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History of falls alters movement smoothness and time taken to complete a functional mobility task in the oldest-old: A case-control study

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A R T I C L E I N F O

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A B S T R A C T

Background: Mobility smoothness assessed by the spectral arc length (SPARC) may reflect the complex biomechanical alterations that occur with aging and may help detect functional mobility changes after experiencing falls. Here, we sought to explore whether smoothness of angular velocities of the trunk measured using SPARC metrics in the instrumented timed-up-and-go (iTUG) test are assoacited with a history of falls in the oldest-old.
Methods: A case-control study. The sample consisted of 64 community-dwelling oldest-old individuals who underwent the following assessments: clinical and sociodemographic questionnaire, Mini Mental State Examination (MMSE), Falls Efficacy-questionnaire International (FES—I), the Activities-specific Balance Confidence (ABC), Functional Reaching Test (FRT), and the iTUG test. We used an inertial measurement unit (IMU) to obtain trunk angular velocities from the IMU's gyroscope, which was used to calculate mobility smoothness (SPARC).
Results: Standard deviation of the mobility smoothness around the anteroposterior axis of rotation (SPARC roll SD) (OR: 6.15 / CI 95 % = 1.58–23.94) and duration (OR: 1.11 / CI 95 % = 1.09–1.22) in the full iTUG test were associated with a history of falls in oldest-old. Using solely the full iTUG duration (59.19 $\pm$ 2.18) or SPARC (61.87 $\pm$ 2.40) resulted in lower probability to detect a history of falls in comparison with the combined measurement (66.21 $\pm$ 2.50).
Conclusion: SPARC roll SD in the full iTUG may be a relevant biomarker to detect mobility smoothness changes in the oldest-old. This study provides evidence the oldest-old with a history of falls may change their functional mobility, in terms of movement duration and smoothness.

1. Introduction

Fall-related injuries account for two-thirds of deaths worldwide (Burns and Kakara, 2018) and nearly 30 % of all moderate to severe injuries in older adults (Sterling et al., 2001). Every year, one in three people aged ≥65 and one in two aged ≥80 will experience a fall (Phelan and Ritchey, 2018) that may result in fractures, functional decay, and institutionalization (Gálvez-Barrón et al., 2020; Li et al., 2021).

Before enrolling individuals in fall-prevention programs, it is essential to develop tools capable of identifying both the likelihood of falls and behavior changes after falling (Lusardi et al., 2017). However, the widely used time-based functional mobility metrics, e.g. the traditional Timed-Up-and-Go (TUG) test, tends to detect changes in functional mobility at a late stage in older adults, when the time window available for fall prevention (primary or secondary) is potentially limited (Kojima et al., 2015; Yamada et al., 2019). Despite this, the duration-based TUG is widely recommended in clinical practice when assessing functional mobility in older adults (Tinetti, 2003; Yeung et al., 2008). The TUG test is feasible, quick to run, and requires minimal materials and setup, which allows this task to be easily adapted for screening individuals at home or in consulting rooms (Barry et al., 2014).

In recent years, inertial sensors have allowed movement assessment beyond the duration-related metrics, which includes the possibility of analyzing movement in the frequency domain (Montero-Odasso et al., 2019; Pau et al., 2020). When an inertial measurement unit (IMU) is donned during the TUG test, it is possible to extract 3-axial linear

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accelerations from the accelerometer and 3-axial angular velocities from the gyroscope. Using this paradigm, more specific information on movement quality during the test, such as smoothness, can be obtained (Lowry et al., 2017; Melendez-Calderon et al., 2021). While smoothness metrics were originally applied to discrete movements of the upper limb (Balasubramanian et al., 2015; Leban et al., 2020), recent studies have proposed adaptations to assess continuous movements, e.g., walking-based tasks (Beck et al., 2018; Garcia et al., 2021; Figueiredo et al., 2020). While inertial sensors have been used to provide more accurate time and/or speed information in the iTUG (Garcia et al., 2021; Figueiredo et al., 2020), to the best of our knowledge, functional mobility smoothness has not yet been studied as a biomarker to estimate risk of falls or to show fall-induced changes in motor control.

Spectral arc length (SPARC) metrics have emerged as a new approach to quantifying gait/mobility smoothness in different populations (Garcia et al., 2021; Figueiredo et al., 2020; Schuch et al., 2020). These measures have proven to be sensitive, robust, and less influenced by the speed or duration of the task (Balasubramanian et al., 2012, 2015; Melendez-Calderon et al., 2021). When quantifying mobility smoothness from an IMU located at the waist, close to the center of mass, it is possible to understand the complex biomechanical pattern of mobility at the system level. Hence, the addition of mobility smoothness metrics in the instrumented TUG test (iTUG) assessment may provide useful information when assessing functional mobility in older adults (Figueiredo et al., 2020). However, the capacity of SPARC metrics measured during the iTUG test in predicting fall-related changes in functional mobility behavior has not yet been determined.

In this study, we sought to assess whether mobility smoothness measured by the SPARC metrics in the iTUG test is changed in the oldest-old with a history of falls. We hypothesized that the oldest-old with a history of falls would change both movement duration and smoothness (SPARC) during a functional mobility task.

2. Methods

2.1. Study design, setting, and participants

This is a case-control study registered in the local Ethics Committee (under report numbers 2,278,707 and 3,317,838). All participants signed the informed consent form and the international guidelines for research involving humans were followed.

Recruitment and data collection occurred between December 2017 to June 2019 at the participants' home. The community-dwelling oldest-old (people aged 80 and older) who had experienced falls (at least once) in the six months before the study were considered a 'case' (faller) and their pairs who did not experience falls in this period were considered 'controls' (non-fallers). A fall was defined as an unexpected and unexplained event in which the individual inadvertently comes to lay on the ground (Deandrea et al., 2010). We did not consider other types of falls to alleviate recall bias.

Oldest-old with ($n = 32$) and without (n = 32) a self-reported history of falls were enrolled in the study by convenience. The inclusion criteria were: aged ≥80 years old; any gender; ability to walk independently (walking devices allowed); and the ability to understand the verbal commands to carry out the proposed assessment. We excluded participants who were uncertain about their history of falls; had been hospitalized for >7 days in the 3 months before the assessment; had a diagnosis of severe orthopedic, neurological, respiratory, cardiovascular, visual, or hearing diseases.

2.2. Procedures and variables of interest

Community-dwelling oldest-old living in Porto Alegre, Rio Grande do Sul, Brazil, were recruited by convenience using local media and 'word of mouth marketing'. Then, potential participants were contacted by phone and those who agreed to participate in the study received a home visit. During the visit, we applied the following assessments: clinical and sociodemographic questionnaire; Mini Mental State Examination (MMSE) (Folstein et al., 1975); Activities Specific Balance Confidence Scale (ABC) (Powell and Myer, 1995); and Fall Effectiveness Scale - International (FES—I) (Yardley et al., 2005). We also assessed the functional reach test (FRT), blood pressure, body mass index, and 3 trials of the iTUG test.

The iTUG-related metrics, mainly iTUG duration and SPARC, were tested as potential predictors of functional mobility changes in the oldest-old with a history of falls. The other collected measures were considered as potential effect modifiers.

To perform the iTUG test, a standard armless chair (height = 43 cm) and a cross (30 × 30 cm) marked on the floor with tape were used. The participants were asked to stand up and walk as fast as possible after the verbal command "get up and go". They changed from the sitting to standing position (sit-to-stand phase), walked forward 3 m (walk 1 phase), performed a 180° turn around the cross (turn phase), returned walking 3 m (walk 2 phase), and turned to sit in the same chair (stand-to-sit phase). During the iTUG test, the oldest-old wore an IMU (G-Walk®, BTS Bioengineering, MA, United States), positioned between the L5 and S1 vertebrae using an neoprene belt provided by the manufacturer. This belt provides an specific area to fix the IMU, thus minimizing axis-related acquisition bias during donning and doffing of the IMU (Figueiredo et al., 2020; Pau et al., 2018). The IMU device, incorporating a triaxial accelerometer and gyroscope, is Bluetooth compatible with a sampling rate of 100 Hz. The angular velocities were acquired in the vertical (V, yaw; SPARC yaw), medio-lateral (ML, pitch; SPARC pitch), and anteroposterior (AP, roll; SPARC roll) axes. The angular velocity raw data were extracted using the G-sensor® software and exported in ASCII format.

Mobility smoothness was estimated using the SPARC metrics (Beck et al., 2018; Pinto et al., 2019). The algorithm was optimized following the recent recommendations for estimating SPARC from IMUs (Melendez-Calderon et al., 2021). We used the 3 calibrated angular velocities (yaw, roll, and pitch) (in° / s) from the IMU gyroscope data, mean subtractions were used to remove the direct current (DC) components from the raw angular velocity data. We also implemented a windowing procedure to reduce the effects of long, continuous data windows - very long windows may increase the fast Fourier transform (FFT) resolution and the signal frequency complexity, respectively, which can induce a duration effect on SPARC calculation (Figueiredo et al., 2020). Thus, we used a conservative non-overlapping window size of 3 s (300 frames). The phases of the TUG test were detected by visual inspection using a custom graphical user interface in LabVIEW (previously described and tested for reliability in Figueiredo et al., 2020) (Fig. 1). Each of the cropped angular accelerations from the respective TUG phase was replicated 4 times creating a long time series containing the respective TUG test phase. This procedure was conducted to increase the power spectra of the frequencies contained in the respective phase. Each cropped window (300 frames) was zero-padded to double the FFT frequency resolution (to 600 frames), after which SPARC was calculated. For SPARC calculation we applied a low pass filter by removing frequencies above 25 Hz. To determine the adaptive cut-off frequency (ωc), we used an amplitude threshold of 0.01 of the normalized FFT [Eq. (1)]. We also calculated the SPARC using the norm of the 3 angular velocities [Eq. (2)]. This procedure was conducted to remove any variability resulting from improper placement of the IMU sensor on the trunk.

The SPARC [$\lambda_S^v(\mathbf{V})$] was determined for each 3-s window and the average of all SPARC windows contained in the iTUG trial was calculated.

$$\lambda_S^v(\mathbf{V}) \triangleq -\int_0^{\omega_c} \sqrt{\left[\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\widehat{V}(\omega)}{d\omega}\right)^2\right]}\, d\omega \tag{1}$$

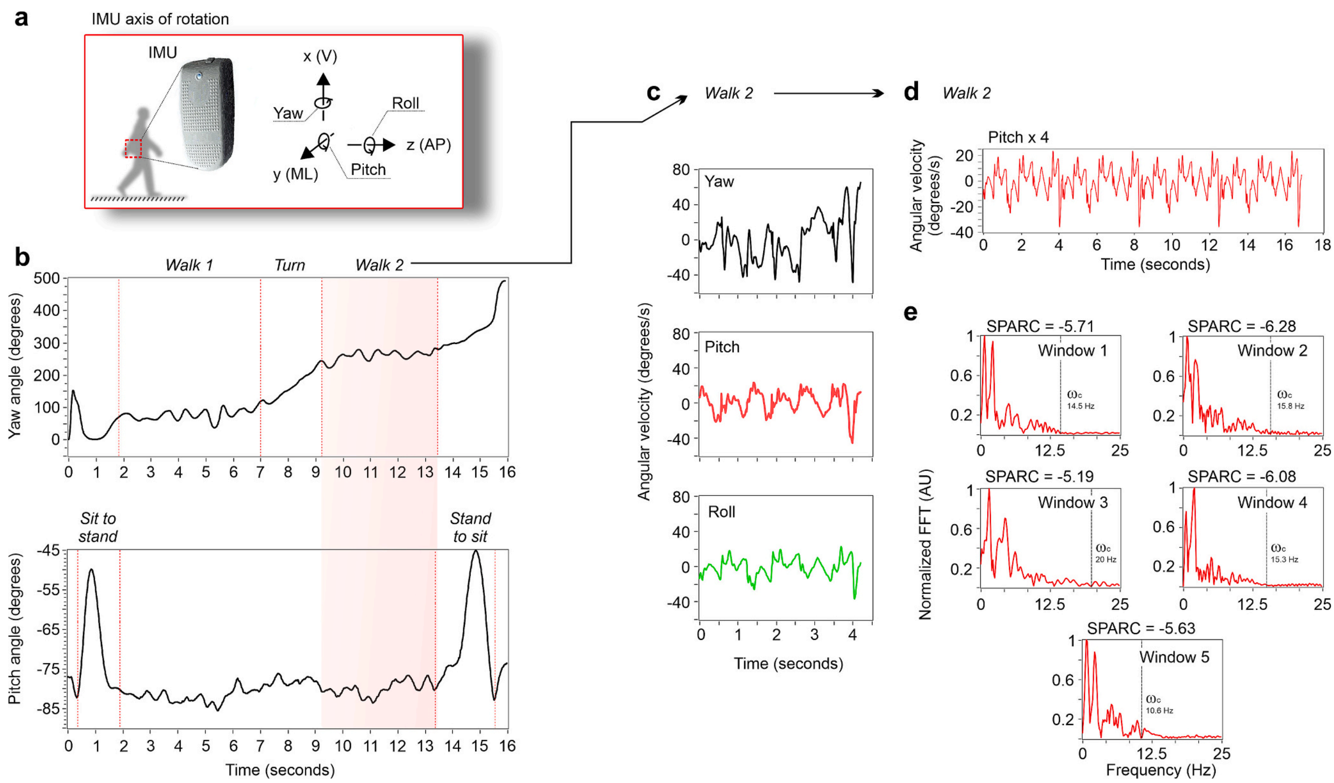

Fig. 1. Inertial measurement unit (IMU) axis of rotation and the spectral arc length (SPARC) analysis. (a) The IMU was attached to the waist and measured angular velocities around the vertical (V), medio-lateral (ML), and anteroposterior (AP) axis of rotation, these angular velocities were used to calculate SPARC yaw, SPARC pitch, and SPARC roll, respectively. (b) The yaw and pitch angles were used to manually detect the instrumented Timed-Up-and-Go (iTUG) phases (Figueiredo et al., 2020). (c) Angular velocities during the Walk 2 phase of the iTUG test in the yaw (black), pitch (red), and roll (green) directions of a subject with representative smoothness in the pitch direction. (d) The angular velocities were repeated 4 times to increase the data length for the frequency-domain analysis. (e) Frequency-domain analysis (Fast-Fourier Transform; FFT) of the angular velocities in the pitch direction (shown in d) for each of the 3 s windows (5 windows), and respective adaptice cut-off frequency (ωc) and SPARC values. IMU = Inertial measurement unit; SPARC = Spectral Arc Length; V = Vertical; ML = Medio-lateral; AP = anteroposterior; iTUG = instrumented Timed-Up-and-Go test. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\widehat{V}(\omega) = \frac{V(\omega)}{V(0)}; V(\omega) = \left|\mathscr{F}\left(\|\mathbf{V}(t)\|_2\right).\right|$$

where V (t) represents the velocity (angular) of a movement in the time domain, F(•) is the Fourier transform operator, ωc is an adaptive cut-off frequency (see Melendez-Calderon et al., 2021 for details).

$$Norm\ Angular\ Velocity = \sqrt[2]{Angular\ Velocity\ Yaw^2 + Angular\ Velocity\ Pitch^2 + Angular\ Velocity\ Roll^2} \quad (2)$$

Movement arrest periods may increase the complexity of the frequency composition, which is captured by the SPARC analysis. Because of the negative sign, lower SPARC values indicate less movement smoothness (increased frequency domain complexity). Spectral analysis metrics followed the assumption that unsmooth movements are more complex in terms of their frequency composition. In other words, lower SPARC values indicate less movement smoothness (Gulde and Hermsdörfer, 2018).

Potential sources of bias were controlled by minimizing the influence of the task duration on SPARC metrics, following the above-mentioned procedure. Potential recall bias regarding the history of falls (exposure assessment bias) was minimized by confirming fall occurrence with the participants at least twice and by checking the information with relatives and/or caregivers.

2.3. Sample size

The sample size was based on the study from Figueiredo et al., 2020. The online resource from the University of British Columbia (Brant, 2017) was used to calculate the sample size. Adopting a power of 80 % and an alpha of 0.05 the sample was set at 64 oldest-old, 32 cases, and 32 controls.

2.4. Quantitative variables

Quantitative variables were measured as described above and registered in a spreadsheet. The SPARC roll, pitch, and yaw were analyzed in the full iTUG and test subphases. However, SPARC standard deviation (SD) metrics were compared only for the full iTUG test to prevent duration bias (<3 s) in the shorter test subphases. All the collected data were double-checked independently by two researchers. Doubts were resolved by consensus.

2.5. Statistical methods

Continuous variables are shown as mean and standard deviation (when normally distributed) while categoric variables are presented using frequencies. Bivariate binary logistic regression (falls as the dependent variable vs an independent predictor) was applied to find the most relevant factors to include in the multivariate binary logistic regression. To prevent multicollinearity, all the multivariate analyses included only uncorrelated/weakly correlated independent variables – tested using Spearman's correlation rank. When a between-variable correlation was found, we selected the variable exhibiting the lowest *p*-value in the bivariate analysis. This is the reason independent multivariate analyses were performed for each iTUG test subphase. The variables included in the multivariate analyses were determined by considering the p level ($p \leq 0.15$) in the previous bivariate analysis. The Receiver Operating Characteristic Curve (ROC curve) was used to identify the cut-off points for the significant predictors. The independent *t*-test was used to compare the gain of each multivariate model in terms of the ability to predict functional mobility changes in the oldest-old with and without a history of falls. Significance was set at $\alpha < 0.05$ and statistical analyses were performed in the Statistical Package for the Social Sciences (SPSS) version 22.0.

3. Results

A total of 90 potentially eligible participants were invited to take part in this study. 84 were examined for eligibility and 64 were included. The reasons for exclusions were: medical diagnosis of severe orthopedic, cardiovascular, or visual diseases; uncertainty regarding the history of falls (information obtained with the participant and their relatives/caregivers did not match). Six eligible participants declined to participate in the study. All the 64 included participants were analyzed (no missing data occurred in this case-control study).

The participants were aged 89 years (85 to 101 years old), and most were female (81.25 %). Age, gender, ethnicity, years of schooling, body mass index, polypharmacy, blood pressure, marital status, and self-reported smoking and drinking did not differ between fallers and non-fallers. The sample characteristics are shown in Table 1. For the SPARC analysis, we report an average of 14.8 Hz for the adaptive cut-off frequency (ωc), with a max of 20.86 Hz and a minimum of 8.02 Hz.

The bivariate analysis showed FES-I (OR: 2.74, $p = 0.06$); ABC (OR: 0.97, $p = 0.03$); FRT (OR: 0.95, $p = 0.13$) and SPARC roll SD (OR: 2.09, $p = 0.12$) were the most likely relevant variables to differentiate case and control groups in the full iTUG. The SPARC metrics did not differ statistically between case and controls in the iTUG test subphases. The bivariate analyses are shown in Table 1.

Independent multivariate logistic regressions are shown in Table 2. SPARC roll SD (OR: 6.15, $p = 0.009$), test duration (OR: 1.11, $p = 0.018$) and ABC (OR: 0.94, p = 0.009) were the most relevant independent variables in the full iTUG regression model to predict fall-induced changes in functional mobility. Overall, the model combining SPARC roll SD and test duration provided the best predictive value when compared with the prediction obtained in SPARC or duration-only multivariate models (Table 3).

Concerning the characteristics of the participants for whom the model was able to predict a history of falls, the obtained model best-predicted falls in the participants that were older, presented lower MMSE scores, and fewer years of formal schooling.

Finally, we performed a ROC curve analysis that revealed SPARC roll SD cut-off points in the full iTUG are not accurante to detect the oldest-old with a previous six-month history of falls. Duration in the full iTUG test provided the most balanced cut-off point to predict a history of falls in the studied sample (Table 4).

4. Discussion

In this study, we sought to address whether smoothness of angular velocities of the trunk measured using SPARC metrics in the instrumented timed-up-and-go (iTUG) test are assoacited with a history of falls in the oldest-old. Our findings confirmed that changes in SPARC metrics and the full iTUG test duration may be consequence of a previous six-month history of falls when compared with duration or SPARC-only models. The full iTUG regression model including test duration, SPARC roll SD, ABC and FRT metrics showed 183.60 % better predictive capacity in comparison with the duration-only model (31.34 % vs 17.07 %). Similarly, the SPARC-only model did not exhibit any substantial advantage in predicting falls in the studied sample when compared with the duration-only model (22.52 vs 17.07 %). These findings agree with the literature suggesting both duration and movement smoothness are important factors to determine the task performance (Figueiredo et al., 2020; Schoene et al., 2013).

A few studies have applied accelerometry-based metrics of mobility smoothness by extracting rotational data in the pitch, roll, and yaw directions to calculate mobility smoothness (Garcia et al., 2021; Pinto et al., 2019). Our findings indicate the most relevant smoothness metrics to predict falls in the oldest-old is the variability of the roll component – which is related to movement arrest periods in the anteroposterior direction (Fig. 1). This agrees with the reduced smoothness found in this component during the full iTUG test in the present study. Oscillations of the roll angle refer to the body displacement and to the quality of trunk control (Asai et al., 2017; Garcia et al., 2021), which are important for balance and axial stability while walking (Magnani et al., 2021). Moreover, a recent study revealed severely impaired stroke survivors exhibited highly variable movement smoothness in a walking-based test. The authors show SPARC scores correlated with those of lower limb spasticity (Garcia et al., 2021). This finding is interesting because lower limb spasticity can trigger trunk oscillation as a compensatory walking mechanism in stroke survivors, therefore, leading to walking instability (De Luca et al., 2020). Postural instabilities also contribute to decrease functional mobility in Parkinson's Disease (Lencioni et al., 2021). These individuals typically exhibit reduced mobility smoothness in the full iTUG test duration, 180° turn, and stand-to-sit phases in comparison with their paired-matched controls (Pinto et al., 2019). A previous case-control study from our research group also suggests oldest-old fallers exhibit an unsmooth-based motor strategy during the iTUG test (Figueiredo et al., 2020). Altogether, the current findings agree with the literature and highlight the role of SPARC as a potential marker to screen for unsmooth mobility in the oldest-old with a history of falls.

While combining SPARC metrics with duration in the regression model provided an exciting improvement in the capacity of the iTUG to predict falls, the obtained model is far from ideal. Falls are multifactorial and a single balance and/or mobility test will rarely show high predictive capacity to identify potential fallers (Rajagopalan et al., 2017; Sun and Sosnoff, 2018). A previous systematic review demonstrated the time-based TUG test has limited ability to predict falls in older adults and recommended the test should be complemented by additional tests (Barry et al., 2014). Nevertheless, the TUG test is a feasible and widely used screening tool in the context of the routine of geriatric/gerontologic evaluation (Herman et al., 2011; Rosa et al., 2019). Hence, adding SPARC roll SD to the iTUG test duration can provide a substantial increase in the ability to detect fall-related behavioral changes in functional mobility.

This research focused on the oldest-old due to their higher tendency to exhibit movement instability and experience falls (Araújo et al., 2014; Verma et al., 2016) and because they constitute one of the most challenging populational groups to study fall-induced adaptations using a limited source of predictors. As people get older, their functional ability tends to deteriorate, particularly for those aged 80 years and over (Harrison et al., 2015). Moreover, the oldest-old are typically underrepresented in falling-centered investigations – most of the studies

Table 1
Sociodemographic and clinical characteristics of participants and their relationship with a history of falls.

Variable	Fallers (n = 32)		Non-Fallers (n = 32)		OR	OR CI 95 %	p
	Mean/n (category)	SD	Mean/n (category)	SD			
Age	89.94	4.38	88.59	4.06	1.08	0.95–1.30	0.23
Gender (0 = male / 1 = female)	7(0)/25(1)	n.a.	5(0)/27(1)	n.a.	0.80	0.22–2.95	0.74
Ethnicity (0 = white / 1 = brawn or black)	26(0)/6(1)	n.a.	31(0)/1(1)	n.a.	7.15	0.81–63.30	0.08
Body Mass Index	26.17	3.62	25.50	4.34	1.04	0.92–1.19	0.51
Number of Drugs	5.28	2.79	4.40	2.34	1.14	0.94–1.39	0.18
Systolic pressure (mmHg)	127.34	11.07	127.50	11.63	0.99	0.95–1.04	0.95
Diastolic pressure (mmHg)	77.65	12.50	74.68	8.02	1.03	0.98–1.08	0.23
Years of schooling	7.85	5.66	7.87	4.15	0.99	0.90–1.10	0.99
Marital Status (single/widow = 0 / married = 1)	22(0)/10(1)	n.a.	24(0)/8(1)	n.a.	1.36	0.45–4.06	0.58
Tobacco use (0 = no / 1 = yes)	31(0)/1(1)	n.a.	31(0)/(1)	n.a.	1.00	0.06–16.71	1.00
Alcohol use (0 = no / 1 = yes)	26(0)/6(1)	n.a.	27(0)/5(1)	n.a.	1.25	0.34–4.59	0.74
MMSE	25.84	3.62	26.84	2.46	0.90	0.77–1.05	0.18
FES-I	24.31	7.58	22.03	2.74	1.08	0.99–1.17	0.06
ABC	73.45	21.14	81.99	11.58	**0.97**	0.94–0.99	**0.03**
FRT	26.31	10.15	30.12	7.78	0.95	0.89–1.01	0.13
full iTUG							
SPARC Roll	−5.48	0.96	−5.51	0.75	1.03	0.58–1.84	0.91
SPARC Roll SD	1.28	0.64	1.05	0.48	2.09	0.83–5.26	0.12
SPARC Pitch	−4.93	0.89	−5.29	1.15	1.42	0.86–2.35	0.17
SPARC Pitch SD	1.60	0.73	1.83	0.98	0.72	0.40–1.36	0.28
SPARC Yaw	−4.64	0.55	−4.59	0.62	0.86	0.36–2.02	0.73
SPARC Yaw SD	1.18	0.47	1.19	0.58	0.97	0.37–2.50	0.95
SPARC NORM	−5.01	0.56	−5.10	0.79	1.22	0.58–2.54	0.60
Test duration (*sec*)	22.80	18.40	14.64	6.43	**1.10**	1.01–1.19	**0.02**
Sit-to-stand iTUG subphase							
SPARC Roll	−5.18	1.77	−5.34	1.25	1.07	0.77–1.49	0.68
SPARC Pitch	−3.45	0.94	−3.53	0.82	1.10	0.63–1.95	0.73
SPARC Yaw	−5.38	1.39	−5.62	1.66	1.11	0.79–1.54	0.53
SPARC NORM	−4.15	0.74	−4.56	1.15	1.60	0.90–2.84	0.11
Test duration (sec)	2.09	0.80	1.74	0.41	**2.63**	1.07–6.47	**0.04**
Walk 1 iTUG subphase							
SPARC Roll	−6.30	1.41	−6.09	1.04	0.86	0.57–1.30	0.48
SPARC Pitch	−5.96	1.49	−6.70	2.25	1.24	0.94–1.63	0.13
SPARC Yaw	−5.59	1.06	−5.21	1.08	0.71	0.44–1.15	0.17
SPARC NORM	−6.73	1.31	−6.87	1.63	1.07	0.76–1.50	0.70
Test duration (sec)	6.31	4.72	4.12	1.84	**1.35**	1.05–1.72	**0.02**
Turn iTUG subphase							
SPARC Roll	−5.76	1.50	−5.69	1.10	0.96	0.65–1.40	0.83
SPARC Pitch	−5.84	1.20	−6.36	1.81	1.25	0.89–1.76	0.19
SPARC Yaw	−3.89	0.77	−3.83	0.81	0.78	0.48–1.78	0.78
SPARC NORM	−4.13	0.87	−3.80	0.58	0.96	0.54–1.69	0.89
Test duration (sec)	3.04	2.35	2.06	0.59	2.43	0.91–6.48	0.08
Walk 2 iTUG subphase							
SPARC Roll	−6.21	1.29	−6.14	1.18	0.96	0.64–1.43	0.84
SPARC Pitch	−6.19	1.766	−6.47	1.87	1.09	0.83–1.44	0.53
SPARC Yaw	−4.77	0.96	−4.76	0.97	0.99	0.59–1.66	0.96
SPARC NORM	−6.01	1.26	−6.27	−6.01	1.13	0.80–1.60	0.48
Test duration (sec)	5.48	4.49	3.77	2.20	1.22	0.97–1.54	0.09
Stand-to-sit iTUG subphase							
SPARC Roll	−3.97	0.57	−4.28	0.85	1.85	0.87–3.94	0.11
SPARC Pitch	−3.21	0.42	−3.41	0.58	2.22	0.78–6.27	0.13
SPARC Yaw	−3.57	0.56	−3.52	0.54	0.84	0.34–2.09	0.71
SPARC NORM	−4.13	0.87	−3.80	0.58	0.52	0.25–1.10	0.09
Test duration (sec)	4.72	2.12	3.99	1.16	1.33	0.97–1.82	0.07

Notes: OR = Odds ratio obtained in bivariate binary logistic regression including the independent variable and falls (dependent variable). SD = standard deviation; CI 95 % = 95 % confidence interval; mmHg = millimeter of mercury; p = significance level (bold values denote statistical significance); MMSE = Mini-mental status examination; FES-I = Falls Efficacy Scale-International; ABC = Activities-specific Balance Confidence; FRT = functional reaching test; SPARC = spectral arch length; Roll, Pitch and Yaw are inertial measurement unit axes (please, see the methods for details).

Table 2
Multivariable binary logistic regression models to predict the oldest-old with a history of falls.

Model: full iTUG *(SPARC and duration)*	OR	OR CI 95 %	p
ABC	**0.94**	**0.89–0.98**	**0.009**
FRT	0.94	0.87–1.01	0.09
SPARC Roll SD	**6.15**	**1.58–23.94**	**0.009**
Full test duration (*sec*)	**1.11**	**1.09–1.22**	**0.018**
Spearman's rank correlation			
	ABC	FRT	Full test duration (sec)
SPARC Roll SD	***r* = 0.41 (*p* = 0.001)**	*r* = 0.06 (*p* = 0.65)	*r* = − 0.04 (*p* = 0.78)
Model: full iTUG *(Duration only)*	OR	OR CI 95 %	p
ABC	0.97	0.93–1.00	0.09
Full test duration (sec)	**1.10**	**1.02–1.19**	**0.02**
Spearman's rank correlation			
	ABC		
Full test duration (sec)	r = − 0.04 (*p* = 0.74)		
Model: full iTUG *(SPARC only)*	OR	OR CI 95 %	p
ABC	**0.94**	**0.90–0.98**	**0.006**
FRT	0.93	0.88–1.00	0.06
SPARC Roll SD	**5.52**	**1.57–19.36**	**0.008**
Spearman's rank correlation			
	ABC	FRT	
SPARC Roll SD	**r = 0.41 (p = 0.001)**	r = 0.06 (p = 0.65)	
Model: Sit-to-stand	OR	OR CI 95 %	p
Phase duration (sec)	**2.63**	**1.00–6.93**	**0.05**
Spearman's rank correlation			
	ABC		
SPARC NORM	*r* = 0.10 (*p* = 0.41)		
Model: Walk 1	OR	OR CI 95 %	p
Phase duration (sec)	**1.38**	**1.06–1.80**	**0.02**
Spearman's rank correlation			
	Phase duration		
SPARC Pitch	***r* = 0.33 (*p* = 0.007)**		
Model: Turn	OR	OR CI 95 %	p
Phase duration (sec)	**2.51**	**1.05–6.03**	**0.04**
Spearman's rank correlation			
	Phase duration		
SPARC Pitch	*r* = 0.19 (*p* = 0.14)		
Model: Walk 2	OR	OR CI 95 %	p
ABC	0.97	0.94–1.00	0.06
FRT	0.95	0.89–1.01	0.10
Spearman's rank correlation			
	ABC	FRT	
SPARC NORM	***r* = − 0.30 (*p* = 0.02)**	*r* = 0.08 (*p* = 0.52)	
Model: Stand-to-sit	OR	OR CI 95 %	p
ABC	0.97	0.94–1.00	0.06
FRT	0.95	0.89–1.01	0.10
Spearman's rank correlation			
	ABC	FRT	
SPARC NORM	*r* = 0.05 (*p* = 0.68)	*r* = − 0.14 (*p* = 0.28)	

Notes: SPARC = spectral arc length; OR = Odds ratio obtained in multivariable binary logistic regression including independent variables and falls (dependent variable). SD = standard deviation; CI 95 % = 95 % confidence interval; p = significance level (bold values denote statistical significance); *sec* = seconds; ABC = Activities-specific Balance Confidence; FRT = Functional Reach Test; Roll, Pitch and Yaw are inertial measurement unit axes and NORM is a measure to represent all axes (please, see the methods for details). Spearman's rank correlation was used to show the relationship between independent variables inserted in each multivariable model.

Table 3
Between-group difference (average of the predictive gain) using different regression models.

Model predicted probability (%)	Fallers (mean ± SD)	Non-Fallers (mean ± SD)	Δ	t-value	p
full iTUG (SPARC Roll SD and duration)	66.21 ± 2.50	34.87 ± 2.23	31.34	–5.23	0.0001
full iTUG (SPARC Roll SD only)	61.87 ± 2.40	39.35 ± 1.85	22.52	–4.15	0.0001
full iTUG (duration only)	59.19 ± 2.18	42.12 ± 1.61	17.07	–3.53	0.001

Notes: Δ = predictive gain using the studied regression models to detect falls. t-value = size of the difference relative to the variation in the sample data calculated in the Student-*t*-test; p = significance level (bold values denote statistical significance). Note the full iTUG model including SPARC Roll SD[£] and duration metrics exhibited the best ability to predict a history of falls. [£]SPARC Roll SD was the most relevant SPARC-related metric in the multivariable binary logistic regression models using the full iTUG data (see Table 2).

Table 4
Receiver Operating Characteristic Curve (ROC curve) to predict a history of falls. The cut-off values of the SPARC Roll SD and full iTUG duration[a] were selected considering the highest possible sensitivity without compromising specificity.

Variable	Area (CI 95 %)	Cut-off value	sensitivity	Specificity	p
SPARC Roll SD	0.59 (0.45–0.73)	1.07	0.62	0.55	0.20
Full iTUG duration (*sec*)	**0.73 (0.61–0.85)**	**14.33**	**0.72**	**0.68**	**0.001**

[a] SPARC Roll SD and full iTUG duration were chosen due to their relevance in the multivariable binary logistic regression (see Table 2). Bold values denote statistically significant difference.

include participants from 65 to 79 years old (Larsson et al., 2021; Tomas-Carus et al., 2019) – due to difficulties in recruitment, adherence, and controlling potential confounders (Cherubini et al., 2010). In our sample, both case and controls exhibited results in the full iTUG duration higher than 13.5 s, which means both groups were at higher risk of falling using this traditional cut-off value (Bohannon, 2006). The non-fallers might have reduced their exposure to daily situations that increase the odds of falling, e.g., only walking limited distances, using adequate shoes, having a constant caregiver presence, and avoiding irregular flooring or environments with high cognitive-motor demands. As a result, the differences found between fallers and non-fallers may be underestimated. Even so, adding SPARC metrics in the regression model enhanced the detection of functional mobility profiles in the oldest-old with and without history of falls.

Unfortunately, the study failed to obtain an ideal SPARC roll SD cut-off value with both sensitivity and specificity higher than 70 %. The finding is not exactly unexpected because SPARC metrics are more likely to be influenced by movement subcomponents and the motor strategies adopted by each individual, being less scalable than the iTUG duration. Furthermore, the framework to obtain the SPARC metrics in continuous movements warrants further refinement. Although the SPARC metric was created for discrete point-to-point reaching tasks with excellent ability to deal with duration effects, the analysis of continuous movements extracted from IMUs is still under development. The influence of duration in smoothness calculations may hamper the interpretation of the specific effects of smoothness and duration. As such, reduced smoothness may be strongly correlated with the test duration, as previously reported (Pinto et al., 2019). In this study, we optimized the SPARC calculation for continuous movements using a proper signal processing procedure. It was evident that several components of SPARC were independent of test duration. Using this optimized analysis, we were able to show that fallers tend to increase the time taken to complete the iTUG test to maintain mobility smoothness. In the previous research from our group involving the oldest-old, the reported SPARC outcomes were still affected by the abovementioned effects of duration (Figueiredo et al., 2020). This fact reinforces the need for further development in signal processing to obtain duration-independent SPARC metrics when using IMUs to analyze smoothness of continuous movements. In the future, we expect the calculation of SPARC metrics could be standardized by consensus and adjusted to provide more accurately scalable results in the iTUG test. Notwithstanding, this study provides an initial step towards the understanding of cut-off points to predict the functional mobility profile in the oldest-old with a history of falls, and may contribute to advancing the field.

The characteristics of the participants for whom the model was more likely to predict a history of falls included the more aged, who exhibited lower scores in MMSE and fewer years of schooling, which is in line with the literature (Araújo et al., 2014; Kim, 2020; Seppala et al., 2018).

To use SPARC metrics in the iTUG, a researcher must consider some methodological aspects of the SPARC metrics in general. For instance, we should consider the methods used when calculating the FFT, including the level of zero-padding. Greater zero-padding levels increase the frequency resolution and, respectively the SPARC magnitude; we recommend careful reporting of the respective methodology to ensure study reliability. Another factor influencing SPARC magnitude is the amplitude threshold defined to determine the adaptive cut-off frequency (ωc). Different thresholds will also influence SPARC magnitude. Thereby, firstly, we recommend careful reporting of the above-mentined methods and parameters. Secondly, these factors may hamper the determination of specific cut-off values based on the SPARC magnitude for the iTUG test. We, therefore, recommend that SPARC must be used in combination with test duration to reveal nuances about movement quality during the test.

It is important to recognize that the importance of movement quality in the iTUG test is a recent research area and requires much more thought, understanding and development. Therefore, any improvement in test duration should be complemented by metrics such as SPARC, which places a focus on mobility smoothness, establishing additional relevant information regarding the functional mobility assessment.

One of the main study limitations is the convenience sample, which may reduce the external validity of our data. Although 81 % of the sample were female and 89 % were self-declared white and 72 % were widow/single, this profile is compatible with the oldest-old population living in the south of Brazil (Rigo and Bós, 2020). Another issue may be the natural recall-bias existent in case-control studies based on self-reported conditions. Despite all the efforts to minimize bias, we cannot exclude some mismatching in both case and control participants, which may have influenced the obtained results. Finally, the existence of correlation among several variables of interest introduced difficulty to enter data in the regression models without generating multicollinearity. To overcome the situation, we analyzed regressions including only uncorrelated/weakly correlated variables, which limited the number of independent predictors in the models.

Overall, to the best of our knowledge, this is the first study to show combined effects of mobility smoothness and time taken to complete the iTUG task in predicting functional mobility profile of the oldest-old with and without a previous six-month history of falls. This is of great significance in the fields of geriatrics, gerontology, and motor control as we could add a movement quality outcome in the traditional duration-based iTUG test. Further prospective studies including a wider range of ages and behavioral profiles in the sample are required to obtain definitive results regarding SPARC ability to detect falls in older adults. Nonetheless, the current findings encourage using both duration and smoothness-based outcomes in the iTUG test

5. Conclusion

This study suggests that oldest-old with a history of falls adapt functional mobility to maintain movement smoothness at the expense of a greater duration to complete the mobility task. Further prospective studies are encouraged to establish accurate models and cut-off values of SPARC metrics to predict falls in the oldest-old.

CRediT authorship contribution statement

AF carried out the data collection, conceived and planned the experiments, and contributed to the writing of the manuscript. GB designed the model framework, performed signal analyses, analyzed the data, and contributed to the writing of the manuscript. FB, AS and MSU carried out the data collection, contributed to the writing of the manuscript. RGM conceived of the presented idea, analyzed the data, wrote, and reviewed the manuscript. All authors discussed the results and contributed to the final version of the manuscript.

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Declaration of competing interest

The authors declare that the research has no commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability

Data will be made available on request.

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