Validation of minimal number of force sensitive resistors to predict risk of falling during a Timed Up and Go test

Johannes C. Ayena[1*] and Martin J.-D. Otis[2]

[1] Department of Electrical Engineering, Ecole de Technologie Supérieure, 1100 Rue Notre-Dame Ouest, Montréal, H3C1K3, Québec, Canada.
Communications and Microelectronic Integration Laboratory

[2] Department of Applied Sciences, University of Quebec at Chicoutimi (UQAC), 555 Blvd of University, G7H2B1, Quebec, Canada.
Laboratory of Automation and Robotic interaction (LAR.i), REPARTI Centre;

martin_otis@uqac.ca

* Corresponding author: Johannes C. Ayena

Email: cossoun-johannes.ayena.1@ens.etsmtl.ca

Abstract

Purpose: Several studies use force sensitive resistors (FSR) to compute gait and balance parameters related to falls without investigating the number of sensor units required to produce useful information. We propose a model with minimal sensors for an instrumented insole by investigating and optimizing the location and variety of sensors required to efficiently detect people at risk of falling.

Methods: Datasets previously recorded on twelve Parkinson's disease (PD) participants (67.7 ± 10.07 years), nine healthy elderly (66.8 ± 8.0 years) and ten young healthy adults (28.27 ± 3.74 years) were used in this study. We compared the datasets obtained from the use of four FSRs with those of three, two, one and no FSR; each set was combined with an inertial measurement unit (IMU).

Results: During the walking activity, the risk of falling scores from four FSRs and IMU (acceleration in y-axis only) were not significantly different compared with two FSRs and IMU ($p > 0.05$), whereas significant difference was found for three FSRs and IMU and one FSR and IMU ($p < 0.001$) in the elderly population. During sit-to-stand and stand-to-sit activities, the risk scores from four FSRs were not significantly different compared with three FSRs ($p > 0.05$).

Conclusions: We concluded that it is feasible to estimate the risk index after reducing the number of sensing units from four to two FSRs during walking test and from four to three FSRs during sit-to-stand and stand-to-sit tests. The FSRs should be placed at strategic positions to avoid information loss.

Keywords: Falls; iTUG test; Elderly; Force sensors

1 Introduction

The risk of falling among the elderly is generally assessed by clinical tests such as the Timed Up and Go (TUG) test. This test is comprised of basic everyday movements: stand up from a chair, walk three meters, turn around (180°), walk back and sit down again [1]. During the test, instrumented insoles [2] enable the analysis of human gait and balance parameters for fall risk assessment [3]. To compute both temporal and spatial parameters, these measurement systems are usually manufactured with an inertial measurement unit (IMU) and several force sensitive resistors (FSRs), up to forty eight FSRs [4]. Although the use of a high number of sensors may aid in providing an accurate risk assessment, these devices can be expensive. Thus, for a wide commercial range available in the retail trade, researchers are challenged to reduce the overall cost using less sensors with carrying out an effective risk evaluation.

In this regard, nowadays, very few studies have investigated the possibility of optimizing the number of sensors used and their location. With respect to an IMU, the average number of sensors reported by several studies as summarized by Brognara et al. [5] is 3.2 ± 2.4. Salarian et al. [6] were able to estimate the movements of the thighs from the movements of the shanks after reducing the number of gyroscopes from four to two. Other studies [3,7] proposed the use of four FSRs to minimize the cost of the device for commercial users and companies. Their results showed that the sensors under the big toe and midfoot better represent the gait asymmetries for healthy controls, while the sensors under the forefoot and midfoot are more representative for stroke survivors [7]. Carbonaro et al. [8] used two FSRs and a triaxial accelerometer for gait phase detection. Hsu et al. [9] used five FSRs for static and dynamic trials. Two FSRs were placed at the heel area and three around the toe. Their different configurations were used in static position, i.e., the subjects had to look straight ahead with their sides. The number of pressure sensors varies among different studies, and a possible shortcoming of these studies is that the gait analysis is the most common process reported without any optimization process and comparison. When a single (IMU) sensor is used, it is most frequently worn on the lower back [5].

We investigate in this study the use of minimal number of FSR sensors to predict risk of falling (ROFA) among Parkinson's disease (PD) and healthy elderly participants using the Timed Up and Go (TUG) test. We believe that reducing the number of sensors in an instrumented insole will help to reduce the manufacturing cost, power consumption and embedded memory size. Also, this can improve the physical integration of sensors and electronics packaging. During this process, our main goal is to maintain or increase the reliability of the system. The main objective of this paper is, therefore, to determine if a reduced set of sensors (using both a 3D- accelerometer with either one, two or three FSRs) would yield the same ROFA level compared with a combination of a 3D- accelerometer and four FSR sensors. By using the 3D-accelerometer, we focus only on the y-axis accelerometer (the direction of walking progression, attached to the ankle, along the lower limb in standing posture).

2 Methods

2.1 Datasets

Datasets from our previous studies [10,11], obtained from twelve Parkinson's disease (PD) participants (67.7 ± 10.07 years), nine healthy elderly participants (66.8 ± 8.0 years) and ten young healthy adults (28.27 ± 3.74 years), were used in the current study. Each PD participant of our study was rated using the Unified Parkinson's Disease Rating Scale (UPDRS). The durations of their diseases were between 1 and 20 years (10.67 ± 6.05); Hoehn and Yahr scales were between 1 and 4 (2.5 ± 0.88), and the total UPDRS score was 43.42 ± 14.9 (16-72). More information about participants' characteristics can be found in [10,11]. These data were acquired during a Timed Up and Go (TUG) test using an instrumented insole containing four FSR sensors and a 3D-accelerometer. The FSRs, manufactured by Interlink Electronics, were used for assessing the force distribution under the foot. Two FSRs (diameter, 13 mm, FSR402) were placed underneath the heel pad, one medially and the other laterally. The two others were placed under the first and fifth metatarsals approximately. The sensors were in the same anatomical location for all participants. According to the sensors' positions, the datasets from the four FSR sensors were reduced in different configurations combined with a y-axis accelerometer (Ay): a) 3FSR+Ay; b) 2FSR+Ay; c) 1FSR+Ay; d) 1FSR and e) Ay (see Figure 1 and Figure 2 for FSRs locations). The 3-axis accelerometer (ADXL345) was located on the electronic board and attached to the foot (see Figure 1 in [12] for more details). The ADXL345 is a complete 3-axis acceleration measurement system requiring ultralow power and is well suited to measure the static and dynamic acceleration of gravity in order to detect human falls. It measures acceleration with a high resolution (13-bit) of up to ±16g. In this study, the accelerometer is used only in walking activity since there is no foot motion in sit-to-stand and stand-to-sit activities.

All our previous studies were approved by the UQAC Ethics Committee, and the study participants signed an informed consent form. A second approbation was granted by the UQAC Ethics Committee in order to access the database (subsequent use of secondary data).

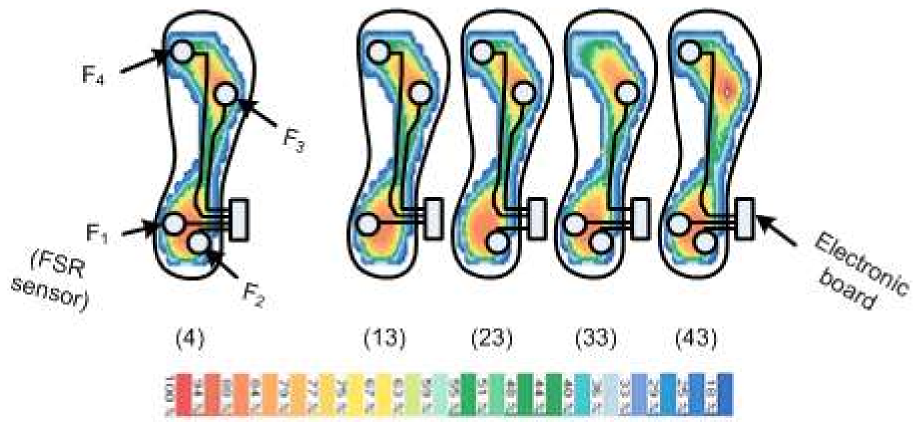

Fig. 1 The position of the four FSRs and the different configurations and locations of three FSRs over the instrumented insole

Note: Each number (cn) represents both the configuration (c) and the number (n) of FSR used as defined below:

4FSR = (F_1, F_4, F_2, F_3); **4-3FSR** = (F_2, F_1, F_4); **3-3FSR** = (F_2, F_1, F_3); **2-3FSR** = (F_2, F_3, F_4); **1-3FSR** = (F_3, F_1, F_4).

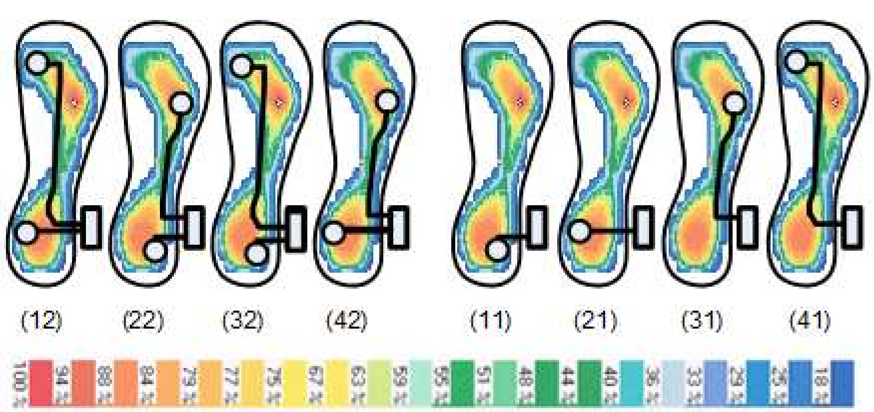

Fig. 2 Different configurations and locations of two and one FSRs over the instrumented insole

Note: Each number (cn) represents both the configuration (c) and the number (n) of FSR used as defined below:

4-2FSR = (F_1, F_3); **3-2FSR** = (F_2, F_4); **2-2FSR** = (F_2, F_3); **1-2FSR** = (F_1, F_4); **4-1FSR** = F_4; **3-1FSR** = F_3; **2-1FSR** = F_1; **1-1FSR** = F_2. The Y-axis accelerometer (Ay) is located in the electronic board.

2.2 Risk of falling (ROFA) assessment

We developed an automated algorithm to segment the TUG test mainly into sit-to-stand (S2ST), walking (Wa) and stand-to-sit (ST2S) phases. For the S2ST and ST2S, we used the FSR sensors to compute five standard parameters from the center of pressure (COP) displacement and velocity related to falls [13-17]. These parameters are given below: (1) the root mean square (RMS), (2) the jerk of the COP displacement, (3) the maximal, (4) the mean, and (5) the RMS of the COP velocity. Regarding the walking phase, we carried out segmentation into different strides following an algorithm [18]. From several studies [19-27], we computed twelve standard temporal and spatial gait parameters related to falls, such as swing, stance, stride and step times, cadence, swing to stance time ratio, stance to swing time ratio, two types of ratio (swing and stance times per stride time), step frequency, stride and step lengths.

Our proposed method tries to improve the gait variability index (GVI) suggested by Schwartz et al. [28] for analyzing gait instability. Some studies [26,29,30] supported the use of the GVI as a valid outcome to measure gait variability. However, although, the GVI seems to contribute to a better interpretation of the gait variability measures, some issues remain owing to their 1) high scores (above 100) without specific interpretation and 2) the direction specificity problem (the same score used both for high and low variability). We focused on the first problem since we are only interested in the absolute value of the gait variability, which can be decreased or increased around the reference value. We propose a single method that can be used not only for gait analysis but also for other activities, such as sit-to-stand and stand-to-sit. Our objective was to propose a simple score between 0 and 100, which can be interpreted easily by the clinician. For this, contrary to the initial distance metric proposed by Schwartz et al. [28] and the new one proposed by Gouelle et al. [26,31] , we suggest dividing this distance by the variability of individual participant as follows:

$$V_k^{\alpha,YO} = \| \frac{f_k^{\alpha} - f_k^{YO}}{f_k^{\alpha}} \| \qquad (1)$$

where f_k^{α} is the gait/balance parameter (k) value of an individual α (each participant); f_k^{YO} is the mean of each gait-balance parameter (k) computed in the young population (YO), which represents our reference.

The deviation index (DI) of any parameter is equal to the natural logarithm ($log(V_k^{\alpha,YO})$) of the variability $V_k^{\alpha,YO}$ while computing also their mean and standard deviation (SD). Moreover, according to [28], we calculated a Z-score with respect to the reference for each healthy elderly (HE) and PD participant as follows:

$$Z_k^{HE,PD} = \frac{DI_k^{HE,PD} - mean(DI_k^{\alpha,YO})}{SD(DI_k^{\alpha,YO})} \quad (2)$$

Contrary to previous studies [26,28,31], we used the absolute value of the Z-score to compute the risk index (ROFA) for walking, S2ST and ST2S activities as shown in (3):

$$Rofa^{\,\alpha} = \sum_{i=1}^{N_k} \gamma_k * (100 - \beta_k * \|Z_k^{\alpha}\|) \quad (3)$$

where N_k is the total number of parameters. We used equal coefficients γ_k. However, this can be adjusted by physicians, clinicians, or domain experts to tailor the instability assessment for a personalized analysis.

In accordance to GVI method and the goal of this study, we chose to fix the coefficient at $\beta_k = 10$. In this regard, to avoid negative values, we should have $0 \leq Z_k^{\alpha} \leq 10$. The suggested variability ($V_k^{\alpha,YO}$) satisfies this constraint and forces the *ROFA* index not to rise above 100. We hold the opinion that the index presented in (3) may help identify those at greatest risk.

2.3 Statistical analysis

The ROFA scores were compared across the number of sensors using one-way analysis of variance (ANOVA-1) with pairwise comparisons. Also, the relationship between the ROFA scores from 4FSR+Ay and other configurations was assessed with F-test.

3 Results

A combination of four FSR sensors and an accelerometer (4FSR+Ay) was used as reference and compared with different configurations (c = 1, 2, 3, 4) of a reduced FSR sensor (*c*-*n*FSR+Ay) where *n* = 3, 2, 1, 0, based on sensor positions as shown in Figure 1 and Figure 2.

3.1 Sensor reduction effects during walking

When we reduced the number of sensors, ANOVA analysis revealed a significant difference for $n = 3$ ($p = 0.0043$ and $9.941*10^{-5}$ respectively for HE and PD), $n = 2$ ($p = 0.0015$ for PD), $n = 1$ ($p = 1.52*10^{-4}$ and $1.257*10^{-17}$ respectively for HE and PD) and a non-significant difference for $n = 0$ ($p > 0.05$ for HE and PD) whatever the configuration c (Table 1). However, no significant difference was found for $n = 2$ among HE ($p = 0.1370$). We also compared 4FSR+Ay and 1FSR, and a significant difference was found ($p = 0.0062$ and $5.531*10^{-15}$ respectively for HE and PD). Compared with 4FSR+Ay, Tukey tests showed a significant difference for 4-3FSR+Ay and 4-1FSR+Ay for HE; in addition to 3-3FSR+Ay, 1-1FSR+Ay and 1-1FSR for PD participants. All other pairwise comparisons showed a non-significant difference (Table 1).

Table 1 p-values of the statistical tests from sensor reduction during walking

	Healthy Elderly (HE)			PD participants			All participants	
	Pairwise comparison		F-test	Pairwise comparison		F-test	Anova_group	
Number (n) of FSR + Acceleration component	p-value	s/ns	s/ns	p-value	s/ns	s/ns	Total (p-value)	HE vs PD
4FSR + Ay vs 1-3FSR + Ay	0.0043	ns	ns	$9.941*10^{-5}$	ns	ns	0.437	ns
4FSR + Ay vs 2-3FSR + Ay		ns	ns		ns	s*	0.5626	ns
4FSR + Ay vs 3-3FSR + Ay		ns	ns		s*	ns	0.0131	ns
4FSR + Ay vs 4-3FSR + Ay		s**	ns		ns	ns	0.0028	ns
4FSR + Ay vs 1-2FSR + Ay	0.1370	N/A	ns	0.0015	ns	ns	0.0219	ns
4FSR + Ay vs 2-2FSR + Ay			ns		ns	ns	0.6667	ns
4FSR + Ay vs 3-2FSR + Ay			ns		ns	s**	0.3286	ns
4FSR + Ay vs 4-2FSR + Ay			ns		ns	ns	0.0941	ns
4FSR + Ay vs 1-1FSR + Ay	$1.52*10^{-4}$	ns	ns	$1.257*10^{-17}$	s**	s**	$1.14*10^{-11}$	s**
4FSR + Ay vs 2-1FSR + Ay		ns	s**		ns	ns	0.0471	ns
4FSR + Ay vs 3-1FSR + Ay		ns	s*		ns	ns	0.2622	ns
4FSR + Ay vs 4-1FSR + Ay		s**	s**		ns	s**	0.0003	s*
4FSR + Ay vs 1-1FSR	0.0062	ns	ns	$5.531*10^{-15}$	s**	s**	$9.26*10^{-8}$	s**

4FSR + Ay vs 2-1FSR		ns	s**		ns	s*	1.05* 10^{-5}	ns
4FSR + Ay vs 3-1FSR		ns	s*		ns	s**	5.29* 10^{-8}	ns
4FSR + Ay vs 4-1FSR		ns	s**		ns	s**	0.0068	s**

Note : **ns** : non-significant ; **s** : significant ; **N/A** : Not Applicable ; ** p<0.01; * p<0.05 ; **Ay** = y-axis accelerometer

3.2 Suggested sensors configurations

3.2.1 Use of three FSRs and one axis of 3D- accelerometer

To suggest the best configuration, we performed an F-test. As shown in Table 1, our first rule was to exclude configurations with significant difference s* (p<0.05) and s** (p<0.01), when we compared the reduced sensor with the reference. Configurations 3-3FSR+Ay and 4-3FSR+Ay showed significant difference with 4FSR+Ay. Furthermore, these configurations respectively showed significant difference (p = 0.0131 and 0.0028) across groups (PD and HE) and conditions (four and three FSRs), which revealed the effect of sensor reduction. Thus, we kept configurations 1-3FSR+Ay and 2-3FSR+Ay where no significant difference was found. The F-test showed significant difference (p = 0.0198 < 0.05) for configuration 2-3FSR+Ay among PD participants. Therefore, we suggest that the best configuration for reducing the number of sensors without losing information could be 1-3FSR+Ay (Figure 3a).

3.2.2 Use of two FSRs and one axis of 3D- accelerometer

For all configurations, no significant difference was found after a pairwise comparison for the study participants. In this case, compared with four FSRs, we suppose that two FSRs could be enough to compute the same gait parameter values. The difference with the three FSRs' configurations may result from the position of the third FSR. Since configurations 3-2FSR+Ay and 1-2FSR+Ay showed significant difference using F-test (p = 0.00068 for PD participants) and ANOVA-1 (p = 0.0219), we suggest that configurations 2-2FSR+Ay (Fig.3b) and 4-2FSR+Ay are the best possible options (Table 1).

3.2.3 Use of one FSR with or without 3D- accelerometer

These configurations produced interesting results. However, based on our previous criteria, no configuration can be chosen as best. The F-test showed significant difference for all configurations (Table 1) except 1-1FSR and 1-

1FSR+Ay for HE as well as 2-1FSR+Ay and 3-1FSR+Ay for PD participants. ANOVA analysis revealed significant difference across groups and conditions, which indicates the effect of sensor reduction, except for configuration 3-1FSR+Ay (p = 0.2622, Fig.3c). Thus, in this case, we think that each group can have a different best configuration contrary to the use of three and two FSRs. In most situations, the 1FSR configuration (use of one FSR without accelerometer) results showed significant difference across the two groups (Table 1 and Fig.3d).

3.2.4 Use of a single axis of 3D- accelerometer

Given that the FSRs and IMU are synchronized with 100Hz sampling frequency, the temporal gait parameter values computed with 4FSR+Ay are approximately equal to those of the use of Ay sensor only (Fig.3d). The results were inconsistent; however, this case is interesting for future works with respect to choosing between the IMU and FSRs in computing the risk of falling during walking activity.

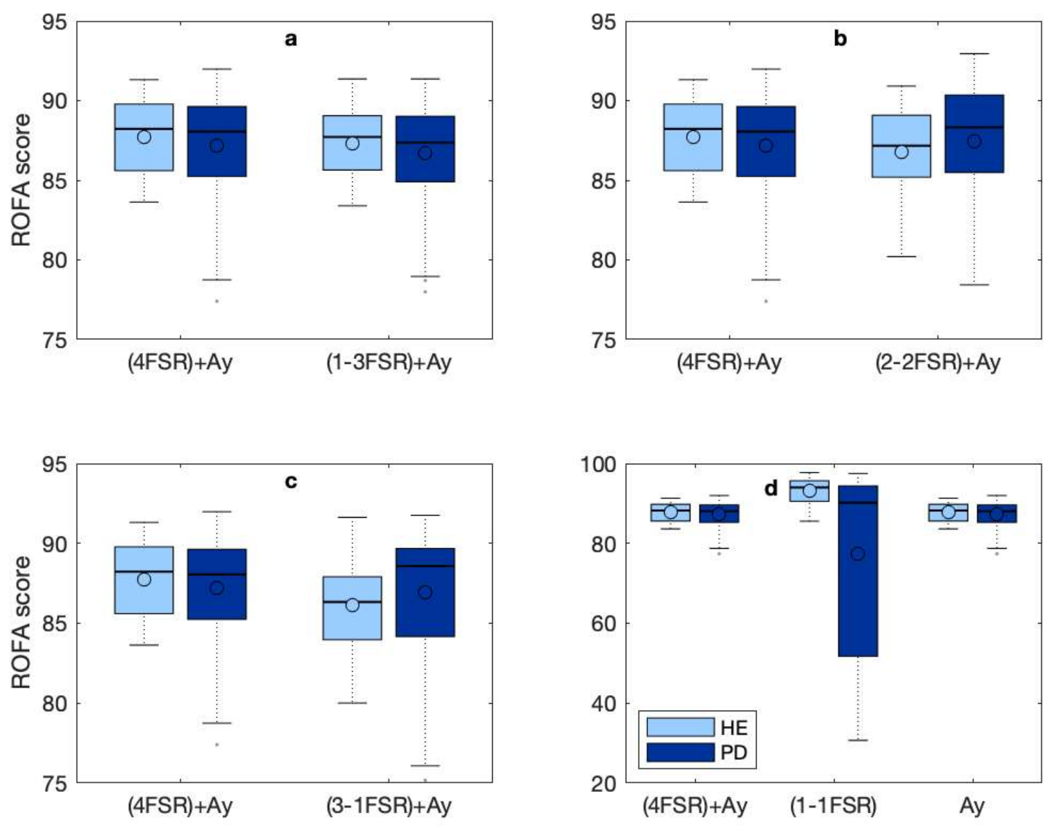

Fig. 3 Risk scores of the best configurations for reducing the number of FSRs during walking phase without losing information

Note: HE: Heathy Elderly; PD: Parkinson's disease participants

3.3 Sensor reduction effect during S2ST and ST2S

Our IMU located on an electronic board is attached to the shoe (see Figure 1 in our previous study, [10]). Therefore, for S2ST and ST2S activities, we think that the position of the IMU is not adequate to detect the risk of falling. From the analysis reported in Section 3.2, we then used configuration 1-3FSR to compare the ROFA scores among HE and PD participants during S2ST and ST2S (Fig.4). Although the configuration with two FSRs can also be used, we think that it would not be enough to represent the force distribution under the foot.

ANOVA analysis showed no significant difference between 1-3FSR and 4FSR (p = 0.9903 and 0.9438 respectively for HE and PD participants) during S2ST (Fig.4a) and (p = 0.4861 and 0.3070 respectively for HE and PD participants) during ST2S (Fig.4b).

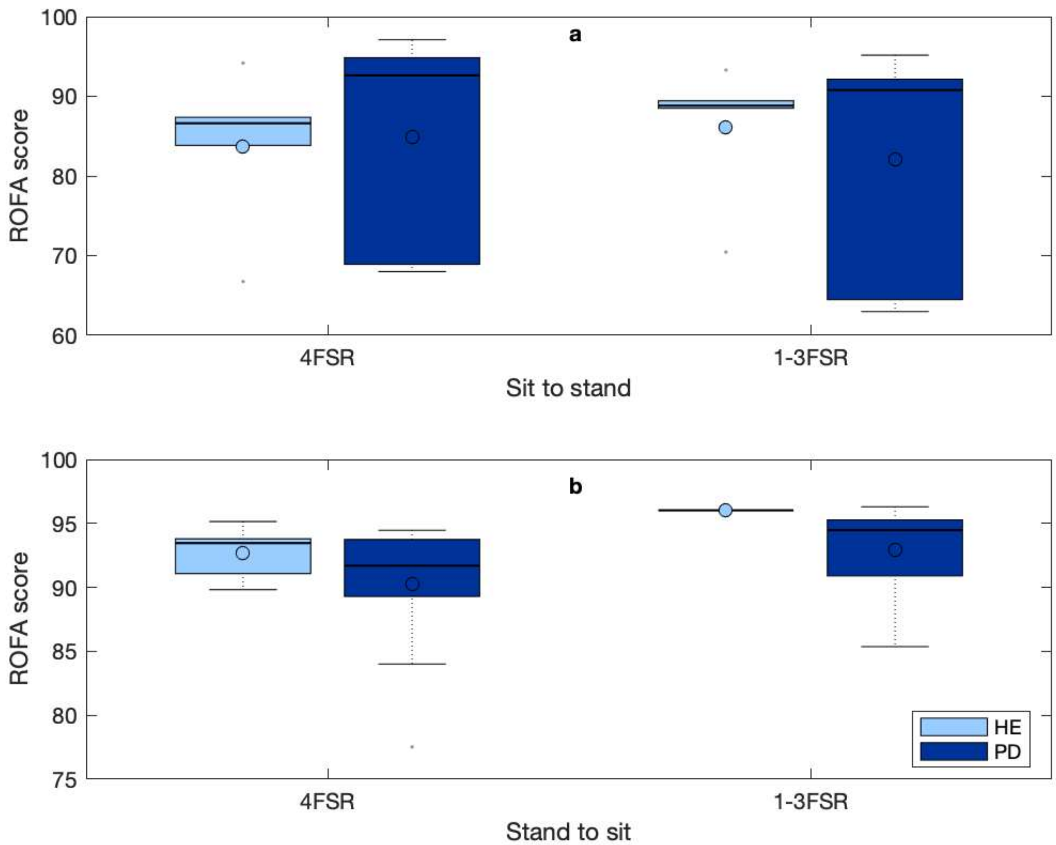

Fig. 4 Model of minimal FSRs to compute risk scores for sit-to-stand and stand-to-sit activities

Note: HE: Heathy Elderly; PD: Parkinson's disease participants

4 Discussion

The results of this study suggest that the ROFA index calculated with minimal number of sensors is a promising tool for risk analysis in real time, as it provided statistically similar information to risk analysis with a larger number of sensors.

These findings support our hypothesis that it may be possible to use a smaller number of FSRs to estimate the risk of falling, thereby reducing energy consumption. Indeed, the results of Barkallah et al. [32] suggest that at 10 kΩ, the FSR sensor maximally consumes 0.33 mA. In total, 4FSRs, 3FSRs and 2FSRs consume 1.32 mA, 0.99 mA and 0.66 mA respectively. Thus, the battery life is affected when all sensors are activated. Furthermore, since the target price of one insole should be less than one hundred dollars, at this current stage, one FSR is around $12.39 (Canadian). The results reported are encouraging and show that the proposed system may potentially be useful as a research tool for studying fall risk and as a clinical tool for long-term fall monitoring at home. Compared with previous studies [8,33,21,10], the proposed instrumented insole with minimal pressure sensors also demonstrate the capability to calculate the variation of gait and balance parameters and highlight the instability of balance of an elderly person. The combination of 3FSRs and a single 3D accelerometer axis has been shown to provide the optimal result for assessing the risk of falls in the healthy elderly and PD participants.

The results reported in Table 1 suggest that three FSRs would be enough to estimate the risk index during walking (Figure 3), sit-to-stand and stand-to-sit (Figure 4) activities. We also investigated different locations of the FSR sensors, and as observed, the F-test and pairwise comparison did not reveal nonsignificant effect across the sensor locations in all cases among the study participants (Table 1). This indicates the importance of investigating sensor locations [34]. We concluded that the use of one FSR at the heel and two FSRs at the toes (configuration 1-3FSR) seem to be suitable for estimating the same risk of falling level without losing information.

However, this study has several limitations. Firstly, our study used a small number of participants mainly in the reference population. Thus, generalizability of the reference values may be limited. However, increasing the sample size does not ensure an improvement in accuracy [35]. In this study, saturation of data for optimization coming from the number of participants was reached for young people (the reference), as the standard deviation monotonically tends to a constant and the mean changes slowly in this population. Secondly, the chosen location of the sensors could be moved. For example, the IMU could be located under the arch of the foot and not attached to the shoe. Of course, the impact of the location of the IMU should be limited since the shoe and the insole could be seen as a solid body, but it is still an assumption. The number of force sensors mainly depends on the final end-user application. The insole can contain a matrix of very small force sensors providing a very accurate measurement of the COP and can provide an image of the pressure under the foot. In our application, the risk of falling should not be dependent on the resolution of the force sensors. For this reason, we can optimize the number of sensors to be used and their locations.

Our findings showed a reduced set of FSRs for a reduced set of gait and balance parameters, which could be used as a first step in machine learning process and parameter selection to differentiate fallers and non-fallers.

5 Conclusion

The aim of this paper is to validate a minimal model that may predict the risk of falling among the elderly. To achieve this, we present a new approach that can provide the same set of risk of falling index. We also demonstrated that this prediction method can be used among people with Parkinson's disease. We concluded that it is feasible to estimate the risk index after reducing the number of sensing units from 4 to 2 FSRs during walking test and from 4 to 3 FSRs during sit-to-stand or stand-to-sit tests. In future works, the validation of the proposed model should be improved and used in a more prospective population that can predict fall incidents and determine the accuracy of the prediction with short and long-term follow-up. Moreover, in future, we want to be able to efficiently and easily identify individuals with PD at the early stage of the disease; they are difficult to distinguish from healthy elderly individuals.

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