Automatic Identification of Motor Patterns Leading to Freezing of Gait in Parkinson's Disease

An Exploratory Study

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Abstract: Freezing of gait (FOG) is a common and disabling gait disturbance among patients with advanced Parkinson's Disease (PD). FOG episodes are often overcome using attention or cues from the environment. Hence, identification of events prior to FOG may be very effective to improve mobility in PD patients. Previous work has suggested that there are changes in the gait pattern just prior to freezing. Nonetheless, little work has been done to explore the possibility of identifying motor patterns that are characteristic of the pre-FOG phase (few seconds before the FOG). We analysed the acceleration signals from sensors worn on the ankle, thigh, and trunk of eight patients with PD who experienced freezing. We translated windows of the raw signals in symbols by using Symbolic Aggregate approXimation. The aim was to discriminate the patterns of symbols characterizing pre-FOG from the ones characterizing normal activity (standing and walking with no FOG). Sensitivity over 50% and Specificity over 70% were obtained by using a classifier on symbolic data, with different combinations of sensor position/sampling/windows duration. These preliminary findings demonstrate that it is possible to automatically identify (some of) the motor patterns that eventually lead to FOG events before they occur by using wearable sensors.

1 INTRODUCTION

Freezing of gait (FOG) is a disabling gait disturbance that is common among patients with advanced Parkinson's Disease (PD). FOG can manifest as an impairment of the initiation and termination of gait and as a sudden interruption of walking (Nieuwboer, 2004). During the FOG episode the patients feel as if their feet are glued to the ground and cannot resume walking. Recent work has focused on using wearable motion sensors to detect freezing of gait (FOG) as soon as it starts (Bächlin, 2010); (Moore, 2013); (Mazilu, 2013), obtaining satisfactory accuracies. Although previous work has suggested that there are changes in the gait pattern just prior to freezing (Nieuwboer, 2004), only one work has recently explored the possibility of identifying motor patterns that are characteristic of the pre-FOG phase (i.e., a few seconds before the FOG happens) (Mazilu, 2013). FOG episodes are often overcome using attention or cues; hence, identification of events prior to FOG may be very effective to improve mobility in PD patients by producing an auditory cue just before the FOG starts. This is why in the current study we focused on identification of the pre-FOG phase: we analyzed the acceleration signals from sensors worn on the ankle, thigh, and trunk of eight patients with Parkinson's disease who experienced freezing (Bächlin, 2010). We translated windows of the raw signals in sequences of symbols by using SAX (Symbolic Aggregate approXimation) (Lin, 2002; 2003). A previous work applied this technique to study gait symmetry in patients with PD (Sant'Anna, 2011). The aim of the current study was to discriminate the patterns of symbols characterizing pre-FOG from the ones characterizing normal activity (i.e., standing and walking with no FOG).

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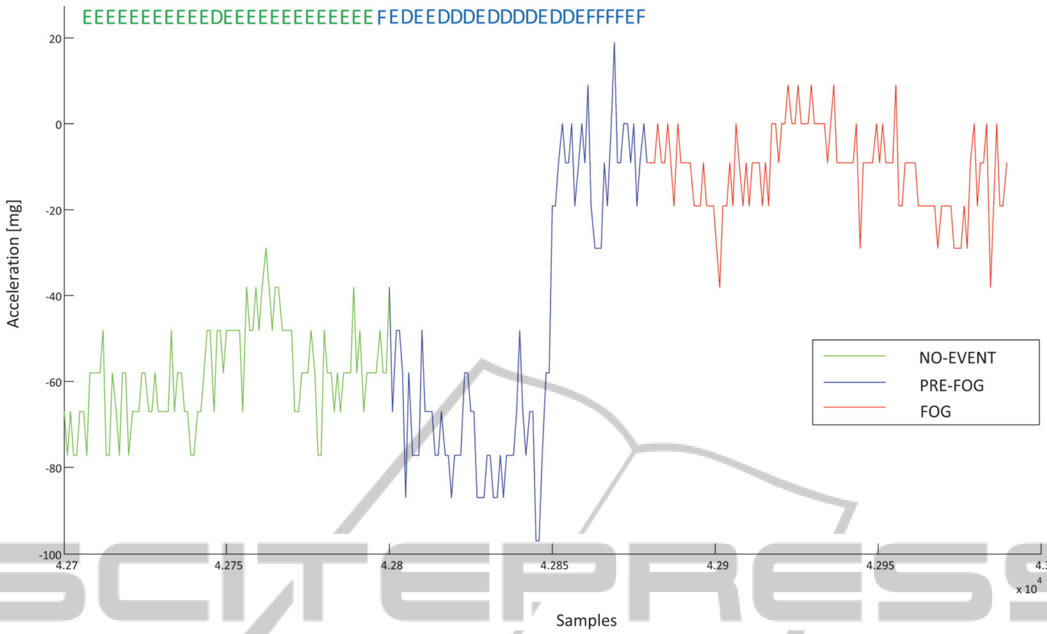

Figure 1: Acceleration signal converted in symbols.

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2 METHODS

Symbolic data analysis was applied on the Daphnet Database, which was described in (Bächlin, 2010)., and which stores acceleration signals from acceleration sensors positioned monolaterally on the ankle, thigh and trunk of 8 patients with PD who experienced freezing (the two patients who did not experience freezing were not considered in this study). The acceleration signals available for each sensor were: Antero-Posterior (forward), Medio-Lateral (horizontal), and Vertical. We chose to consider the norm of the three acceleration signals for the following analysis.

Parts of signal which did not correspond to the experiment part (as explained in the Daphnet documentation) were deleted. Resulting signals were normalized (z-score).

As exemplified in Fig. 1, we divided the signals in a No-Event part (i.e., standing and walking with no FOG), followed by a pre-FOG window (i.e., few seconds before the FOG happened), followed by a FOG part (i.e. during FOG).

The FOG part was not considered in this exploratory analysis, since we were interested in identifying the difference between normal activity and pre-FOG.

The pre-FOG window was defined as a period of 1, 2, or 3 seconds before the FOG. Correspondingly, the “No-Event” part of the signal was divided in consecutive No-Event windows of the same duration as the pre-FOG windows.

Since the No-Event part of the signal was generally much longer than the pre-FOG window, the No-Event windows were much more than the pre-FOG windows, resulting in an unbalanced dataset (Table 1): later in this section, this issue will be dealt with.

The different windows duration were considered in order to see if there was a duration which could allow a better identification of the pre-FOG patterns.

When the time between two following FOG events was less than 3 seconds, no pre-FOG window was considered, for any window durations.
This was done for two reasons:

- In order to obtain a fair comparison between different window durations: in fact in this way the number of pre-FOG windows is the same for all the different durations (see Table 1).
- In order to avoid that the pre-FOG window would partly capture patterns of the previous FOG.

Table 1: Mean and std values of the number of pre-FOG and No-Event windows across all subjects.

Win Duration	num. pre-FOG windows	num. No-Event windows
1	25.75±14.2	1427±409
2	25.75±14.2	693±203
3	25.75±14.2	448±134

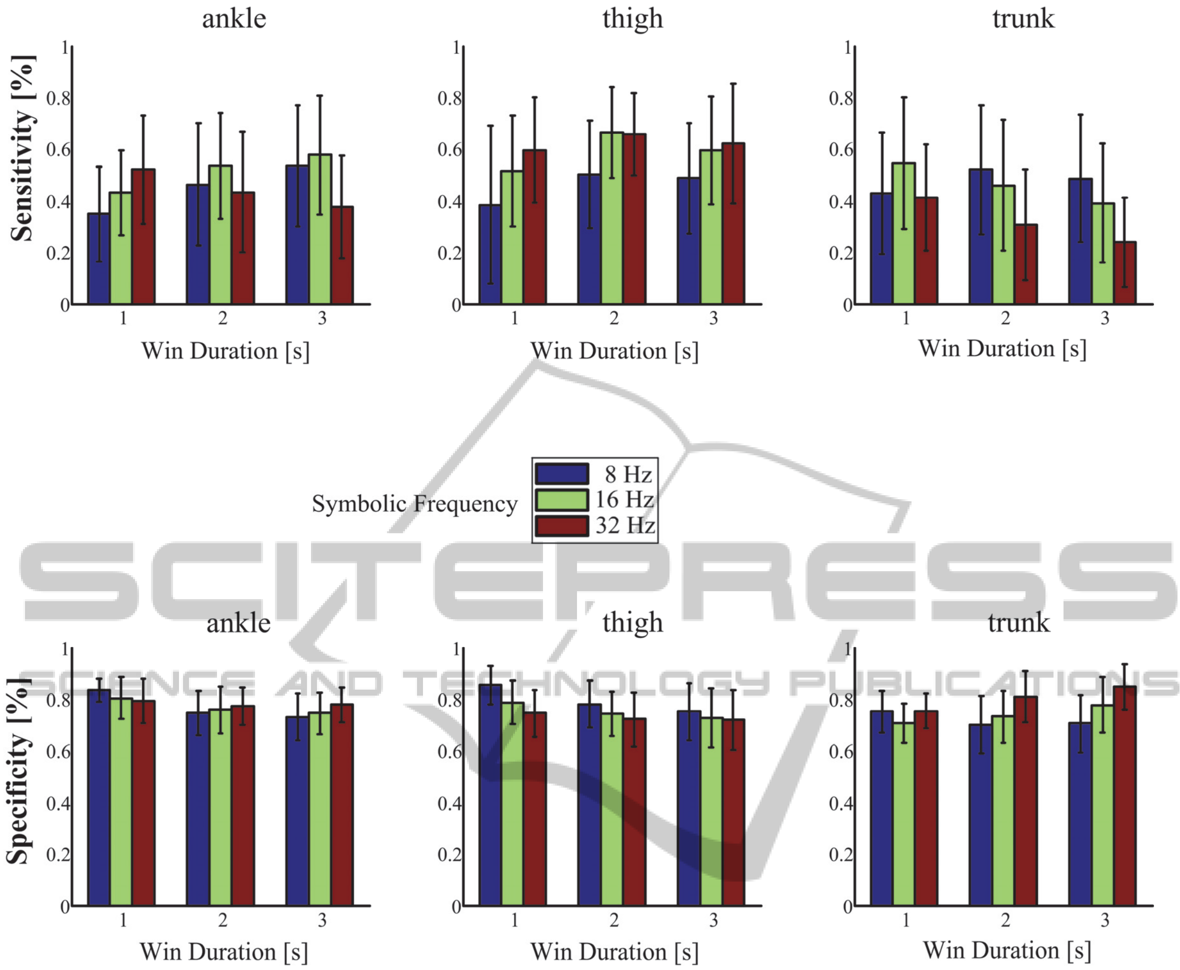

Figure 2: Results of sensitivity (± STD) and specificity (± STD) as function of different combinations of observation window duration, symbolic frequency, and sensor position.

The obtained windows were translated into sequences of symbols by using the SAX algorithm (Lin, 2003). Symbols can be considered as letters from an alphabet (we arbitrarily considered a 10 symbols alphabet) that represent the considered window instead of the raw acceleration values (as shown in Fig. 1).

In SAX, a single symbol represents consecutive samples of the raw signals in the considered window, thus automatically performing dimensionality reduction. Therefore the symbolic data will have a new (lower) sampling frequency. The original sampling frequency of acceleration signals was 64 Hz: in order to choose the optimal symbolic sampling frequency (how many symbols in one second), we considered different options: 8, 16, and 32 Hz, corresponding to translate 8, 4, 2 original samples in one symbol respectively.

In order to find patterns of symbols which are characteristic of the pre-FOG window (Fig. 1), and to discriminate them from the No-Event windows, we used the K-nearest neighbour's classifier (with k=1). Instead of the Euclidean distance, we used the symbolic distance between sequences of symbols, which is defined in (Lin, 2002; 2003).

In order to obtain a method that would be as generalizable as possible and that would perform well regardless of the different patients considered, we used a leave-one-subject-out cross validation to determine the accuracy of the proposed approach. In the leave-one-subject-out cross validation the data of one patient (all his/her signal segments) is classified by using the data captured from the rest of patients.

The results will be presented in terms of sensitivity (proportion of pre-FOG windows which are correctly identified) and specificity (proportion of No-Event windows which are correctly identified).

Since the dataset is highly unbalanced between the two classes (see Table 1), a random under-sampling of the majority class (No-Event) was performed in the training phase of the classifier. This was done in order to have the same number of Pre-FOG and No Event windows to train the classifier with. If no under-sampling had been performed, the classifier would have "learned" mostly No-Event patterns thus leading to high specificity but very poor sensitivity.

In order to test the significance of results, a random classifier was made, which randomly assigned "No-Event" or "pre-FOG" classes based on the proportion of classes in the under-sampled training set. One would expect such a classifier to perform with sensitivity and specificity around 50%.

3 RESULTS AND DISCUSSION

Results are reported in Fig. 2.

The best obtained result, in terms of trade-off between sensitivity and specificity (arithmetic mean), was

- Sensitivity: 66.5 %
- Specificity: 73.9 %,

In the following, the details of all the parameters of the data analysis corresponding to this result are listed:

- Thigh sensor
- Norm of the signal
- Symbolic Frequency of 16 Hz
- Duration of the windows of 2 seconds
- Alphabet size of 10

Both sensitivity and specificity of this combination resulted significantly better than the ones of the random classifier (Fig. 3), which performed, as expected, with sensitivity and specificity around 50%.

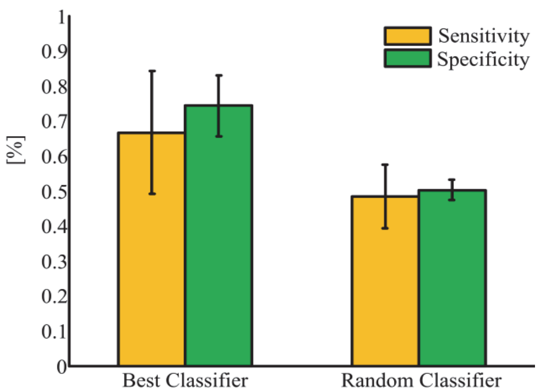

Figure 3: Comparison between the performance of the best classifier and of the random classifier.

From results in Fig. 2 it can be noted that different combinations of sensors/signals/ frequency can lead to higher specificity or higher sensitivity (but not to both).

From results in Fig. 2 it can also be noted that thigh sensor seems to perform generally better than ankle and trunk sensors in sensitivity, and comparably in specificity.

Also, sensitivity estimates tend to be less consistent (higher variability of performance across subjects) than specificity estimates.

Although the best result is obtained with a 2-seconds window, it seems that there is not a clear difference or pattern in considering windows of different durations.

Finally, considering different symbolic frequencies leads to different combinations of sensitivity and specificity but no consistent pattern can be observed (e.g. higher symbolic frequency always leads to better sensitivity/specificity).

Interestingly, the sensitivity in discriminating between pre-FOG patterns and normal activity is comparable to the sensitivity in discriminating between FOG patterns and normal activities obtained by previous studies (73.1% in Bächlin 2010, 66.3% in Mazilu 2012, 68.5% in Mazilu 2013).

On the other hand, specificity is lower than the ones obtained in those studies (81.6% in Bächlin 2010, 95.4% in Mazilu 2012, 86.8% in Mazilu 2013).

However, an overall lower performance was expected because the task of discriminating the patterns before the event occurs is generally more complex than detecting the event after it has happened.

These preliminary findings demonstrate that it is possible to identify (some of) the motor patterns that eventually lead to FOG events before they occur, support the idea that the gait pattern changes prior to freezing, and suggest that this pre-event period can be automatically identified by using wearable sensors.

As a limitation of this study, the algorithm presented in this study was not optimized for speed; in future work, a real-time implementation should be done.

Moreover, the use of different classifiers and the fusion of decisions made from different combinations of sensors, time windows and frequencies, could possibly permit to improve the obtained results.

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