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Semi-supervised monitoring of gait for fall risk estimation using smartphones

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1. Introduction

Falls in older adults have great medical, social and financial impacts. On the other hand, smartphones, as gait analysis tools, are gaining attention because they are ubiquitous, cheap, and integrated with Inertial Measurement Units (IMUs). Several falling risk parameters can be derived from monitoring gait using IMUs. The ability of measuring these parameters using smartphones is practically useful for ambulatory semi-supervised monitoring where the person records structured activities such as walking for a given period of time in his/her own environment. Several phone applications exist for semi-supervised monitoring of gait and other clinical tests (Manor et al. 2018). However, none exist for fall risk estimation and fall prediction.

IMU-based fall classification models that use gait signals to identify fallers are present (Drover et al. 2017). However, these models rely on features calculated from IMU sensors placed in a fixed position and orientation. Flexibility in orientation and placement is important for real-life implementation. Therefore, one must consider features derived from the norm of the signal and not affected by position and orientation. In this study, we adapt the feature calculation to the norm of signal instead of different signal components. The chosen adaptable features are gait temporal and frequential variability, Lyapunov exponent, sample entropy, and harmonic ratio (Nouredanesh et al. 2021).

In this study, we aim at using a smartphone to calculate relevant falling risk features from the norm of signals collected during a semi-supervised walking test. We test whether these features are able to differentiate elderly fallers from non-fallers. The objective is to check whether a smartphone and semi-supervised test can give insights on falling risk.

2. Methods

2.1. Subjects

Forty older adults (75 ± 5y, 74 ± 18kg, 1.7 ± 0.1 m, 11 Female and 29 Male) participated in this observational

Table 1. Median and interquartile range of calculated features.

Parameter	Non-faller	Faller	P-value
Amplitude dominant frequency (psd)	4.8 (3.3)	2.6 (3.2)	0.056
Slope at dominant frequency (psd/Hz)	32 (23)	21 (21)	0.048
Width at dominant frequency (Hz)	0.16 (0.02)	0.16 (0.03)	0.95
Sample entropy	0.56 (0.11)	0.48 (0.13)	0.1
Harmonic ratio	1.4 (0.6)	1.3 (0.5)	0.48
Lyapunov	1.24 (0.2)	1.23 (0.24)	0.42
Number of steps per passage	36 (5)	43 (9)	0.01
Mean stride time (s)	1.04 (0.13)	1.04 (0.13)	0.48
Standard deviation stride time (ms)	32 (9)	37 (19)	0.17
Coefficient of variance of stride time (%)	3.14 (0.81)	3.66 (1.31)	0.17
Standard deviation step time (ms)	22 (12)	23 (15)	0.23
Coefficient of variance of step time (%)	4.1 (2.04)	4.56 (2.16)	0.3

study. Subjects were not diagnosed with any gait or balance disorders and were cognitively intact. They were classified as 9 fallers (F) and 31 non-fallers (NF) based on their self-report of previous falls. If subject had at least 1 fall in the previous years, they were considered as fallers.

2.2. Protocol and data acquisition

Participants walked for 6 minutes back and forth in a 30 m hospital corridor at fast speed. With a custom-made application and a smartphone loosely placed at their waist, the acceleration signals were recorded at 100 Hz while walking. Each participant signed an informed consent. This observational study was approved by the ethical committee (Comité de Protection des Personnes; ID-RCB: 2020-A03302-37) sponsored by Médipôle Hôpital Mutualiste.

2.3. Derived measures

Data was segmented into straight walking and turns sections. Turns are detected when there is a significant drop in acceleration norm (Drover et al. 2017). Only straight walking sections and acceleration norms are used in the calculation of the features. They can be divided into three categories:

Temporal: Number of steps per passage in corridor, standard deviation, mean and coefficient of variance of stride time and step time. Steps are detected using the method proposed by (Al Abiad et al. 2021).

Frequency-based: Harmonic ratio calculated by method found in (Riva et al. 2013), Amplitude, width and slope at dominant frequency as described in Weiss et al. (2013). These parameters are calculated for each passage then the median is taken.

Non-linear: sample entropy is calculated with vector length of 5 and tolerance radius of 0.3 and, Lyapunov exponent is calculated using Rosenstein algorithm (Rosenstein et al. 1993) with an embedding

dimension of 5 and time delay of 10. They are calculated on first 200 strides in signal.

2.4. Statistics

Wilcoxon rank-sum were performed to compare between the F and NF, as classified based on fall history, for the features obtained.

3. Results and discussion

Table 1 shows the median and the interquartile range of calculated features between F and NF. Amplitude and slope at dominant frequency show significant differences between both groups. In line with the study of (Weiss et al. 2013), both parameters are lower for fallers signifying the higher gait variability. Although not significant, the coefficient of variance of stride time is higher and the sample entropy is lower for fallers. Gait variability is an important falling risk factor present throughout many studies (Hausdorff 2005). In addition, the number of steps per corridor passage is greater for fallers indicating that they have shorter step length as participants' height did not differ significantly between both groups. A shorter step length is known to also be a relevant falling risk factor (Barak et al. 2006). These parameters, being calculated using smartphones during a semi-supervised test, can decrease the burden of having a dedicated device for research and gait monitoring. The rest of the parameters such as Lyapunov exponent, harmonic ratio...etc. failed to provide any group differences. This can be caused by the nature of the test, by the low number of participants or even that the norm, unlike the 3 components of signals, is not able to show gait instabilities. This is to be confirmed with a larger number of participants. Moreover, one must note that parameters related to history of falls are not necessarily related to future falls. In fact, (van Schooten et al. 2015) found that amplitude and slope at dominant frequency are not related to future falls. Future studies must consider prospective falls.

4. Conclusions

This outcome shows that smartphones parameters are able to differentiate between fallers and non-faller.

This study encourages using smartphones for future research on fall prediction models. Limitations of the study are the low number of subjects.

Disclosure statement

No potential conflict of interest was reported by the authors.

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