Dimensional reduction of balance parameters in risk of falling evaluation using a minimal number of force sensitive resistors

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Abstract:

Purpose: As the instrumented insole is for a wide commercial range available in the retail trade, this study aims to reduce its overall cost using less sensors with carrying out an effective risk of falling evaluation. **Methods**: We compared the effect of reducing balance parameters by using four and three force sensing resistors (FSRs) of an instrumented insole. The data were previously collected among elderly participants during a Timed Up and Go (TUG) test. **Results**: While reducing the number of balance parameters, during sit-to-stand and stand-to-sit activities, the risk scores using four FSRs were not significantly different compared with three FSRs. Parameters reduction did not show any significant loss of information among the study population using four FSRs. For certain configurations of three FSRs, a significant effect of loss information was found in the study participants, which revealed the importance of investigating the sensor locations in the process. **Conclusions**: We concluded that it is feasible to estimate a risk index during a TUG test not only after reducing the number of needed sensing units from four to three FSRs but also after reducing the number of balance parameters. The three FSRs should be located at strategic positions to avoid a significant loss of information.

Keywords: Falls; TUG test; Elderly

1. Introduction

Falls are a major public health problem associated with longevity, especially in industrialized countries, and it is clear that the risk of falling increases with age and level of frailty [1]. To provide an objective risk assessment, fall detection methods have used several wearable devices in the last few decades. Measurement systems for analyzing human gait and balance parameters are usually manufactured with sensors such as accelerometer, gyroscope, force sensing resistor (FSR), blood pressure sensor, electromyography, etc. [2]. From different studies summarized in [3-6], a large number of body-worn-sensors can be placed on the human body to evaluate its ability to maintain balance using clinical tests such as a Timed Up and Go (TUG) test [7]. The average number of an inertial measurement unit (IMU) sensors used and reported from several studies summarized by Brognara et al. [8] is 3.2 ± 2.4. Nowadays, a combination of 3D accelerometer, gyroscope and magnetometer [9]; four [10,11], seven [12] or forty-eight [13] FSRs have been used in computing temporal and spatial parameters. This often results in a very large number of parameters [14], and the parameters are mostly strongly correlated with each other or less important. Although the risk assessment may seem to be better with a high number of sensors or sensor fusion, the challenge remains an effective risk assessment with an inexpensive device.

In this regard, very few studies have investigated the possibility of optimizing the number of sensors used and their location. Usually, the IMU sensor when it is single, is worn on the lower back [8]. Salarian et al. [15] were able to estimate the movements of thighs from the movements of the shanks after reducing the number of gyroscopes from four to two. Organero et al. [16] proposed the use of four FSRs to minimize the cost of the device for users. Their results showed that the sensors in the forefoot and midfoot are more representative for stroke survivors. Carbonaro et al. [17] used two FSRs and a triaxial accelerometer for gait phase detection. Hsu et al. [18] used five FSRs where two were placed at the heel area and three around the toe. A possible shortcoming of these studies is that the gait analysis is the most common process reported without any reduction of the number of balance parameters and investigation of the best sensor's location. Currently, it has become necessary to have not only a reduced number of sensors but also a reduced set of balance parameters that represent only useful information for better interpretation.

We investigate in this study the dimensional reduction of the number of FSR sensors among Parkinson's disease (PD) and healthy elderly participants while reducing the number of balance parameters during a TUG test. Dimensionality reduction is the transformation of high-dimensional data into a meaningful representation. Simply stated, reduce N initial parameters (original dimension) to M parameters (reduced dimension) where M < N. Ideally, the reduced representation should have a dimensionality that corresponds to the useful information on the data. In our present study, this corresponds to the minimum number of balance parameters and FSR sensors needed to estimate a risk of falling (ROFA). As a result, in various fields of application such as clinical biomechanics, medical rehabilitation, prosthetics and sports science, etc., where the human gait analysis is an important area of study, dimensionality reduction facilitates, among others, classification, visualization, and compression of high-dimensional data [19,20]. Indeed, to classify healthy and PD participants or fallers and non-fallers, it is better to have a small subset of parameters to avoid the curse of dimensionality [21]. Furthermore, small dimensionality may lead to optimal computational burden for a best classification rate when using a classifier such as an artificial neural network for balance evaluation [22] in daily activities. The daily activities included in the TUG test such as the sit-to-stand (S2ST) activity, enable the measurement of the lower limb strength. Although, during this task, many studies showed evident correlation between center of pressure (COP) displacements and falls in the elderly, to the best our knowledge, no work has investigated the number of sensor units required and their location to compute useful information related to the risk of fall. To avoid redundancy, our method was to determine if the use of three FSRs could predict the same ROFA level compared with the use of four FSRs where each set of FSR is combined with an accelerometer. During walking activity, we focus on an accelerometer system that uses only the y-axis (the direction of walking, attached to the ankle, along the lower limb in standing posture). During S2ST and stand-to-sit (ST2S), only a set of FSRs (without y-axis accelerometer) is used since there is no foot swing motion in these activities. We are of the opinion that reducing the number of sensors and dimensional reduction of the gait and balance parameters will help to reduce the power consumption, memory size, manufacturing cost and improve the physical integration of sensors and electronics packaging. Such reductions will also increase the reliability of systems such as an instrumented insole. Therefore, the first purpose of this study is to investigate the effect of a reduced number of FSR sensors during walking activity. After identifying the number of FSR sensors required, the second goal is to analyze the effects of dimensional reduction of balance parameters on the ROFA index during S2ST and ST2S activities, i.e., the corresponding reduced set of COP parameters that are most sensitive to the locomotor performance of the elderly without losing information.

2. Methods

2.1. Participants

This study has involved young healthy adults, healthy elderly and PD participants. The twelve PD participants involved had a physician's diagnosis of idiopathic PD (presented as an ability to ambulate independently without assistive device) and were between the ages of 53 and 77 years (67.7 ± 10.7 years) at the time of enrollment. To be enrolled in the research, they must not have an existence of uncontrolled health such as orthopedic disorders, joint prosthesis, etc. Additionally, any other neurological disorders, cognitive impairment, or any comorbidity that may affect gait were thus considered as elimination criteria. Participants meeting the above criteria were recruited. An Unified Parkinson's Disease Rating Scale (UPDRS's test) [23] was performed, followed by the Parkinson's Disease Questionnaire (PDQ-39) [24] and the test of fear of falling [25]. The durations of their diseases were between 1 and 20 years; Hoehn & Yahr (H & Y) scales were between 1 and 4; and the motor UPDRS score was between 9 and 31 (Table 1). This research was completed using data of nine healthy elderly between the ages of 57 and 77 years (66.8 ± 8.0 years) and for baseline, ten young healthy adults from a sample of twelve aged between 23 and 34 years (28.27 ± 3.74 years) at the time of enrollment. The inclusion criteria for all study participants were the ability to walk over different surfaces and an adequate vision and a sufficient hearing acuity. Most of the elderly participants have had one fall in the last six months. This study and all our previous were approved by the University of Quebec at Chicoutimi (UQAC) Ethics Committee and the participants signed an informed consent form.

Table 1. A table describing the experimental conditions and clinical variables of the participants

<table>
<tr><th colspan="3">Variable tested</th><th>PD participant (Mean ± SD)</th><th>Healthy elderly (Mean ± SD)</th></tr>
<tr><td colspan="2" rowspan="8">Clinical characteristic [26]</td><td>Disease’s duration</td><td>10.67 ± 6.05</td><td>------</td></tr>
<tr><td>H & Y scale</td><td>2.5 ± 0.88</td><td>------</td></tr>
<tr><td>Taking medication</td><td>11/12#</td><td>------</td></tr>
<tr><td>UPDRS total score</td><td>43.42 ± 14.9</td><td>------</td></tr>
<tr><td>UPDRS motor score</td><td>20.6 ± 6.5</td><td>------</td></tr>
<tr><td>Fear of falling</td><td>33.83 ± 14.75</td><td>------</td></tr>
<tr><td>PDQ-39</td><td>53.58 ± 29.9</td><td>------</td></tr>
<tr><td>TUG time (sec.)</td><td>12.7 ± 1.99</td><td>8.9 ± 0.89</td></tr>
<tr><td rowspan="4">Experimental condition</td><td rowspan="3">Independent variable</td><td>Reduced sensors (4FSR)</td><td colspan="2">1-3FSR; 2-3FSR; 3-3FSR; 4-3FSR</td></tr>
<tr><td>Reduced of ROFA parameters (P+V)</td><td colspan="2">Px; Py; Vx; Vy</td></tr>
<tr><td>Participants</td><td colspan="2">11 Males and 10 Females</td></tr>
<tr><td>Dependent variable</td><td colspan="3">Clinical ROFA score versus computed ROFA score proposed</td></tr>
</table>

Note: FSR = force sensing resistor; 4FSR = use of four FSRs (F_1, F_2, F_3, F_4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); H&Y = Hoehn and Yahr; PD = Parkinson’s disease; PDQ = PD Questionnaire; P = global center of pressure (COP) position; Px = COP position along x-axis; Py = COP position along y-axis; ROFA = risk of falling; SD = standard deviation; TUG = timed up and go; UPDRS = Unified Parkinson’s disease rating scale; V = global COP velocity; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis; # = use of Levodopa mainly.

2.2 TUG test instrumentation

The data were acquired during a TUG test using an instrumented insole containing four FSRs sensors and a 3D-accelerometer. The FSRs (manufactured by Interlink Electronics, USA) were used for assessing the force distribution under the foot. Two FSRs (FSR402, diameter 13 mm) 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 3-axis accelerometer (ADXL345) is located on the electronic board and attached to the foot. The ADXL345 (manufactured by SparkFun Electronics, USA) 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) up to ±16g. In this study, the accelerometer is used only in walking activity since there is no foot motion in S2ST and ST2S activities.

An Android application records the raw data from the four FSR sensors and the accelerometer in order to estimate the user performance that is doing the test. The software incorporates two main sections which are: 1) instructions on how to properly complete the TUG test, 2) gait parameters computation such as cadence, and 3) results visualization such as the ROFA score. As soon as the participant is comfortably seated on the chair, the TUG test could begin by pressing start button on the software. The data from the sensors are sent via Bluetooth to the smartphone at a rate of 100 Hz in real time. By pressing the stop button, the software ending the recording. The daily usage of our TUG software can allow a remote monitoring of elderly and also could inform about the impact of rehabilitation interventions on people with balance disorder disease.

2.3. Experimental protocol

An instrumented insole as presented in [26] was introduced in the shoe of the right foot. The PD participants were reached mostly bilaterally, so we think that a single insole placed on the right foot (usually the dominant foot) could be enough to measure the complete gait cycle of the user. This also makes it possible to reduce the production cost of the device. Before the recording of the data, each participant (healthy young, PD participant and healthy elderly) comfortably performed two or more TUG trials across 3m along a walkway. The goal was to ensure that the participant understood the test. Then, they were asked to perform this test over concrete soil and the data were sent in real time from the insole to the Android application. The tests were carried out preferably in the morning so that the tiredness does not alter results. Moreover, participants were given as much time as requested to rest between tests and fatigue did not appear to limit them.

2.4. Risk of falling evaluation

In [26], we computed the ROFA for walking activity using four FSR sensors and an IMU by segmenting a clinical test (TUG test) mainly into S2ST, walking and ST2S phases. Given that S2ST could be a risky activity for the elderly, in this study, we focused more on this task and compared it with ST2S.

Schwartz et al. [27] proposed the gait variability index (GVI) as a valid outcome to measure gait disorder [28-31]. However, although the GVI seems to contribute to a better interpretation of the gait variability, some issues (high scores, above 100 without specific interpretation) remain concerning the magnitude and the direction specificity problem (both high and low variability are the same score). Our proposed method tries to improve this index and apply it to S2ST, walking and ST2S activities. We focused on the magnitude problems since we are only interested in the absolute value of the variability which can be increased or decreased around a reference value. We then propose a single index that can be used not only for gait analysis but also for other activities such as S2ST and ST2S. This simple score (0 to 100) can be interpreted easily by nonprofessionals. To achieve this goal, contrary to the initial distance proposed by Schwartz et al. [27] and the new and improved one proposed by Gouelle et al. [28,29], we suggest dividing the metric distance by the variability of the individual as follows:

$$V_k^{\alpha,YO} = \left\| (f_k^{\alpha} - f_k^{YO}) / f_k^{\alpha} \right\|, \tag{1}$$

where α = study participant; YO = young population as a baseline; k = balance parameter; $V_k^{\alpha,YO}$ = new variability index proposed for the balance parameter with respect to the baseline; f_k^{α} = value of the balance parameter of an individual α; f_k^{YO} = mean of the balance parameter computed in our reference population YO.

The deviation index (DI) of the 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. Moreover, according to [27], we calculated the Z-score with respect to the young population for each healthy elderly and PD participant as follows:

$$Z_k^{\alpha} = (DI_k^{\alpha} - mean(DI_k^{\alpha,YO})) / SD(DI_k^{\alpha,YO}), \tag{2}$$

where k = balance parameter; α = study participant (healthy elderly or PD participant); Z_k^{α} = Z-score of the balance parameter computed for α; $DI_k^{\alpha} =$ deviation index of the balance parameter computed for α; YO = young population as a baseline; $DI_k^{\alpha,YO} =$ deviation index of the balance parameter computed in the baseline YO for α; SD = standard deviation.

Contrary to previous studies [27-29], we used the absolute value of the Z-score to compute the risk index (ROFA) between 0 to 100 as presented in (3). In accordance to Schwartz et al. [27] 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 not to rise above 100. Finally, we compute the ROFA index ($ROFA$) of the S2ST, walking and ST2S for each elderly participant by combining all proposed balance parameters into one single score:

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

where α = study participant; $ROFA^{\alpha}$ = risk of falling index for individual α; k = balance parameter; N_k = total number of balance parameters; γ_k = first weighting coefficient for the risk index according to the balance parameter; β_k = second weighting coefficient for the Z-score; Z_k^{α} = Z-score of the balance parameter computed for α.

We used equal coefficients γ_k. However, for a personalized analysis, this can be adjusted by physicians, clinicians, or domain experts to tailor the instability assessment. With the differences in the balance measures identifying the young, healthy elderly, and PD participants, we hold the opinion that an index such as that presented in (3) may help identify those at greatest risk. DI and other variables are an intermediate computation of ROFA. A user-friendly interface will only display ROFA score which can be interpreted easily by the clinician.

2.5. Dimensional reduction of the number of parameters in ROFA evaluation

The instrumented insole should reach a commercial value by optimizing its functions. For doing so, this section investigates the reduction of the total number of parameters (N_k) in ROFA evaluation by reducing both the number of sensors used and the number of balance parameters computed.

The data from four FSR sensors were reduced to the data of three FSRs, following four different configurations according to sensors' positions (Figure 1). Based on previous research [32-35] in which divers balance parameters have been computed, we used the FSR sensors to compute five important scalar parameters of the COP often used to identify a balance deficit [10,36]. The pressure from each FSR contributes in providing the coordinates of the COP as presented in [10]. Despite there are many parameters available, not all measures derived from the COP were able to successfully distinguish fallers and non-fallers. This could be a first process for reducing the number of risk parameters. For example, in this study, it was the maximum and minimum of COP positions; and thus, they were not considered as critical predictive parameters in ROFA index. Therefore, based on the literature, the COP parameters proposed for S2ST and ST2S activities, and available for reducing process are presented in Table 2. Furthermore, we segmented the walking phase into different strides following an algorithm described in [37]. From several studies [14,29,38-45], we computed twelve standard temporals and spatial gait parameters related to falls as showed in Table 2. Indeed, previous studies found that these parameters are the most sensitive variables particularly in early PD participants [46], so we used them. Moreover, previous works have shown that these parameters have good to excellent test-retest reliability [47,48].

2.6. Statistical analysis

The statistical analysis was performed using Statistical Package for the Social Sciences (SPSS version 20.0), and statistical significance was set as $p < 0.05$. In SPSS, the Shapiro-Wilk test was used to check the normality of the data tested.

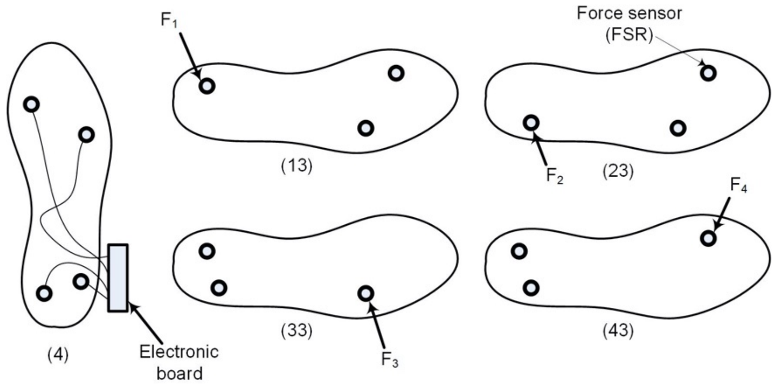

Figure 1. Different sensor positions over the insole.

Note: FSR = force sensing resistor; (4) = use of four FSRs (F1, F2, F3, F4); (43) = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions; (33) = use of F2, F1 and F3; (23) = (F2, F3, F4); (13) = (F3, F1, F4).

Table 2. Parameters computed during the TUG test for dimensional reduction analysis

Parameter	Activity in the TUG test
mean and max of V, Vx, Vy; RMS of V, Vx, Vy; max of P, Px, Py; Jerk of P, Px, Py; RMS of P, Px, Py	S2ST/ST2S
step and stride length; cadence, step frequency; step and stride times; stance and swing times; swing time/stride time; stance time/stride time; stance time /swing time; swing time/stance time	Walking

Note**:** P = global center of pressure (COP) position; Px = COP position along x-axis; Py = COP position along y-axis; RMS = root mean square; S2ST = sit-to-stand; ST2S: stand-to-sit; TUG = timed up and go; V: global COP velocity; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis.

The two-way analysis of variance (ANOVA) was used to analyze measures from walking phase and to determine the interaction between participants (healthy elderly and PD participants) and conditions (4FSR vs 3FSR). The dependent variable was the score of the ROFA, and the two independent variables were 1) the conditions: the reduced set of sensors (4-FSR, 1-3FSR, 2-3FSR, 3-3FSR, 4-3FSR), and 2) the participants, as shown in Table 1. Post hoc analysis with Tukey tests were conducted for pairwise comparisons. For validation, firstly, T-test was also used to compare measures between conditions (4FSR vs each configuration of 3FSR). It was used to evaluate the effect of the reduced number of sensors. Secondly, F-test was added to assess the relationships between outcome measures from the reduced sensors. To analyze the results from S2ST and ST2S, one-way ANOVA was used with post-hoc analysis and Bonferroni corrections were used during all analyses.

Finally, we also calculated a percentage of change of the ROFA defined as follows:

$$\% \, change = (ROFA_i - ROFA_{Opt})/ROFA_i, \tag{4}$$

where $\% \, change$ = percentage of change of ROFA; $ROFA_i$ = initial value of the ROFA using four FSR sensors (i.e., without using a reduced set of sensor and parameters); $ROFA_{Opt}$ = value of the ROFA after using a reduced set of sensors and/or parameters. Here, we are considering the percentage as negative (increase) and positive (decrease).

2.7. Margin error

Determining the appropriate sample size is crucial to obtaining accurate information. In this study, we are interested in calculating the margin error from our sample. According to previous studies [49,50], a Canadian national sample showed that about 27.18% of Canadians are aged between 20-39 years; healthy elderly people aged between 55-79 years account for 25.49%, and people with PD aged 40 years and above account for 0.4%. Then, we calculated the precision (or absolute error) at type 1 error of 5% using the formula below [51,52]:

$$E = Z_{1-\alpha/2} \times \sqrt{P(1-P)/N}, \tag{5}$$

where E = absolute error or precision (the margin error) calculated as output; $Z_{1-\alpha/2}$ = standard normal variate. At 5% type 1 error (p<0.05), it is 1.96 and at 1% type 1 error (p<0.01), it is 2.58 [53]. In majority of studies, p-values are considered significant below 0.05, therefore, $Z_{1-\alpha/2} = 1.96$ is used in this study; P = expected proportion in the population based on previous or pilot studies; N = sample size of each group used in this study.

Table 3: Results of the two-way analyze of variance (ANOVA) applied to ROFA scores using different sensors configurations during walking

Source	Sum of square (type III)	df	Mean square	F	p-value
Corrected model	350.086	9	38.898	4.207	< 0.001
Participant	13.595	1	13.595	1.470	0.226
Condition	224.143	4	56.036	6.060	< 0.001
Participant × Condition	24.052	4	6.013	0.650	0.627
Error	5464.499	591	---	---	---
Corrected total	5814.585	600	---	---	---

Note: df = degree of freedom; ROFA = risk of falling.

3. Results

3.1. Effects of sensor reduction during walking

Four FSR sensors and a y-axis accelerometer were used as reference and compared with a reduced sensor set (c-nFSR + Ay; where n = 3 with different configurations c = 1, 2, 3, 4 according to sensor positions represented in Figure 1).

The two-way ANOVA results yielded a significant effect for the conditions ($F = 6.06$, $p < .001$), such that, the average difference of ROFA score was significant when compared 4FSR versus 4-3FSR (1.634 ± 0.457). The main effect of participants was non-significant ($F = 1.47$, $p = 0.226 > .05$). Furthermore, the interaction effect between participants and conditions was non-significant ($F = 0.65$, $p = 0.627 > .05$), indicating that the participants effect was not greater in the conditions (Table 3). It also showed that the difference in means of the conditions (2-3FSR vs 3-3FSR; 2-3FSR vs 4-3FSR and 4FSR vs 4-3FSR) +Ay was significant at 0.05. All other comparisons were not significant. Tukey tests showed a significant difference between 4FSR+Ay and 4-3FSR+Ay for healthy elderly and between 4FSR+Ay and 3-3FSR+Ay for PD participants (Table 4). To suggest the best configuration, we also performed an F-test. Our rule was to exclude the configurations with a significant difference ($p<0.05$) when we compared the reduced situation with the reference. Firstly, the configurations 3-3FSR+Ay and 4-3FSR+Ay showed a significant difference with 4FSR+Ay ($p = 0.0131$ and 0.0028 respectively) across study groups and FSR conditions (four vs three), which revealed the effect of sensor reduction. Thus, at this step, we kept the configurations 1-3FSR+Ay and 2-3FSR+Ay, which showed no significant difference ($p = 0.437$ and 0.5626) across the study population. Also, T-test and post hoc analysis showed no significant difference (Table 4). Secondly, the F-test showed a significant difference ($p < 0.05$) for the configuration 2-3FSR+Ay among PD participants. Therefore, we suggest that the best configuration and sensor location for reducing the number of sensors to three FSRs without losing information could be the configuration 1-3FSR+Ay (Figure 2), in which no significant effect was found for all participants regardless of the statistical tests. Also, we note that compared with 4FSR+Ay, no significant difference was reported between PD and healthy elderly participants. This result is, therefore, consistent and independent of the population (Table 3).

Table 4. Performance (p-values) of the different statistical tests used during walking

Reduced set of FSRs configuration number	4FSR+Ay versus 3FSR+Ay					
	Healthy elderly			PD participant		
	T-test	P-comp.	F-test	T-test	P-comp.	F-test
1-3FSR	0.4551	0.9560	0.8050	0.3446	0.8764	0.4738
2-3FSR	0.9271	1.0000	0.8166	0.2047	0.7506	0.0397
3-3FSR	0.1445	0.5285	0.3778	0.0110	0.0320	0.1931
4-3FSR	0.0014	0.0060	0.5721	0.0093	0.0700	0.2370

Note: Ay = y-axis of the acceleration; FSR = force sensing resistor; 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); P-comp = Pairwise comparison; PD = Parkinson's disease.

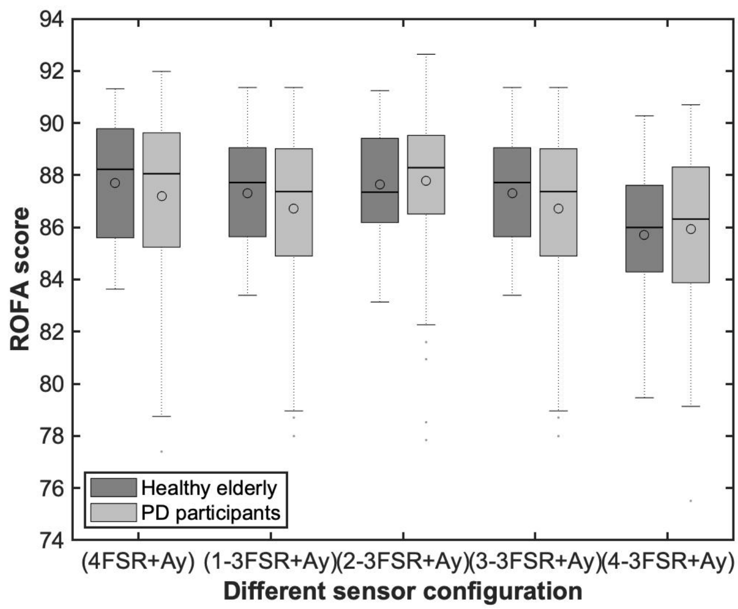

Figure 2. Risk scores from different sensor configurations during walking. The boxplots display the distribution of the data as minimum, first quartile (Q1), median, third quartile (Q3), and maximum.

Note: Ay = y-axis of acceleration; FSR = force sensing resistor; 4FSR = use of four FSRs (F1, F2, F3, F4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); PD = Parkinson's disease; ROFA = risk of falling.

Table 5. Significant p-values from PD participants for reduced sensors and reduced parameters during S2ST

Feature compared		p-value
P+V (3-3FSR)	Px (4FSR)	0.02046
	Px (3-3FSR)	0.00784
	Px (4-3FSR)	0.00840
	Py (1-3FSR)	0.00940
	Vy (2-3FSR)	0.00987

Note: FSR = force sensing resistor; 4FSR = use of four FSRs (F_1, F_2, F_3, F_4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); PD = Parkinson's disease; P = global center of pressure (COP) position; Px = COP position along x-axis; Py = COP position along y-axis; V = global COP velocity; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis.

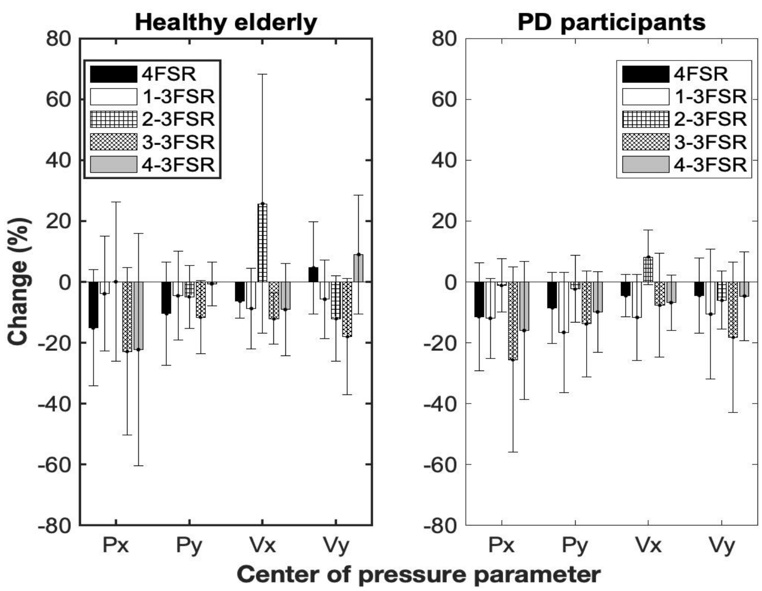

Figure 3. Percentage change of different FSR configurations during S2ST. The mean values are reported. The errors bars indicate the standard deviation of the values.

Note: FSR = force sensing resistor; 4FSR = use of four FSRs (F1, F2, F3, F4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); PD = Parkinson's disease; Px = center of pressure (COP) position along x-axis; Py = COP position along y-axis; S2ST = sit-to-stand; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis.

Table 6. Significant p-values from PD participants for reduced sensors and reduced parameters during ST2S

Feature compared		p-value
P+V (1-3FSR)	Vx (2-3FSR)	0.04309
P+V (4-3FSR)	Vx (2-3FSR)	0.02206
P+V (4-3FSR)	Vy (3-3FSR)	0.03517
Px (4FSR)	Vx (2-3FSR)	0.03736
Px (3-3FSR)	Vx (2-3FSR)	0.00371
Px (3-3FSR)	Vy (2-3FSR)	0.01686
Px (3-3FSR)	Vy (3-3FSR)	0.00641
Px (4-3FSR)	Vx (2-3FSR)	0.01960
Px (4-3FSR)	Vy (3-3FSR)	0.03143
Py (4FSR)	Vx (2-3FSR)	0.03394
Vx (4FSR)	Vx (2-3FSR)	0.00594
Vx (4FSR)	Vy (2-3FSR)	0.02549
Vx (4FSR)	Vy (3-3FSR)	0.01006
Vx (1-3FSR)	Vx (2-3FSR)	0.01373
Vx (1-3FSR)	Vy (3-3FSR)	0.02242
Vx (3-3FSR)	Vx (4-3FSR)	0.01662
Vx (4-3FSR)	Vy (3-3FSR)	0.02689

Note: FSR = force sensing resistor; 4FSR = use of four FSRs (F_1, F_2, F_3, F_4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); PD = Parkinson's disease; P = global center of pressure (COP) position; Px = COP position along x-axis; Py = COP position along y-axis; V = global COP velocity; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis.

3.2. Effects of sensor and parameter reduction during S2ST and ST2S

Since the IMU is located on the electronic board and attached to the foot (as shown in Figure 1 of the reference [26]), for S2ST and ST2S activities, this sensor cannot measure any motion. Therefore, the accelerometer's position is not appropriate to detect a risk of falling, and here, we exclude this sensor. We exploited the configurations presented above to compute a ROFA during S2ST and ST2S activities for healthy elderly and PD participants. Using position and velocity of COP along x-axis and y-axis, respectively Px, Py, Vx and Vy; and combining the global position and velocity of COP as P+V, we computed five COP parameters and then the ROFA score. For healthy elderly, one-way ANOVA analysis performed on ROFA scores showed no significant difference ($p = 0.4274$) during S2ST whereas a significant difference was found during ST2S ($p = 0.0241$). For PD participants, ANOVA analysis showed a significant difference during S2ST ($p = 0.0002$) and ST2S ($p = 3.51\times10^{-7}$). A pairwise comparison revealed no effect for parameter reduction when we compared the ROFA scores of 4FSR (P+V) with 4FSR (Px), 4FSR (Py), 4FSR (Vx) and 4FSR (Vy) among healthy elderly. However, during S2ST and ST2S in PD participants, a significant effect for certain comparisons was found, as presented in Tables 5 and 6, which revealed, among participants with more balance disorder, the effects of sensor locations on the reduced set of parameters (e.g.: 3-3FSR(P+V) versus 2-3FSR(Vy)).

Depending on the value of the ROFA score, the risk can be defined in different levels [41]. For example, Rosa et al. [54] consider range from 0 to 100 where values from 0 to 30 indicate low fall risk; from 31 to 70 a medium fall risk and from 71 to 100 indicate a high fall risk. In our study, we consider that there would be a loss of information when the defined percentage change exceeds ±20%, which could cause an important change from one level of the risk to another. By reducing the number of variables from P+V to Px and the number of FSR sensors from 4 to 3, we can notice that the percentage change is -22.8% ± 27.44% and -22.23% ± 38.06% respectively for configurations 3-3FSR and 4-3FSR in healthy elderly during S2ST (Figure 3). When P+V are reduced to Vx, the percentage change is 25.68% ± 42.60% for the configuration 2-3FSR during S2ST (Figure 3). Among PD participants, according to the proposed procedure, we observe a loss of information of -25.54% ± 30.40% when the variable is reduced from P+V to Px for the configuration 3-3FSR during S2ST (Figure 3). All other experimental conditions and number of variables is less than ±20%; also, during the ST2S (Figure 4).

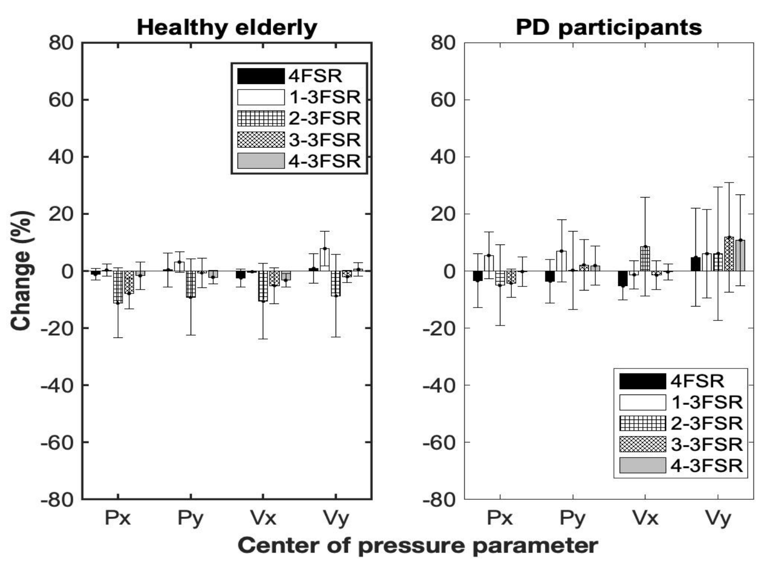

Figure 4. Percentage change of different FSR configurations during ST2S. The mean values are reported. The errors bars indicate the standard deviation of the values.

Note: FSR = force sensing resistor; 4FSR = use of four FSRs (F1, F2, F3, F4); 4-3FSR = use of three FSRs (F2, F1, F4), i.e. 3FSRs at different positions (see Figure 1); 3-3FSR = use of F2, F1 and F3; 2-3FSR = (F2, F3, F4); 1-3FSR = (F3, F1, F4); PD = Parkinson's disease; Px = center of pressure (COP) position along x-axis; Py = COP position along y-axis; ST2T = stand-to-sit; Vx = COP velocity along x-axis; Vy = COP velocity along y-axis.

4. Discussion

4.1. Discussion on the dimensional reduction effect

Several parameters are often computed from the TUG signals, and it is clear that the number of parameters computed is related to the number and positions of sensors used. Usually, the IMU sensor when it is single, is worn on the lower back [8]. In this study, we used one axis of 3D accelerometer combined with a reduced set of FSR sensors. Compared to [17], our findings showed that a reduced set of FSR allowed the computation of gait parameters for ROFA assessment in healthy elderly and PD participants. While some studies can use a small number of sensors for gait analysis [17], this study also investigates the feasibility of reducing the number of FSR sensors in S2ST and ST2S activities by computing some COP parameters from the distribution of the force under the foot. The distribution of the force can be measured using an instrumented insole system with multi-sensors placed at different anatomical areas [8,16,18,55].

While ROFA index has been examined with four FSRs [2] and seven FSRs [12] in literature, it is important to emphasize that the use of three FSRs may provide statistically similar information for computing the ROFA levels. For doing so, datasets from TUG test are exploited. The results showed a non-significant effect for the use of three FSRs in almost cases, making it suitable for risk assessment (Table 4). These findings support our hypothesis that it may be possible to use a smaller number of sensing units to estimate a ROFA index, thereby reducing the power consumption. Indeed, Barkallah et al. [56] findings suggest that at 10 kΩ, the FSR sensor maximally consumes 0.33 mA. In total, 4FSRs and 3FSRs consumes 1.32 mA and 0.99 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 $8.64 USD [57]. The results reported in Table 4 suggest that three FSRs could be enough to estimate the risk index during walking activity (Figure 2). In our method, we also investigate different locations of the three FSRs sensors, and as observed, the F-test and the pairwise comparison did not reveal nonsignificant effect across the sensor locations in all cases among the study participants (Table 4). This indicates the importance of sensor locations [18], and we concluded that the use of one FSR at the heel and two FSRs at the toes (configuration 1-3FSR) seems to be suitable for estimating the same ROFA level during walking activity without losing information (Figure 2).

Based on this first conclusion, three FSRs were exploited to estimate the risk index during S2ST and ST2S activities (Figures 3 and 4). We computed different balance parameters from the COP displacements and compared it with the reference (use of four FSRs). No significant difference was found between P+V(4FSR) vs V(1-3FSR). This means that a dimensional reduction of the balance parameters and the number of sensors for all the study population could be possible in order to avoid redundancy. These findings reinforce our hypothesis that a small number of FSR sensor units can be used to estimate a risk index in different populations without losing significant information. Moreover, the reduced set of sensor and parameter V(1-3FSR), which includes global COP velocity, could be enough to quantify efficiently the neuromuscular activity required to maintain balance. At the beginning of the S2ST, we observed that the COP is located between two pressure points at the heel and could move towards the external pressure (F_1) or the internal pressure (F_2) depending on the side where the participant is leaning the most. After this preparatory phase, the COP can move to the middle of the foot depending on the pressure exerted on the two pressure points at the toes. This could explain the nonsignificant difference observed between the use of four and three FSRs and could also indicate why the use of one FSR at the heel and two FSRs at the toes seemed to be suitable for estimating the same ROFA level in these activities. In addition, we note that only this configuration (1-3FSR) did not provide a significant loss of information among the study population (Figures 3 and 4). Indeed, comparing P+V to Px, we report that the percentage change is -22.8% ± 27.44% and -22.23% ± 38.06% respectively for configurations 3-3FSR and 4-3FSR in healthy elderly during S2ST (Figure 3). Reducing P+V to Vx, the percentage change is 25.68% ± 42.60% for the configuration 2-3FSR during S2ST (Figure 3). In PD participants, we observe a loss of information of -25.54% ± 30.40% when used Px instead of P+V for the configuration 3-3FSR during S2ST (Figure 3). All other experimental conditions with reduced number of variables have a loss of information less than ±20%, and also during the ST2S (Figure 4). Thus, these results are consistent with the findings observed during the walking where the configuration 1-3FSR could be the best configuration to achieve the purpose of reducing the number of variables (number of sensors and balance parameters) while reducing information loss in all study population.

In Tables 5 and 6, we note nevertheless, a difference between the components (antero-posterior and mediolateral) of COP in PD participants across sensor configurations, which revealed the important effect of sensor location on dimensional reduction of the balance parameters among these participants. This could be due to the side that is most affected in PD participants. It is possible that the affected side may have generated a significant difference between mediolateral and anteroposterior sway, and better justifying the significant difference in the ROFA index (for example, the significant difference between configurations 3-3FSR using Vy and 4-3FSR using Vx). Moreover, the participants pay more attention to S2ST contrary to ST2S in which the pressure on the force sensors can be random and introduce more significant effect or inconsistent results. We note that this significant difference between the two components is not observed in healthy elderly.

During the S2ST and ST2S activities, the IMU was excluded. However, the chosen location of the sensors could be changed. 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 approximation. 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 as an image of the pressure under the foot. In our application, the ROFA is not dependent on the resolution of the force sensors. For this reason, we can optimize the number of sensors to be used and their locations.

4.2. Implications and limitations of this study

We hold the opinion 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. We also think that the ROFA index computed with minimal gait and balance parameters should allow the clinician to better identify the patient at risk of falling. The ROFA index with the reduced set of parameters is computed by our instrumented insole [58] and can be transmitted wirelessly to a mobile device. In this case, the information displayed on the mobile device can be understood easily by clinicians and patients. This monitoring is important to assess the progression of disease related to gait disorders and the improvement between the clinical visits. In addition, it can give information to the neurologist to adjust drug prescription as needed. The longitudinal change information is important for rehabilitation and probably can help to decrease the number of visits to physicians and clinicians. The collected data will be useful for extracting some information in real time to suggest a correction in regard of gait deficits and some other motor complications, like motor fluctuations.

This study used a small number of participants, so the margin error of the young adults, healthy elderly and PD participants is respectively 0.2907, 0.2847 and 0.1109. Thus, generalizability of the outcomes may be limited; however, increasing the sample size does not ensure an improvement in accuracy [52]. In this study, saturation of data for optimization coming from the number of participants is reached for young people (the reference population) as the standard deviation monotonically tends to a constant and the mean changes slowly in this population. The first evaluation shows encouraging results with consistency between walking and other activities (S2ST and ST2S), and it could be more investigated for usage at home. Our findings showed a reduced set of FSRs and a reduced set of balance parameters, which could be used as a first step in machine learning process and parameter selection to differentiate fallers and non-fallers.

5. Conclusions

The use of a high number of sensors may aid in providing an accurate risk assessment. However, 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. To achieve this goal, the number of sensors, gait and balance parameters needs to be reduced adequately. In this study, an optimized instrumented insole is proposed specifically as a relatively accessible tool for detecting human balance. We first conclude that it is feasible to estimate the risk index after reducing the number of needed sensing units from four to three FSRs for walking, S2ST and ST2S activities. Indeed, the use of three FSR sensors should allow us to have a longer life for the battery and a hardware price reduction of at least $8 USD. We also demonstrated the effect of dimensional reduction of balance parameters while reducing the number of sensors. Reducing both the number of sensors and balance parameters will help to reduce the acquisition cost of an instrumented insole for home usage. In future works, more research is needed to be developed. The validation of the optimized device 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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