

Wearable Sensors Technology as a Tool for Discriminating Frailty Levels During Instrumented Gait Analysis

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Abstract

Background: One of the greatest challenges facing the healthcare of the aging population is frailty. There is growing scientific evidence that gait assessment using wearable sensors could be used for prefrailty and frailty screening. The purpose of this study was to examine the ability of a wearable sensor-based assessment of gait to discriminate between frailty levels (robust, prefrail, and frail).

Methods: 133 participants (≥ 60 years) were recruited and frailty was assessed using the Fried criteria. Gait was assessed using wireless inertial sensors attached by straps on the thighs, shins, and feet. Between-group differences in frailty were assessed using analysis of variance. Associations between frailty and gait parameters was assessed using multinomial logistic models with frailty as the dependent variable. We used receiver operating characteristic (ROC) curves to calculate the area under the curve (AUC) to estimate the predictive validity of each parameter. The cut-off values were calculated based on the Youden index.

Results: Frailty was identified in 37 (28%) participants, prefrailty in 66 (50%), and no Fried criteria were found in 30 (23%) participants. Gait speed, stance phase time, swing phase time, stride time, double support time, and cadence were able to discriminate frailty from robust, and prefrail from robust. Stride time (AUC = 0.915), stance phase (AUC = 0.923), and cadence (AUC = 0.930) were the most sensitive parameters to separate frail or prefrail from robust. Other gait parameters, such as double support, had poor sensitivity. We determined the value of stride time (1.19s), stance phase time (0.68s), and cadence (101 steps/min) to identify individuals with prefrailty or frailty with sufficient sensitivity and specificity.

Conclusions: The results of our study show that gait analysis using wearable sensors could discriminate between frailty levels. We were able to identify several gait indicators apart from gait speed that distinguish frail or prefrail from robust with sufficient sensitivity and specificity. If improved and adapted for everyday use, gait assessment technologies could contribute to frailty screening and monitoring.

Background

According to the 2015 EU Ageing Report, the percentage of citizens aged over 65 years is predicted to rise from 18–28% by 2060. One of the greatest challenges facing the healthcare of the aging population is frailty. In Europe, 15% of older people aged 65 and over are considered as frail (1). Frailty is defined as a syndrome of decreased reserve and resistance to stressors, resulting from cumulative declines across multiple physiologic systems and causing vulnerability to adverse outcomes, such as worsening mobility, disability, incident falls, hospitalizations, and mortality (2). There is much potential for frailty to be reversed, particularly in its early stages (3–5). For that reason, the early identification and management of frailty is an important priority for both healthcare providers and healthcare policy makers (6–8).

One of the most accepted definitions of frailty is the classification proposed by Fried et al. using five criteria: weight loss, exhaustion, inactivity, slow gait speed, and weakness (2). However, its use may have limited feasibility and reliability in a routine care setting (9, 10). The criteria of weight loss, exhaustion,

slowness, and low energy expenditure are usually self-reported measures and may be prone to bias (9, 11, 12). An objective frailty screening tool may be more appropriate for routine assessment.

Slow gait speed has been reported as the most easily identifiable feature of physical frailty (2, 13). Moreover, slow gait speed is a good predictor of future physical disability, falls and fractures, requirement for a caregiver, hospitalizations, and death (13). Gait speed evaluated by the 4-meter walking test could be used for frailty screening (14). Regarding recent studies, other temporal-spatial gait characteristics may have a strong association with frailty (15, 16). A systematic review reported that frailty is associated with some temporal-spatial gait parameters beyond speed, including high stride time variability, reduced step length, and increased double support time (15). However, most studies are conducted in the laboratory environment using camera systems (17, 18), force platforms (18), or computerized walkways (19) that, due to the high costs related to acquisition and application in everyday clinical practice, are not available in every healthcare institution. Therefore, more accessible alternatives could be used, such as wearable sensors, which are easier to use, more practical, and require fewer resources. There is growing scientific evidence that gait assessment using wearable sensors could be used for prefrailty and frailty screening (20–23). Simple and easy-to-use sensors (such as those incorporated into a smartphone) could be used to investigate gait at home and offer advantages in frailty evaluations where the full application or interpretation of Fried criteria is impracticable. There is currently a lack of data regarding which gait indicators are sensitive and specific for determining frailty and the appropriate thresholds for distinguishing between prefrailty and frailty.

The purpose of this study was to examine the ability of wearable sensor-based assessments of gait to discriminate between frailty levels (robust, prefrail, and frail). Firstly, we sought to determine which sensor-derived gait parameters are able to discriminate between the three frailty levels. Secondly, we aimed to determine the cut-offs of the most sensitive gait parameters that separated the frailty levels. We hypothesized that we could separate the frailty groups (robust, prefrail, and frail) using a sensor-based assessment of gait. We also hypothesized that frailty is associated not only with slow gait speed, but also with longer stride time, stance phase, and double support time.

Methods

Study population

Participants in this cross-sectional study were recruited from two secondary health care institutions and from the population who lived independently in community. A convenience sample of older adults was utilized for this study. All participants were community-dwelling adults and were eligible to participate if they were aged 60 and older and reported being able to ambulate 12 meters without an assistive device. Exclusion criteria were a Lithuanian version of the Mini-Mental State Examination (MMSE) (24) score < 21, Parkinson's disease, recent stroke, terminal illness, or unwillingness to participate. Eligible subjects provided signed written informed consent based on the principles expressed in the Declaration of Helsinki (25). Ethical approval was obtained from the Vilnius Regional Ethics Board for Biomedical Research. Data collection occurred between May 2019 and February 2020. Initially, 165 subjects were invited, of whom 7

met the exclusion criteria (Parkinson's disease = 2, recent stroke = 5), and 25 were rejected due to incomplete measurement. Data from 133 participants (86 women and 46 man) with an average age 75.1 ± 8 years were analysed.

Data collection

The research team conducted face-to-face interviews using structured questionnaires to record the required characteristics, such as age, sex, years of formal education, self-reported chronic diseases, number of prescribed and over-the-counter medications, self-reported history of falls in the previous 12 months, and use of an assistive device (yes/no). Height was obtained using a tape measure, weight was measured using a bathroom scale (Clatronic PW 3368, Clatronic®, Kempen, Germany), and BMI was calculated based on height and weight. Interviewer-administered questionnaires included MMSE and the Falls Efficacy Scale-International (FES-I) (26).

Assessment of frailty criteria

Frailty was assessed using the five components proposed by Fried et al. (2). Weight loss was determined by self-reported unintentional weight loss of > 4.54 kg over the past year. Weakness was evaluated by a grip strength measurement using a hydraulic hand dynamometer (Jamar®, Sammons Preston Rolyan, Bolingbrook, IL, USA). Three measures were performed, and the arithmetic mean was used to identify this criterion. Weakness was defined according to sex and the BMI cut-offs used by Fried et al. Exhaustion was evaluated by two statements of the Centre for Epidemiologic Studies Depression Scale (CES-D) questionnaire (27): 'I felt everything I did was an effort' and 'I could not get going'. The frequency of 'occasionally' or 'most of the time' as a reply to either of these statements was considered as an indication of exhaustion. Slowness was defined by a walking speed of 4 m distance at the usual pace measured by a stopwatch and stratified by gender and height using the cut-offs defined by Fried et al. Low physical activity was determined using the Physical Activity Scale for Elderly (PASE) (28). PASE scores less than 64 for men and less than 52 for woman were used to indicate a positive response of low physical activity.

Participants were scored one point for each criterion found, totalling a score that could range from 0 to 5. Frailty level was categorized following Fried et al. (2): robust = no criteria; prefrail = one or two criteria, and frail = three or more criteria.

Physical performance tests

The timed up and go test (TUG) (29) is widely used for the identification of older adults at a high risk of falling. Savva et al. (2013) (30) proposed that the TUG test is a sensitive and specific measure of frailty. In our study, participants were told to sit on a chair (seat height, 46 cm). Participants were then instructed to stand, to walk at their normal pace for a distance of 3 meters, to turn at the endpoint, to walk back the same distance, and sit on a chair. Total time starting from standing up to full sitting down was recorded. The time of one trial was taken as the TUG test score.

The participants were then evaluated using the dynamic gait index (DGI) (31) for the assessment of the gait in response to changing tasks, such as turning the head while walking, stepping over the obstacle, climbing the stairs, and others. This index consists of eight tasks. Each task is scored from 0 to 3 points, with 0 being the worst and 3 being the best performance. The maximum score is 24 points. A result less than 19 points indicates impaired gait and a risk of falling.

Sensor-Based assessment of gait

We used a total of six wireless inertial sensors (Shimmer Research, Dublin, Ireland) attached by straps on the thighs, shins, and feet (Fig. 1).

Each sensor includes triaxial accelerometer, gyroscope, and magnetometer and is able to measure linear acceleration, angular velocity, and magnetic heading in three dimensions. The data from sensors was acquired via a Bluetooth wireless connection at a sampling frequency of 256 Hz. Participant walked a distance of 4 m (13 feet) at the self-selected usual pace. Data from three trials was used. From all the data obtained from the inertial sensors, we selected shank angular velocity and foot linear acceleration to determine heel-strike and toe-off characteristic points. This data was filtered using a Butterworth second order low pass filter with an 8 Hz cut-off frequency and an additional least square method 25th order filter with a 10 Hz cut-off frequency for composite foot acceleration data. A gait event detection algorithm was made by picking toe-off points from the angular velocity data (32) and heel strike points from composite foot acceleration data (33). Gait parameters were calculated based on these gait events. The following quantitative gait parameters were calculated: stance phase time, swing phase time, stride time, on right and left leg accordingly, double support time, and cadence (steps/min).

Statistical analysis

Demographic and clinical characteristics were compared between frailty groups using one-way analysis of variance (ANOVA) for continuous variables and Pearson's chi-squared test for categorical variables. One-way ANOVA was used to compare the frailty group scores on physical performance tests and gait parameters derived from sensor data. The presence of overall statistically significant results in the ANOVA was followed with post-hoc Tukey analysis to identify significant pairwise associations. Effect sizes were calculated as Cohen's d. The guidelines (34) for interpreting this value are: 0.02 = small effect, 0.5 = moderate effect, and 0.8 = large effect.

Multinomial logistic regression (35), with the robust group as the reference, was then used to investigate the gait parameters that discriminate the three frailty levels. The dependent variable was frailty, modelled as two indicator variables of prefrail and frail referenced to the category of robust. The independent variables were TUG time, DGI score, and eight different sensor-based gait parameters. The independent variables assessed had Cohen's d effect sizes ≥ 0.8 for both prefrail versus robust and frail versus robust. Each of the independent variables was fitted in a separate univariate logistic regression model for a total of ten models. Each model estimated the odds ratios for prefrail relative to robust and frail relative to

robust. Linear regression diagnostics were performed to evaluate multicollinearity and normality. There were no major deviations from normality and multicollinearity.

We used receiver operating characteristic (ROC) curves to calculate the area under curve (AUC) to estimate the predictive validity of each parameter. The cut-off values were calculated based on the Youden index. Sensitivity and specificity were calculated based on the cut-off values. All analysis was performed using IBM SPSS for Windows software, version 20.0. Statistical significance was set at a p value less than 0.05.

Results

Frailty was identified in 37 (28%) participants, prefrailty in 66 (50%), and no criteria were found in 30 (23%) participants. Demographic and clinical characteristics are shown in Table 1.

Table 1
Demographic and clinical characteristics.

Characteristic	Total sample (n = 133)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	p value
Age, mean ± SD	75.1 ± 8	73 ± 6.3	73.9 ± 8.5	78.9 ± 7.3	0.002
Women, n (%)	86 (67.7)	20 (83.3)	41 (62.1)	25 (67.6)	0.163
BMI, mean ± SD	27.6 ± 5.8	28.9 ± 5.6	27.7 ± 5.7	26.5 ± 6.1	0.244
Right calf circumference, cm, mean ± SD	35.1 ± 69.2	38.3 ± 38.4	34.3 ± 84.5	33.7 ± 47.4	0.012
Number of comorbidities, mean ± SD	3.1 ± 1.7	2.9 ± 2	3 ± 1.6	3.5 ± 1.8	0.210
Number of medications, mean ± SD	3.4 ± 2.4	3.7 ± 2.1	3 ± 2.2	4.1 ± 2.8	0.078
MMSE score, mean ± SD	27.5 ± 2.2	28.1 ± 1.9	27.6 ± 1.8	26.6 ± 2.6	0.068
Physical activity scale for elderly score, mean ± SD	97.9 ± 52.7	109.9 ± 31.3	106.6 ± 61	72.9 ± 42.3	0.002
History of falls in previous 12 months, n (%)	60 (47.6)	5 (20.8)	33 (50.8)	22 (59.5)	0.010
History of falls in previous 3 months, n (%)	28 (22.2)	3 (12.5)	13 (20.0)	12 (32.4)	0.155
FES-I score, mean ± SD	22 ± 7.4	17.6 ± 3.3	23.3 ± 7.3	23.5 ± 8.7	< 0.001
Reported fear of falling, n (%)	73 (56.2)	9 (9.0)	43 (66.2)	21 (60.0)	0.004

Values are presented as means ± SD or n (%). SD = standard deviation. BMI = body mass index. MMSE = Mini-Mental State Examination. FES-I = Falls Efficacy Scale-International. Statistically significant values are highlighted.

We did not find any significant differences in gender, BMI, comorbidities, or number of medications used between these three groups. Frail participants were significant older, they had a smaller calf circumference, had a higher proportion of fallers, and higher FES-I scores, while prefrail subjects had a higher fear of falling prevalence than in other groups. Compared to prefrail individuals, frail individuals had a significantly higher prevalence of weak hand grip strength and weight loss criteria.

Characteristic	Total sample (n = 133)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	p value
Frailty criteria, n (%)	89 (70.1)	0	54 (81.8)	35 (94.6)	< 0.001
Slow gait velocity	39 (30.7)	0	22 (33.3)	17 (45.9)	0.001
Low physical activity	26 (20.5)	0	4 (6.1)	22 (59.5)	< 0.001
Low hand grip	25 (19.7)	0		21 (56.8)	< 0.001
				33 (89.2)	
Weight loss	52 (40.9)	0	4 (6.1)		< 0.001
Exhaustion			19 (28.8)		
Values are presented as means ± SD or n (%). SD = standard deviation. BMI = body mass index. MMSE = Mini-Mental State Examination. FES-I = Falls Efficacy Scale-International. Statistically significant values are highlighted.					
We did not find any significant differences in gender, BMI, comorbidities, or number of medications used between these three groups. Frail participants were significant older, they had a smaller calf circumference, had a higher proportion of fallers, and higher FES-I scores, while prefrail subjects had a higher fear of falling prevalence than in other groups. Compared to prefrail individuals, frail individuals had a significantly higher prevalence of weak hand grip strength and weight loss criteria.					

The comparison of scores of physical performance tests and sensor-derived gait parameters between three frailty groups is presented in Table 2.

Table 2
Results of the gait assessment stratified by frailty status.

Variable	Total sample (n = 33)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	<i>p</i> value ^a			Effect size ^b		
					R vs. P	P vs. F	R vs. F	R vs. P	P vs. F	R vs. F
TUG, s	12.34 ± 5.03	7.68 ± 1.86	12.71 ± 4.56	15.56 ± 4.87	< 0.001	0.004	< 0.001	-1.28	-0.61	-2.07
Dynamic gait index, score	16.25 ± 4.04	18.90 ± 3.63	16.12 ± 3.52	14.32 ± 4.15	0.003	0.053	< 0.001	0.78	0.48	1.16
Gait speed, m/s	0.68 ± 0.22	0.98 ± 0.17	0.63 ± 0.13	0.52 ± 0.13	< 0.001	< 0.001	< 0.001	2.40	0.86	3.14
Stride time, s	1.31 ± 0.24	1.06 ± 0.16	1.35 ± 0.16	1.46 ± 0.25	< 0.001	0.010	< 0.001	-1.79	-0.59	-1.89
Swing phase time, s	0.49 ± 0,08	0.44 ± 0.06	0.51 ± 0.08	0.50 ± 0.09	< 0.001	0.952	0.003	-0.92	0.06	-0.84
Stance phase time, s	0.83 ± 0.19	0.63 ± 0.11	0.84 ± 0.13	0.96 ± 0.21	< 0.001	0.001	< 0.001	-1.77	-0.74	-1.96

Physical performance tests scores and gait parameters (mean ± SD) derived from sensor data for different frailty status groups are presented. R = robust, P = prefrail, F = frail. TUG = timed up and go test. Statistically significant values are highlighted.

^a: One-way ANOVA, followed with post-hoc Tukey analysis to identify significant pairwise associations.

^b: Effect sizes have been calculated as Cohen's d.

All the comparisons revealed statistically significant differences, except the DGI score and swing phase time between prefrail and frail subjects. The discriminatory power of all variables was higher for robust versus prefrail and robust versus frail subjects ($d = 0.78-3.14$) compared to prefrail versus frail subjects ($d = 0.06-0.86$). Gait velocity best discriminated robust versus frail participants ($d = 3.14$), whereas the second best discriminator was cadence ($d = 2.50$). When comparing the means of stride time, stance phase and swing phase time on the left and right leg, we obtained identical results, so only the parameters from the right leg were used for this and further analyses.

The results of multinomial logistic regression are presented in Table 3.

Variable	Total sample (n = 33)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	<i>p</i> value ^a			Effect size ^b		
Swing phase, %	37.58 ±	41.29 ±	37.59 ±	34.53 ± 5.05	0.001	0.003	< 0.001	0.90	0.66	1.55
	4.97	3.35	4.40							
Stance phase, %	62.42 ±	58.71 ±	62.40 ±	65.47 ± 5.05	0.001	0.003	< 0.001	-0.90	-0.66	-1.55
	4.97	3.35	4.40							

Physical performance tests scores and gait parameters (mean ± SD) derived from sensor data for different frailty status groups are presented. R = robust, P = prefrail, F = frail. TUG = timed up and go test. Statistically significant values are highlighted.

^a: One-way ANOVA, followed with post-hoc Tukey analysis to identify significant pairwise associations.

^b: Effect sizes have been calculated as Cohen's *d*.

All the comparisons revealed statistically significant differences, except the DGI score and swing phase time between prefrail and frail subjects. The discriminatory power of all variables was higher for robust versus prefrail and robust versus frail subjects ($d = 0.78-3.14$) compared to prefrail versus frail subjects ($d = 0.06-0.86$). Gait velocity best discriminated robust versus frail participants ($d = 3.14$), whereas the second best discriminator was cadence ($d = 2.50$). When comparing the means of stride time, stance phase and swing phase time on the left and right leg, we obtained identical results, so only the parameters from the right leg were used for this and further analyses.

The results of multinomial logistic regression are presented in Table 3.

Variable	Total sample (n = 33)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	<i>p</i> value ^a			Effect size ^b		
Double support time, s	0.15 ±	0.08 ±	0.15 ±	0.20 ±	< 0.001	< 0.001	< 0.001	-1.12	-0.74	-1.83
	0.08	0.04	0.07	0.09						
Cadence, steps per min	95.38 ±	117.17 ±	91.35 ±	84.89 ±	< 0.001	0.033	< 0.001	2.09	0.53	2.50
	17.29	13.18	11.92	12.71						
Physical performance tests scores and gait parameters (mean ± SD) derived from sensor data for different frailty status groups are presented. R = robust, P = prefrail, F = frail. TUG = timed up and go test. Statistically significant values are highlighted.										
^a : One-way ANOVA, followed with post-hoc Tukey analysis to identify significant pairwise associations.										
^b : Effect sizes have been calculated as Cohen's d.										
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The results of multinomial logistic regression are presented in Table 3.										

Table 3
The parameters for discriminating three frailty levels (robust, prefrail, and frail).

Variable	Prefrail vs. robust			Frail vs. robust		
	OR	95% CI	<i>p</i> value	OR	95% CI	<i>p</i> value
TUG time, s	2.36	1.68–3.31	< 0.001	2.67	1.89–3.78	< 0.001
Dynamic gait index, score	0.80	0.70–0.92	0.001	0.71	0.60–0.83	< 0.001
Gait speed, cm/s	0.93	0.90–0.95	< 0.001	0.92	0.89–0.95	< 0.001
Stride time, ms	1.006	1.003–1.009	< 0.001	1.006	1.003–1.009	< 0.001
Swing phase time, ms	1.007	1.001–1.013	0.028	1.008	1.001–1.015	0.024
Stance phase time, ms	1.009	1.005–1.013	< 0.001	1.008	1.004–1.012	< 0.001
Swing phase,%	0.80	0.71–0.91	0.001	0.69	0.60–0.90	< 0.001
Stance phase,%	1.24	1.10–1.41	0.001	1.44	1.25–1.67	< 0.001
Double support time, ms	1.02	1.01–1.03	< 0.001	1.01	1.01–1.02	0.002
Cadence, steps per min	0.87	0.83–0.92	< 0.001	0.83	0.78–0.89	< 0.001
Multinomial logistic regression with the robust group as reference. Statistically significant values highlighted.						
OR = odds ratio, CI = confidence interval. TUG - timed up and go test.						
All the evaluated variables were able to discriminate between prefrail and robust and frail and robust levels with statistically significant differences. TUG time, stride, stance time in milliseconds, percentage of gait cycle, and double support time increased the odds of being prefrail versus robust and frail versus robust, whereas a higher DGI score, gait velocity, and cadence decreased the odds.						

Table 4 shows the sensitivity and specificity of different gait parameters when used to identify the frail and prefrail populations and their cut-offs.

Table 4

The most sensitive parameters for discriminating frail from prefrail or robust and prefrail or frail from robust.

Variables	Frail vs. prefrail or robust				Prefrail or frail vs. robust			
	AUC	Cut-off value ^a	Sensitivity (%)	Specificity (%)	AUC	Cut-off value ^a	Sensitivity (%)	Specificity (%)
TUG test time, s	0.790	11.60	86.1	65.6	0.929	9.27	89.2	86.7
Dynamic gait index, score	0.675	15.00	54.1	75.0	0.735	19.0	73.8	56.7
Ch. gait speed, m/s	0.801	0.59	83.8	68.8	0.969	0.74	91.3	90.0
S. gait speed, m/s	0.810	0.60	78.4	75.0	0.958	0.82	94.2	86.7
Stride time, s	0.740	1.27	91.9	51.0	0.915	1.19	90.3	86.7
Stance phase time, s	0.773	0.80	83.8	62.5	0.923	0.68	96.1	73.3
Swing phase time, s	0.569	0.48	59.5	57.3	0.759	0.48	58.3	86.7
Stance phase,%	0.749	63.15	75.7	68.8	0.788	63.27	53.4	96.7
Swing phase,%	0.749	36.85	75.7	68.8	0.790	36.73	53.4	96.7

AUC = area under curve. TUG = timed up and go test. Ch. gait speed measured by a chronometer. S. gait speed derived from sensor data. ^a: Cut-off value based on the Youden Index.

All the variables had higher validity to separate prefrail or frail from robust (AUC = 0.735–0.969) than frail from prefrail or robust (AUC = 0.675–0.810). Among gait parameters, other than gait speed, stride time (AUC = 0.915), stance phase time (AUC = 0.923), and cadence (AUC = 0.930) were the best discriminators to separate frail or prefrail from robust. Other gait parameters, such as stance phase, normalized in percent of gait cycle, and double support time had sufficient validity to separate prefrail or frail from robust, although both had poor sensitivity (53.4% and 62.1%). Among the physical performance tests, TUG test time (AUC = 0.929) emerged as a sensitive parameter to discriminate between prefrail or frail and robust. The predictive validity of the dynamic gait index (AUC = 0.735) was inferior when compared to the other variables.

	Frail vs. prefrail or robust				Prefrail or frail vs. robust			
Double support time, s	0.778	0.16	70.3	76.0	0.858	0.14	62.1	96.7
Cadence, steps per min	0.724	99.54	94.6	44.8	0.930	101.22	84.4	90.0
AUC = area under curve. TUG = timed up and go test. Ch. gait speed measured by a chronometer. S. gait speed derived from sensor data. ^a : Cut-off value based on the Youden Index.								
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Discussion

This study examined the associations between many gait parameters, derived from wearable sensors, and frailty levels and identified which parameters can differentiate between different levels of frailty.

Gait speed was the most sensitive parameter for the identification of frailty. It should be noted that the Fried frailty criteria includes slow gait speed (2), which explains the high discriminative power of this variable. In the present study, the discriminative ability of gait speed can be used as a reference for comparison with other parameters analysed.

We found that the stride time was significantly longer in frail and prefrail compared to robust. This finding is in accordance with the results reported by Montero-Odasso et al. (16), which revealed the mean \pm SD stride time in seconds: 1.2 ± 0.1 in frail, 1.1 ± 0.1 in prefrail, and 1.0 ± 0.1 in non-frail (robust). We suggest that stride time is sensitive for discriminating prefrail or frail from robust and determined a value of stride time for identifying individuals with prefrailty or frailty of 1.19 s, with sufficient sensitivity and specificity. We also found that stride time had a good sensitivity to separate frail from prefrail or robust; however, the specificity and area under the ROC curve were quite modest, thus potentially limiting its clinical usefulness.

Other gait parameters that significantly differed between frailty levels were stance phase and swing phase. In comparisons of the average duration of the stance and swing phase time, the mean percentage of the gait cycle spent in the stance and swing phases was difficult to interpret due to the lack of sufficient data reported in the literature. We found a sufficiently sensitive and specific stance time estimate to separate prefrail or frail from robust, i.e. 0.68 s. The values for the sensitivity, specificity, and AUC of swing phase and stance phase percentage were quite modest.

We found that prefrail and frail subjects had increased double support time. Schwenk et al. (20) identified double support time as one of the most sensitive discriminators between these three frailty levels. However, in our study, double support time had modest validity to discriminate prefrail or frail from robust (AUC = 0.858), poor sensitivity (62.1%), and high specificity (96.7%).

This study revealed that cadence was reduced in frail and prefrail compared to robust; this result is consistent with the results of Montero-Odasso et al. (16), showing variations in mean \pm SD cadence (steps/min) in frail (101 ± 21), prefrail (106 ± 9), and non-frail (robust) (118 ± 6). Our study showed that cadence is a sensitive and specific gait parameter that discriminates prefrail or frail from robust. The estimated cut-off was 101 steps per minute.

Our study has limitations. The sample size was relatively small. The proposed gait parameters derived from our analysis must be validated in a larger sample to evaluate their true predictive potential. Other limitation is related to the gait assessment technique. During the 4-meter walk test, additional sections for the acceleration and deceleration phases were not marked. During these phases, the walking speed was usually slower, which affected the measurement of the 4-meter walking speed and led to errors.

Our study is one of the first to provide thresholds for sensor-derived gait indicators to determine frailty and prefrailty. The hypotheses of the study were confirmed. The sensor technology we uses is quite complex in terms of the sophisticated data processing require due to larger number of sensors we used as compared to a study where a single wearable sensor was able to extract similar gait parameters (21). However, the application of multiple sensors allowed us determine not only temporal but also spatial biomechanical parameters like joint amplitudes during gait, which in turn may provide more quantitative parameters that may be sensitive to distinguishing frailty levels. This information could be useful for clinicians, so it would be useful to conduct further studies with these parameters. Further studies should also include longitudinal follow-up to determine which changes in gait parameters predict frailty over the time.

Conclusions

The results of our study show that gait analysis using wearable sensors can discriminate between frailty levels. We were able to identify several gait indicators that distinguish frail or prefrail from robust with sufficient sensitivity and specificity. We found that frailty is associated not only with slow walking speed, but also with longer stride time, stance phase, double support time, and reduced cadence. If improved and adapted for everyday use, gait assessment technologies could contribute to frailty screening and monitoring.

Abbreviations

ROC

Receiver operating characteristic

AUC

Area under curve

EU
European Union
MMSE
Mini-Mental State Examination
BMI
Body mass index
FES-I
Falls Efficacy Scale-International
CES-D
Centre for Epidemiologic Studies depression scale
TUG
Timed up and go
DGI
Dynamic gait index
SD
Standard deviation
ANOVA
Analysis of variance

Declarations

Availability of data and materials

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Ethics approval and consent to participate

The study was approved by the Vilnius Regional Ethics Board for Biomedical Research. Before participation, written informed consent based on the principles described in the Declaration of Helsinki was obtained from all participants.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Author contributions

AA, VA, MT, KD, and JG were involved in the conception and design of the study. AA drafted the manuscript, with support from VS and DV. MT, AM, KD, VA, and JG offered insights on manuscript revisions. AM, LP, and JG contributed to data interpretation. VS, DV, and LP contributed to data collection and acquisition. All authors read and critically revised the manuscript and approved the final manuscript. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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Figures

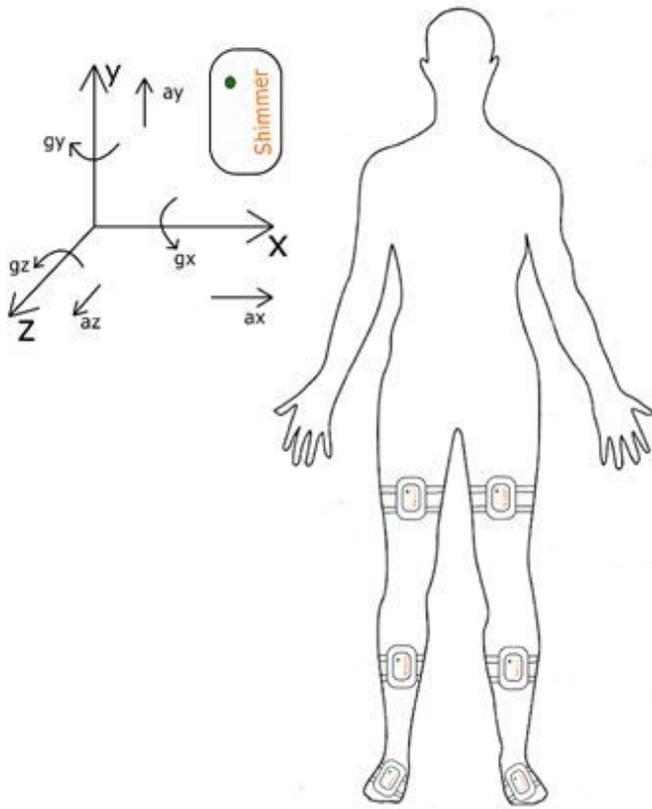


Figure 1

Wireless sensors fixed on the lower limb segments