$=0)));
Out=1; *flag*=1; *last*=k-*buff*;
Else *Out*=0; *flag*=0;
k=k+buf;
End of while
End
Subfunctions:
$[P, FI]$=*ComputePFI*(x) by Eq. 1, 2
$[S_{speco}]$=*ComputeCxy*(x, *Normal*, w, Θ)
i=1; c=0;
While $(i < length(x))$
X_{win}= $x(i:i+w)$;
C_{XY} is computed from *Normal* and X_{win};
N= Count(Peak(C_{XY})> Θ);
$S_{speco}(i:i+w)$= $(N = 0)$;
$i = i+w$;
End of while
} end of subfunction

Positives (FP). Windows labelled as Normal by the proposed method but were annotated as FoG are False Negatives (FN). The window that was labelled as Normal by both are True Negative (TN). The sensitivity was calculated as $\frac{TP}{TP+FN}$ and the specificity was calculated as $\frac{TN}{TN+FP}$. We also use the harmonic mean of precision and sensitivity, F1-score [23]. F1-score=$\frac{2TP}{(2TP+FP+FN)}$ with best being 1 and worst 0.

III. Results

A. Development Stage

To find the optimized parameters, we use the receiver operating characteristic (ROC) versus Θ_{speco} and w. Parameter Θ_{speco} to compute S_{speco} is varied in a wide range ($0 \rightarrow 1$ in steps of 0.1). The window size of sliding method is also examined from $0.2 \rightarrow 1$ s. Fig. 1 shows details of these ROCs measurement. Each illustration point in the figure, that is for a couple of (Θ_{speco}, w), is the mean performance over three sensor locations (ankle, hip, trunk) and across subjects. When Θ_{speco} increases, the sensitivity increases dramatically from 0.28 ± 0.25 to 0.81 ± 0.29 while the specificity decreases slightly from 1.00 ± 0.05 to 0.81 ± 0.06. This suggests a high precision configuration for any subject with a Θ_{speco} range of $0.4 - 0.6$.

With the parameter settings of ($\Theta_{speco} = 0.4$, $w = 0.6s$), the mean $\pm$ SD of FoG event duration we detected was 11 ± 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 $20s$.

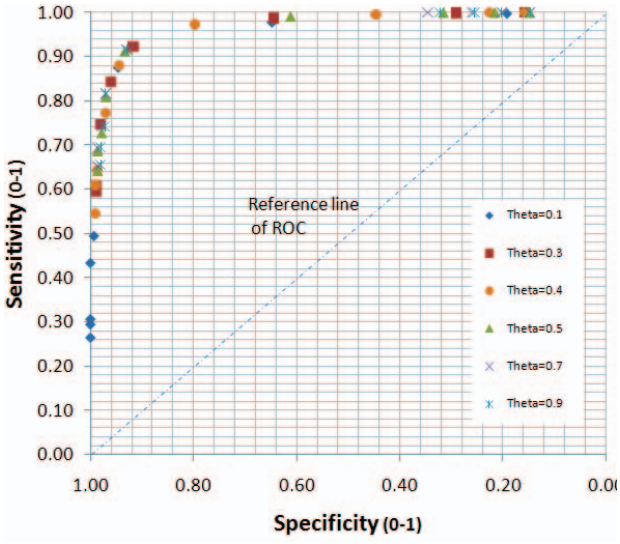

Fig. 1. a: Performance (ROC) of our method versus Θ_{speco} and window size w in a range of interest $(0-1)$. The optimal ($\Theta_{speco} = 0.4$,$w = 0.6s$) is suggested for a subject-independent setting.

Table I demonstrates that our dynamic threshold (settings (a): μ_P, μ_{FI}) are comparable to those personalized parameter of the literature works (settings (b): fixed subject-dependent Power-TH, Freeze-TH).

Among three locations, sensors at the knee yielded a higher sensitivity than the others. The distribution of metrics for are presented in Table. II.

B. FoG Detection Comparisons

Compared with the manual labels by specialists, we noticed the partial concordance of a moderate overall identification of freezing (e.g., fell to 86%) in the case of patient with foot drop (e.g., patient ID1). For participants who had no freezing of gait events, the proposed method also did not dectect any FoG event (e.g.,patient ID10 and ID4).

According to results reported in the literature, the proposed method yields a better subject-independent performance (Table III). The compared results are reported as they were in

TABLE I
COMPARABLE VALUES OF ENERGY THRESHOLDS BETWEEN (A): MEAN DYNAMIC THRESHOLDS FOR EACH SUBJECT AUTOMATICALLY LEARNED IN OUR METHOD AND (B): RANGES OF FIXED THRESHOLDS FOR SUBJECT-DEPENDENT SETTINGS USED IN [15]. NOTE THAT OUR METHOD DOES NOT HAVE TO SPECIFY THESE VALUES BUT AUTOMATICALLY LEARNS AS VARIABLES. THIS ILLUSTRATION IS FOR EXPLANATION PURPOSES ONLY.

	(b) individual in [15]		(a) dynamic thresholds	
Subjects	PowerTH in 2^x	FreezeTH	μ_P in 2^x	μ_{FI}
Patient 01	12	3	17.55	3.55
Patient 02	16	1.8	18.78	2.11
Patient 03	15	4	17.52	3.81
Patient 05	11.5	1.6	17.30	1.67
Patient 06	10	1	17.57	1.34
Patient 07	8.5	2.5	17.04	1.36
Patient 08	8	3	15.44	11.72
Patient 09	7	2.5	16.7	2.19

TABLE II
PERFORMANCE DISTRIBUTION AMONG SENSOR PLACEMENTS.

Sensor	Sensitivity	Specificity	F1-score
Ankle	$94.91 \pm 2.3\%$	$94.18 \pm 2.9\%$	$91.73 \pm 1.6\%$
Knee	$91.09 \pm 4.1\%$	$95.91 \pm 1.3\%$	$90.18 \pm 2\%$
Hip	$88.13 \pm 5\%$	$96.63 \pm 0.7\%$	$89.83 \pm 3\%$

TABLE III
FOG DETECTION PERFORMANCE AGAINST EXISTING METHODS [15] [a] [17] [b] [18][19] [c] [d]) ACROSS CONFIGURATIONS [e] AND DATASETS. PERFORMANCE IN %.

	Settings			Performance (%)	
Method	*Input*	*Win*	*Tol*	Sensitivity	Specificity
CNR [15]	Single channel, FI0y, Psum0y	4s	*2s*	73.1[a]	81.6[a]
Learning [17]	Single channel, Mean0y, Std0y, FI0y, Energy0y	4s	1s	66.25 [b]	95.38 [b]
Global [18]	Multi-channel, FI012y[d], $\overline{FI} = 3$	7.5s	-	84.3 [c]	78.4 [c]
Global [19]	Single channel,FI2x, $\overline{FI} = 1.47$	2s	-	75.0 [c]	76.0 [c]
Anomaly detection based (This work)	Single channel, FI0y, Std, Spectral coherence	6s	0.4s	89.2	95.6

[a] as reported in [15] using CNR classifier and LOOCV.
[b] as reported in [17] using Random Forest classifier and LOOCV.
[c] for event-based calculation while others were for timing-based.
[d] the majority vote of *seven sensors* [18].
[e] *Input*: features, sensors, and axes. '*Tol*': tolerance. '*Win*': window size.

literature works. The first compared work is the work [15] that used CNR classifier and energy features only. The second existing work in the table is also an semi-supervised method that used Random Forest classifier and statistical features apart from energy ones. The other compared methods were not online methods and only focused on freezing index features.

IV. DISCUSSION

Time-frequency domain analysis can provide an objective scheme to detect freezing of gait events while the current practices still are subjective methods such as patient's self-report questionaires (e.g., the Unified Parkinson's Disease Rating Scale-UPDRS, Freezing of Gait Questionnaire [5]) or manual specialies' video analysis of walking [6], [7].

The main difficulty of deploying objective wearable sensors for FoG detection lies on the current moderate accuracy performance in a subject-independent settings. Because of the large variability in motor performance (e.g., due to different walking styles), it is hard to accurately detect FoG in subject-dependent settings. Using anomaly score to dynamically update threshold levels during FoG detection process, our proposed method enables a high accuracy performance achievement in the subject-independent settings. Other challenges for future works of FoG detection include a better understanding of FoG pathogenesis [25] as well as the cerebral basis of FOG and real-life large scale evaluation of out-of-the-lab FoG detector device deployment.

V. CONCLUSION

In this work, a subject-independent FoG detection scheme is proposed. The main points of our system include utilising spectral coherence analysis to define anomaly scores for FoG events. *Normal* events are learned by using energy and freezing index features. Such a subject-independent FoG detection method is a key enabler for a more effective health care system for aged people especially for patients with advanced Parkinson's disease. We compared our FoG detector with expert annotations made by physiotherapists and other existing automated methods. We achieved an overall mean $\pm$SD sensitivity (specificity) of $89.2 \pm 0.3\%$ ($94 \pm 0.3\%$). For the knee, ankle, and hip sensors, the accuracies were $92 \pm 3\%$, $90.1 \pm 2\%$, and $89.8 \pm 3\%$, respectively. To our best knowledge, this is the best performance for subject-independent approaches.

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