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Wearable Sensor-Based In-Home Assessment of Gait, Balance, and Physical Activity for Discrimination of Frailty Status: Baseline Results of the Arizona Frailty Cohort Study

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Conflict of interest: Dr. Michael Schwenk, Dr. Jane Mohler, Christopher Wendel, Dr. Karen D'Huyvetter, Dr. Mindy Fain, Dr. Ruth Taylor-Piliae, and Dr. Bijan Najafi report no financial or personal conflict of interest.

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CONFLICT OF INTEREST

Elements of Financial/Personal Conflicts	*Author 1 Schwenk		Author 2 Mohler		Author 3 Wendel		Author 4 D'Huyvetter		Author 5 Fain		Author 6 Taylor-Piliae		Author 7 Najafi	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Employment or Affiliation		X		X		X		X		X		X		X
Grants/Funds		X		X		X		X		X		X		X
Honoraria		X		X		X		X		X		X		X
Speaker Forum		X		X		X		X		X		X		X
Consultant		X		X		X		X		X		X		X
Stocks		X		X		X		X		X		X		X
Royalties		X		X		X		X		X		X		X
Expert Testimony		X		X		X		X		X		X		X
Board Member		X		X		X		X		X		X		X
Patents		X		X		X		X		X		X		X
Personal Relationship		X		X		X		X		X		X		X

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Abstract

BACKGROUND—Frailty is a geriatric syndrome resulting from age-related cumulative decline across multiple physiologic systems, impaired homeostatic reserve, and reduced capacity to resist stress. Based on recent estimates, 10% of community-dwelling older persons are frail and another 41.6% are pre-frail. Frail elders account for the highest healthcare costs in industrialized nations. Impaired physical function is a major indicator of frailty and functional performance tests are useful for identification of frailty. Objective instrumented assessments of physical functioning that are feasible for home frailty screening have not been adequately developed.

OBJECTIVE—To examine the ability of wearable, sensor-based, in-home assessment of gait, balance, and physical activity (PA) to discriminate between frailty levels (non-frail, pre-frail, frail).

METHODS—In an observational cross-sectional study; in-home visits were completed in 125 older adults (non-frail n=44, pre-frail n=60, frail n=21) in Tucson, Arizona between September, 2012 and November, 2013. Temporal-spatial gait parameters (speed, stride length, stride time, double support, variability of stride velocity), postural balance (sway of hip, ankle, center of mass), and PA (percentage of walking, standing, sitting, lying; mean duration and variability of single walking, standing, sitting, and lying bouts) were measured in the participant's home using validated wearable sensor-technology. Logistic regression was used to identify the most sensitive gait, balance, and PA variables for identifying pre-frail participants (vs. non-frail). Multinomial logistic regression was used to identify variables sensitive to discriminate three frailty levels.

RESULTS—Gait speed (area under the curve, AUC= .802), hip sway (AUC= .734), and steps/day (AUC= .736) were the most sensitive parameters for identification of pre-frailty. Multinomial regression revealed that stride length (AUC= .857) and double support (AUC= .841) were most sensitive gait parameters for discriminating between three frailty levels. Interestingly, walking bout duration variability was the most sensitive PA parameter for discriminating three frailty levels (AUC= .818). No balance parameter discriminated between three frailty levels.

CONCLUSION—Results indicate that unique parameters derived from objective assessment of gait, balance, and PA are sensitive for identification of pre-frailty and classification of a subject's frailty level. Present findings highlight the potential of wearable sensor technology for in-home assessment of frailty status.

Keywords

Frailty; wearable sensors; monitoring; physical function; physical activity

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INTRODUCTION

Frailty is a geriatric syndrome resulting from age-related cumulative decline across multiple physiologic systems, impaired homeostatic reserve, and reduced capacity to resist stress [1].

Frailty increases vulnerability towards adverse health outcomes including falls, hospitalization, institutionalization and mortality [1]. Based on recent estimates, 10% of community-dwelling older persons are frail and another 41.6% are pre-frail [2]. Frail elders account for the highest healthcare costs in industrialized nations [2].

One of the most commonly accepted operational definitions of frailty is the classification proposed by Fried et al [1] (i.e., weight loss, weakness, exhaustion, slowness, low energy expenditure). However, its use may have limited feasibility and reliability in a routine care setting [3–6]. The criteria of weight loss, exhaustion and energy expenditure are usually self-reported measures, and may be prone to bias [3,5,6]. An objective frailty screening tool may be more appropriate for routine assessment.

Impaired physical function is a major indicator of frailty [1] and measures of functional performance are useful frailty screening tools [3,7–12]. Most studies have used subjective or semi-objective (i.e., stopwatch) assessments [3,10–12], despite limitations including self-report bias and non-objective parameters. For instance, the Vulnerable Elders Survey [10] includes self-rating of functional status (among other items), but potential overestimation of physical competence has been discussed as limitation [10,13]. Frailty screening using the Short-Physical-Performance battery [3,12] has acceptable reliability for the 4 meter walk, and 5 sit to stand test, but may have limited reliability for the balance subscale, based on use of a stopwatch [14]. Using an objective stabilometry measure [15] instead of a stopwatch may allow quantification of more sensitive balance parameters for identifying frailty, however, to our knowledge, this has not been adequately explored.

Slow gait speed has been reported as the most easily identifiable feature of frailty [1,16], but it does not provide other temporal-spatial gait characteristics which may have a strong association with frailty [9,11]. A recent systematic review reported that frailty is associated with low performance in several temporal-spatial gait parameters beyond speed, including high stride time variability, reduced step length and increased double support [11]. However, it remains unclear if gait parameters can improve frailty screening, in comparison to using gait speed only. Additionally, studies using quantitative gait assessment in frail have been largely conducted in laboratory or clinical environments using camera systems [17,18], force platforms [18], or electronic carpets [9,19], and are not fully translatable to home and community. It remains unclear if objective assessment of gait characteristics is feasible at home and if it can increase accuracy of frailty screening.

In addition to impairment in physical function, a low level of self-reported physical activity (PA) is a key indicator of frailty [16], and increased level of PA may prevent or even reverse frailty [20]. Whereas frailty-associated functional performance parameters (e.g., reduced gait speed, strength deficits) have been identified [3,7,8], frailty-specific “natural” PA characteristics remain to be elucidated [21]. Self-report questionnaires may not be suitable to document frailty-related PA characteristics, due to limited validity in measuring low intensity activities of daily living (ADL) [22] - the most prevalent activities in frail older adults [23]. In contrast to self-report, objective PA assessment using wearable sensors can provide precise documentation of everyday activities including walking, standing, sitting and lying [24,25], and in turn, may allow identification of frailty-specific PA patterns in the home/community. Different frailty levels may be characterized by differences in everyday PA patterns, such as reduced distances walked continuously (e.g., due to exhaustion and diminishing strength), or reduced complexity of PA. Loss of complexity in the dynamics of physiological systems (i.e., heart rate, hormonal rhythms, postural sway) have been associated with frailty [26], and may also be reflected by less variable PA pattern. However, to our knowledge, existing studies have used step number only for objectively assessing frailty [21], but did not quantify more specific everyday PA characteristics. In recent years, advances in wearable sensor technology have provided a new avenue for measuring both physical function [15,27,28] and PA [24,25] across varying populations. Wearable sensors have the benefits of objectivity, portability and low-cost [28], making these devices useful for frailty assessment in the home and community.

The purpose of the Arizona Frailty Cohort Study is to identify relevant sensor-based markers of physical function (i.e., deficits in gait and balance) and everyday PA (i.e., changes in walking, standing, sitting, lying, and transfer characteristics) useful for home-based frailty screening. This article reports the baseline results, and explores the capability of parameters to discriminate cross-sectionally between non-frail, pre-frail and frail categories. The confirmatory aim of this paper was to 1) evaluate the ability of sensor-based home assessment to identify pre-frailty and frailty based on established outcomes (i.e., gait speed). We hypothesized that we could separate frailty groups (non-frail, pre-frail, frail) through sensor-based assessment of gait speed. The exploratory aim was to 2) identify new objective parameters among gait, balance, and PA measures, which might increase the accuracy of frailty assessment.

METHODS

We performed an observational cross-sectional descriptive study within a large Southwestern academic medical center, affiliated with a statewide Center on Aging, in Tucson, Arizona. Tucson has an estimated 152,000 older adults, with an estimated 16,700 residents (11%) who have clinical frailty syndrome. Participants were recruited from primary, secondary, and tertiary health care settings within our large and highly affiliated academic network, and from community providers and aging service organizations. In-home baseline visits were completed between September 2012 and November 2013.

Participants

Adults aged 65 or over, and without gait or mobility disorders who reported being able to ambulate at least 9.14 meter (30 feet) with or without an assistive device were eligible to be screened for study entry. Exclusion criteria included a Mini-Mental State-Exam [29] (MMSE) score <23, terminal illness, or unwillingness to participate. Eligible subjects signed a written informed consent form approved by the institutional review board of the University of Arizona.

Measures

Demographic and clinical characteristics—A team of two trained clinical coordinators visited patients within the home or assisted living setting for collecting data.

Measures included self-reported history of falls, use of assistive device (yes/no), prescriptions (number). Height was obtained by a tape measure. Weight was measured using a bathroom scale (Ozeri Touch II, OzeriTM, CA, USA) and BMI was calculated based on height and weight. Interviewer-administered questionnaires included the Mini Mental State Exam (MMSE), Mobility-Tiredness Scale [30], Center for Epidemiologic Studies Depression Scale (CES-D) [31], Falls Efficacy Scale International [32], and Barthel ADL scale [33].

Assessment of frailty level—Frailty was operationalized using the five components proposed by Fried et al. [1]. Weight loss was evaluated by self-reported unintentional weight loss of > 4.54 kg (10 pounds) over the past year. Weakness was measured by the grip strength test using a hydraulic hand dynamometer (Fabrication Enterprises Inc., Elmsford, NY, USA). Three measures were taken 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 quantified by two questions of the CES-D questionnaire [31]: “I felt everything I did was an effort” and “I could not get going”. A frequency of “occasionally” or “most of the time” to either of these questions was considered as an indication of exhaustion [1]. Slowness was quantified by 4.57 meter (15 feet) walking time (usual pace) measured by a stopwatch and stratified by gender and height cut using cut offs defined by Fried et al.. Low energy expenditure was measured based on the short version of the Minnesota Leisure Time Activity questionnaire [34], as proposed by Fried et al.. Kcals per week expended were calculated according to the questionnaire’s manual and gender stratified cut off for low activity were used as described by Fried et al..

Participants were scored one point for each criterion found, totaling a score that could range from 0 to 5. Frailty level was categorized following Fried et al. [1]: non-frail= no criteria; pre-frail= one or two criteria; and frail= three or more criteria. Norm-based scoring was performed using a computerized scoring algorithm (Frailty Assessment Tool, The Johns Hopkins Center on Aging and Health, Baltimore, MD), which is based on the criteria of Fried et al..

Sensor-based assessment of gait and balance—We used commercially available technology for gait assessment (LEGSys™, Locomotion Evaluation and Gait System, BioSensics, Cambridge, MA) and balance assessment (BalanSens™, BioSensics, Cambridge, MA). Both systems use the same hardware configuration of five small inertial sensors attached to the shanks, thighs, and lower back. Each sensor module includes a tri-axial accelerometer, magnetometer, and gyroscope (sample frequency 100Hz). Different software were used for extraction of gait parameters (LEGSys™) and balance parameters (BalanSens™), which are based on validated algorithms [15,27,28].

Gait assessment: Gait assessment was conducted under single-task and dual-task (counting backward by 1, starting from 100) conditions. Participants walked a distance of 4.57 meters (15 feet) at a self-selected speed under each condition in their home. Where possible, we assessed gait without a walking aid. Temporal-spatial gait parameters (i.e., speed, stride time, stride length, double support [as percentage of stride time], gait variability defined as coefficient of variation [CV] of stride velocity) were extracted from the raw data using validated algorithms described previously in detail [27,28]. To summarize, the gait phases were determined from the precise moments of heel-strike (initial foot contact) and toe-off (terminal foot contact). These moments were extracted from gyroscopes attached to each shank through a local minimal peak detection scheme [27]. Based on the subject's height and using a two-link inverse pendulum model, temporal-spatial gait parameters were estimated by integrating the angular rate of rotation of the thigh and shank [27].

Balance assessment: Balance was measured during 15-second standing with feet close together and eyes closed. Postural sway parameters including sway of ankle, hip and center of mass (CoM) in in medial-lateral and anterior-posterior direction, were extracted from the raw data using validated algorithms, as described elsewhere in detail [15]. To summarize, data from two sensors (lower back and shank) were used to estimate three-dimensional angles of the hip and ankle joints. Each sensor provided real-time quaternions that were subsequently converted to Euler angles. The resulting three-dimensional angles were used to estimate the trajectory of the subject's ankle and hip. A two-segment model of the body was used to calculate CoM range of motion in AP and ML direction [15]. Area of sway for CoM was calculated by multiplying the range of motion in ML and AP directions after excluding outliers. Outliers were estimated by calculating 5 and 95 percentiles of data [15].

Sensor-based physical activity assessment—PA was quantified during a 24-hour period by a motion-sensor (PAMSys™, BioSensics, Cambridge, MA) inserted into a tee-shirt, with a device pocket located at the sternum. The PAMSys™ is a small (5.1×3×1.6cm), light (24g), long-term recording system containing inertial sensors (tri-axial accelerometer, sample frequency 50Hz) with software developed to identify postural transitions and movements such as walking, standing, sitting, or lying [24,35]. A walking period was defined as an interval with at least 3 successive steps [24]. Activities with less than 3 steps were considered as standing. Steps were estimated by detection of acceleration peak beyond of a pre-defined threshold after using an appropriate filter [36]. The analysis algorithms for step detection and for activity classification (walking, standing, sitting, lying) are described in detail elsewhere [24,35,36]. The PAMSys is sensitive (87–99%) and specific (87–99.7%) for detection of PA patterns in older adults and patient populations [24,35].

PA parameters calculated from raw data included daily duration of walking, standing, sitting, lying (as percentage). Further, specific PA parameters including duration of single walking, standing, sitting, lying episodes, the variability of these durations (expressed as standard deviation), number of steps, and duration of sit-to-stand, and stand-to-sit transfers were calculated (Table 3).

A standardized interview-administered questionnaire using 5-point Likert-scale was used to address acceptability of the PAMSys including comfort in wearing the shirt, awareness of the monitor, interference of monitor with daily activities and sleep, adverse events, and adherence in wearing the monitor.

Statistical Analysis

An *a priori* power analysis was conducted for our first study aim (i.e., separating frailty status groups based on gait speed). A study of 100 community-dwelling elders at least 75 years old observed mean ± SD gait speed of 1.24 ± 0.13 m/s in 25 nonfrail, 0.95 ± 0.21 m/s in 55 prefrail, and 0.80 ± 0.19 m/s in 20 frail subjects [9]. Assuming the same variability from this study and an alpha of 0.017 (0.05/3 to adjust for 3 pairwise comparisons), we would have 80% power to detect a 0.2 m/s difference with 16 per group for non-frail vs. pre-frail, 21 per group for pre-frail vs. frail, and 14 per group for non-frail vs. frail.

We used chi-square tests to evaluate differences in categorical demographic/clinical characteristics across frailty status groups (non-frail, pre-frail, frail). Metric measures including both demographic/clinical data and sensor data were compared (SPSS Statistics Desktop, V22.0.0) using ANCOVA with the Games-Howell post-hoc pairwise test (which controls for a family-wise type 1 error rate and is robust under unequal group sizes and unequal variances) to test for significant differences in each parameter between three frailty status groups.

Discriminative power of each sensor-derived variable was calculated using Cohen's d effect sizes (e.g., d of 0.2 was considered as small, 0.5 as medium, and 0.8 as large.).

We used logistic regression (Stata version 12) to evaluate sensor-based variables with a Cohen's d effect size of at least 0.5, as potential screening measures for pre-frailty. Sequential models estimated the prevalence odds ratios (ORs) for pre-frail relative to non-frail, both unadjusted and adjusted for age. The area under the curve (AUC) was calculated for estimating the predictive validity of each parameter. Variables with highest AUC in each class (gait, balance, PA) representing the most sensitive pre-frailty screening parameters are presented (Table 4). We used multinomial logistic regression [37] (Stata version 12), with reference group pre-frail, to evaluate sensor-based variables that discriminate three frailty levels. Variables assessed had Cohen's d effect sizes at least 0.5 for both non-frail versus pre-frail and pre-frail versus frail. Sequential models estimated the prevalence odds ratios (ORs) for pre-frail relative to non-frail (inverse OR presented) and frail relative to pre-frail, both unadjusted and adjusted for age. The AUC for multinomial models was estimated using the "mlogitroc" command in Stata 12, which generates multiclass ROC curves for classification accuracy using bootstrapping methods and smoothed probability distributions derived from kernel density estimation [38].

RESULTS

Demographic and clinical characteristics

One-hundred and twenty-five individuals were included in the study in which 44 (35.2%) were identified as non-frail, 60 (48.0%) as pre-frail, and 21 (16.8%) as frail according to the Fried criteria. Demographics and clinical characteristics are displayed in Table 1. Compared to non-frail, pre-frail and frail were significantly older, took more medications, had higher BMI, more perceived tiredness, greater fear of falling. Compared to pre-frail, frail had significantly higher levels of depressive symptoms, greater fear of falling, more perceived tiredness, and lower ADL scores. There was an increase in use of assistive devices with increasing frailty level.

Sensor-based gait assessment

For single-task walking speed, stride length and double support significantly discriminated between the three frailty status groups (Table 2). Discriminatory power of these gait variables was higher for non-frail vs. pre-frail (d= 0.93–1.18) compared to pre-frail vs. frail (d= 0.70–0.85). Gait speed best discriminated non-frail vs. pre-frail (d= 1.18), whereas stride length best discriminated pre-frail vs. frail (d= 0.85). Discriminatory power of gait variables was lower for dual-task gait assessment (d= 0.20–1.46), when compared to single-task (d= 0.24–1.64). In this study we found that subjects who used assistive devices had slower gait speed than those without devices, and these differences increased with increasing frailty level.

Sensor-based balance assessment

Results of the sensor-based balance assessment are displayed in Table 2. Balance parameters discriminated between non-frail and pre-frail, with hip sway as the best discriminator (d= 0.62), but not between pre-frail and frail (p= 0.653–0.999).

Sensor-based physical activity assessment

Among the five PA categories measured (i.e., walking, standing, sitting, lying, transfers), parameters related to walking best discriminated between non-frail and pre-frail, with highest effect sizes found for number of steps (d= 0.83) and percentage of walking (d= 0.75) (Table 3). Further, pre-frail adults took significantly fewer continuous steps (d= 0.55). Interestingly, the variability of walking bout duration was significantly lower in pre-frail compared to non-frail (d= 0.52). Besides lower amounts of walking activity, pre-frail adults had an increased percentage of sitting (d= 0.66) when compared to non-frail adults

Importantly, percent walking (p= 0.283), was a poor discriminator compared to other walking parameters, including the longest walking bout duration (d= 0.59), maximum continuous steps (d= 0.62) and variability of walking bouts (d= 0.73), which significantly discriminated between pre-frail and frail.

Acceptability of wearing the tee-shirt embedded motion sensor over a 24-hours period was high. For each question the majority of subjects (66–98%) strongly, or somewhat agreed to positive attributes, with no significant differences by frailty status groups (non-frail 66–98%; pre-frail 68–98%; frail 67–95%; p= 0.13 – 1.00) (supplemental file).

Most sensitive variables for pre-frailty screening

The most sensitive pre-frailty screening variables of each domain (gait, balance, PA) are displayed in Table 4. Single task walking speed had the highest validity for identification of pre-frailty (AUC= .802). Among PA parameters, the number of steps (AUC= .763) emerged as the most sensitive parameter for pre-frailty screening. Predictive validity of balance parameters (hip sway, AUC= .734) was inferior when compared to gait and PA.

Most sensitive variables for discriminating between three frailty levels

Results of the multinomial logistic regression analysis for evaluating the ability of parameters to discriminate between the three frailty levels are displayed in Table 5. Among gait parameters stride length (AUC= .857) and double support (AUC= .841) had the highest validity to separate both non-frail from pre-frail and pre-frail from frail in the age-adjusted model. A smaller AUC was obtained for gait speed (.830) and the ability of this parameter to separate pre-frail vs. frail became non-significant after adjusting for age (p= 0.055). Interestingly, walking bout duration variability emerged as the most sensitive PA parameter to separate the three frailty groups (AUC .818), although ability to separate non-frail vs. pre-frail became non-significant (p= 0.065) after adjusting for age. No other gait, balance or PA parameter was able to discriminate the three groups simultaneously.

DISCUSSION

To our knowledge, this is the first study that compared multiple instrumented assessments for quantifying physical function and PA across levels of frailty in a home and community environment. Gait parameters were found to be the most sensitive for identification of a subject's level of frailty. Additionally, specific PA parameters emerged as sensitive indicators of frailty level, suggesting that continuous monitoring of everyday activities may be a valid and autonomous method for identification of frailty.

Sensor-based gait assessment

Gait speed was the most sensitive parameter for identification of pre-frailty. Results are in accordance with findings from a systematic review which reports gait speed as the best discriminator between non-frail and pre-frail among different gait parameters [11]. It should be noted that the Fried frailty criteria includes slow gait speed as one criterion [1] which explains the high discriminative power of this variable. In the present study, discriminative ability of gait speed can be used as a reference for comparison with other parameters analyzed.

Interestingly, results suggest that stride length and double support are more sensitive for classifying frailty level, compared to gait speed. Reduced stride length is linked to a lack of lower extremity strength [39], and may be an indicator of frailty-associated sarcopenia [40]. Increased double support time is an attempt to minimize postural instability [41], and may indicate deficits in dynamic balance control, associated with frailty. Our findings suggest that specific gait parameters can quantify frailty-related aspects including loss of muscle mass and balance, and may add precision to gait-based frailty screening. Notably, a systematic review identified the same gait characteristics (i.e., stride length, double support) as the most sensitive discriminators between pre-frail and frail [11], among different gait parameters.

Previous studies have reported that adding a cognitively demanding task to gait assessment ("dual tasking") is sensitive in identifying those who may be at risk of developing frailty [19]. In the present study, we did not find any benefit for dual task gait assessment, which is likely related to the fact that we excluded those with cognitive impairment. In addition, the walking distance used in this study (4.57 meters) may not be sufficient to address gait alteration due to dual tasking [42,43].

Sensor-based balance assessment

Present findings suggest that a balance deficit is a specific marker of pre-frailty. These results are in accordance with previous studies, which found significant differences in postural balance between non-frail and pre-frail/frail groups, but not between pre-frail and frail [44,45]. Our results show that hip sway is a more sensitive marker of pre-frailty, compared to ankle sway. This may suggest that the pre-frail used a “hip strategy” rather than an “ankle strategy” to compensate for threatened balance (when standing with eyes closed). Previous studies in older adults suggest that the use of a “hip strategy” is related to a loss of peripheral somatosensation and/or weakness in ankle joint muscles [46]; this strategy is associated with increased fall risk [47].

Sensor-based physical activity assessment

Our results show that PA level is reduced with increasing frailty, which was expected because low PA (based on self-report) is one criterion of the Fried frailty index. On the same note, previous studies have not objectively evaluated the specific impact of frailty on everyday PA characteristics. Results of our sensor-based PA assessment may suggest that different frailty stages can be discriminated by specific PA variables. Non-frail and pre-frail were best discriminated by decline in number of steps, as reported previously [21]. In contrast, differences between pre-frail and frail were characterized by other, more specific, PA characteristics such as reductions in the longest walking bout duration. We speculate that the drastic reduction in longest walking bout duration (−53%) in frail (compared to pre-frail) is related to impairments in physical function and/or exhaustion, both key indicators of frailty [1]. Our results suggest that the sensor-based PA assessment can quantify frailty-associated loss of everyday PA’s, which may help to better estimate the level of frailty and its impact on daily functioning. Interestingly, we observed a continuous reduction in the variability of walking episodes with increasing frailty level. Results indicate more static and less complex PA behavior in frail individuals, characterized predominately by short walking bouts. Our results may suggest that the “loss of complexity paradigm” related to frailty [26] is reflected not only by physiological systems but also by everyday PA behavior as well.

Limitations and future research

Participants of this study were recruited using a convenience sample technique, thus the sample may not represent the general population of community dwelling older adults. The proposed parameters derived from our exploratory analysis must be validated in a larger non-selected sample to evaluate their true predictive potential. However, because we saw participants in both the home and community settings, we were able to include nearly-homebound subjects in our study, who are often excluded in clinic-based studies.

We included assistive device users (canes and walkers), although walking aids may minimize the detection of gait deficits [48]. Despite walking aid usage, gait variables had the highest discriminative power, suggesting that walking aids did not substantially impact on gait-based frailty screening.

The order of the single task and dual-task was not randomized or counter-balanced, which may have biased results of dual task walking due to effects of practice or fatigue.

The 24-hour PA assessment period did not cover day-to-day variability, although PA in older adults is less variable than in younger populations and day-to-day reliability of PA assessment was high in a sample of older adults (> 60 years) [49]. The 24-hour monitoring in our study may therefore have been sufficient to document habitual PA because of low day-to-day variability. However, further research should address whether a longer period of monitoring increases the accuracy of frailty screening.

Multiple frailty concepts have been proposed and no consensus about an operative definition exists [50]. In this study we have used the most widely adopted Fried frailty criteria, which are associated with gait, sarcopenia and PA. Thus, our presented sensor approach of measuring frailty might be overoptimistic then when employing a broader frailty concept inclusive of cognitive, psychological, or social components, or a cumulative concept such as the Rockwood model [51]. Future studies should validate the objective parameters identified in this study using alternative frailty definitions.

The study's cross-sectional design limits inferences of causality. The next step will be a longitudinal analysis using 6-month follow-up data from the same study participants allowing determination of the extent to which different parameters predict changes in frailty status. This may allow development of interventions targeted to discovered decrements.

Conclusions

We found that objective gait, balance, and PA parameters have the potential to provide clinically meaningful surveillance of older adults across frailty status. Particularly, our approach of monitoring frailty-specific PA parameters may be incorporated into mHealth technologies (i.e., smartphone), and may serve as a "frailty meter", similar to a Holter monitor. These are steps towards an objective screening tool for identification of clinical frailty syndrome in older adults.

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Table 1

Demographic and Clinical Characteristics

Characteristic	Non-Frail n=44	Pre-Frail n=60	Frail n=21	P-value[a] Non vs. pre	Pre vs. frail	Non vs. frail
Age (years), mean±SD	74.6±6.5	80.2±8.6	83.4±8.6	.001	.330	.001
Sex, n (%)						
Female	37 (84.1)	45 (75.0)	18 (85.7)	.262	.376	.999
Male	7 (15.9)	15 (25.0)	3 (14.3)			
Race, n (%)						
White	37 (84.1)	50 (83.3)	16 (76.2)	.957	.352	.082
African American	0 (0.0)	1 (1.7)	2 (9.5)			
American Indian	0 (0.0)	1 (1.7)	1 (4.8)			
Asian	0 (0.0)	1 (1.7)	0 (0.0)			
other	7 (15.9)	7 (11.7)	2 (9.5)			
History of falls, n (%)	13 (33.3)	26 (47.3)	11 (57.9)	.177	.425	.075
Use assistance devices[b], n (%)	4 (10.0)	26 (47.3)	14 (73.7)	<.001	.046	<.001
Number of Prescriptions, mean±SD	2.5±1.8	4.1±3.8	6.0±3.4	.021	.138	.001
Number of social activities, n (%)						
0	1 (2.9)	3 (7.3)	2 (13.3)	.079	.025	<.001
1–3	14 (40.0)	25 (61.0)	13 (86.7)			
>3	20 (57.1)	13 (31.7)	0 (0.0)			
Body Mass Index, n (%)						
< 25	24 (54.6)	19 (31.7)	4 (19.1)	.013	.251	.012
25 – 29.9	12 (27.3)	13 (21.7)	9 (42.9)			
30 – 34.9	7 (15.9)	18 (30.0)	4 (19.1)			
≥ 35	1 (2.3)	10 (16.7)	4 (19.1)			
Mini Mental State Exam, mean±SD	29.2±1.1	28.6±1.6	28.7±1.7	.121	.980	.531
Mobility-Tiredness Scale, mean±SD	5.6±0.8	4.7±1.4	2.7±1.8	<.001	<.001	<.001
Center for Epidemiologic Studies Depression Scale, mean±SD	6.6±5.7	6.9±6.8	14.0±7.0	.958	.001	.001
Falls Efficacy Scale, mean±SD	20.8±4.2	28.0±9.5	39.5±12.3	<.001	.002	<.001
Barthel ADL Index, mean±SD	95.5 (14.0)	96.2 (5.5)	88.1 (9.0)	.955	.002	.033

[a]Games-Howell contrasts for continuous measures due to unequal group sizes and in some cases unequal variances;

[b]cane, walker

Table 2

Results of Gait and Balance Assessment Stratified by Frailty Status

	Non-frail	Pre-frail	Frail	P-value[a]			Effect size[b]		
				Non vs. pre	Pre vs. frail	Non vs. frail	Non vs. pre	Pre vs. frail	Non vs. frail
Gait parameter									
Single-task walking									
Speed, m/s	1.17±0.15	0.94±0.23	0.71±0.36	<.001	.033	<.001	1.18	0.76	1.55
Stride time, s	1.08±0.10	1.20±0.19	1.33±0.22	.007	.064	<.001	0.79	0.63	1.43
Stride length, m	1.25±0.11	1.09±.0.18	0.88±0.30	.005	.015	<.001	1.07	0.85	1.64
Double support,%	22.18±4.18	27.19±6.39	32.29±8.11	<.001	.043	<.001	0.93	0.70	1.56
CV stride velocity, %	4.81±3.42	5.76±4.31	7.15±4.24	.507	.449	.181	0.24	0.33	0.61
Dual-task waking									
Speed, m/s	1.06±0.19	0.86±0.25	0.65±0.35	.005	.052	<.001	0.90	0.69	1.46
Stride time, s	1.19±0.17	1.34±0.25	1.44±0.28	.002	.297	.002	0.70	0.38	1.07
Stride length, m	1.23±0.14	1.10±0.21	0.87±0.32	<.001	.018	<.001	0.73	0.85	1.46
Double support,%	24.01±4.95	29.5±7.14	35.86±11.02	<.001	.059	<.001	0.89	0.68	1.39
CV stride velocity, %	6.50±3.76	7.27±3.91	9.59±5.64	.601	.223	.085	0.20	0.48	0.64
Balance parameter									
Ankle sway, deg^2	6.15±4.60	9.46±9.46	13.28±17.98	.057	.653	.229	0.45	0.27	0.54
Hip sway, deg^2	5.91±3.44	12.12±13.76	12.21±16.59	.004	.999	.254	0.62	0.01	0.53
COM sway, mean, cm^2	1.20±0.83	2.07±2.20	2.22±2.24	.021	.964	.159	0.51	0.06	0.58
COM ML sway, cm	0.75±0.36	0.92±0.62	0.93±0.50	.203	.999	.371	0.33	0.03	0.42
COM AP sway, cm	1.51±0.70	1.90±1.03	2.07±1.09	.063	.812	.114	0.44	0.17	0.62
Ankle sway, deg^2	6.15±4.60	9.46±9.46	13.28±17.98	.057	.653	.229	0.45	0.27	0.54

Displayed are spatio-temporal parameters (mean±SD) derived from gait assessment (separately for single-task and dual-task walking) and sway parameters derived from balance assessment for different frailty status groups.

[a] Games-Howell contrasts due to unequal group sizes and in some cases unequal variances.

[b] Effect sizes have been calculated as Cohen's d.

COM= center of mass; AP= anterio-posterior; ML= medio-lateral; CV= coefficient of variation

Table 3

Physical Activity Characteristics from 24-Hour Motion Sensor Measurement Stratified by Frailty Status

Variables	Non-frail	Pre-frail	Frail	P-value[a]			Effect size[b]		
				Non vs. pre	Pre vs. frail	Non vs. frail	Non vs. pre	Pre vs. frail	Non vs. frail
Walking									
Walking during 24 hours, %	8.7±3.9	6.1±3.0	4.7±3.4	.001	.283	.001	0.75	0.44	1.09
Walk bouts mean duration, sec	15.3±3.12	14.3±2.7	13.0±3.1	.201	.257	.030	0.35	0.45	0.75
Walking bout duration variability, SD, sec	26.0±19.6	17.2±13.3	9.5±6.8	.026	.015	<.001	0.52	0.73	1.12
Longest walking bout duration, sec	355±351	212±253	100±79	.063	.012	<.001	0.47	0.59	1.01
Steps during 24 hours, no	6030±3075	3869±1996	3080±2034	<.001	.411	.001	0.83	0.36	1.08
Maximum continuous steps, no	352±375	183±220	83±67	.029	.008	<.001	0.55	0.62	1.00
Standing									
Standing during 24 hours, %	16.8±5.8	14.3±4.6	13.3±6.4	.066	.764	.120	0.48	0.18	0.57
Standing bouts mean duration, sec	29.8±9.8	31.8±7.0	39.0±15.1	.466	.148	.061	0.24	0.61	0.73
Longest standing bout duration, sec	348±392	514±813	497±420	.540	.992	.600	0.26	0.03	0.37
Standing bouts duration variability, SD, sec	38.4±21.7	47.5±45.8	46.2±32.0	.388	.802	.132	0.25	0.03	0.28
Sitting									
Sitting during 24 hours, %	43.8±15.5	53.3±13.2	56.3±14.7	.005	.745	.016	0.66	0.21	0.83
Sitting bouts mean duration, sec	373±189	453±207	572±273	.112	.225	.025	0.40	0.49	0.85
Longest sitting bout duration, sec	5453±3481	6181±2866	7677±4081	.503	.333	.125	0.23	0.42	0.59
Sitting bouts duration variability, SD, sec	774±451	909±394	1048±686	.256	.118	.022	0.30	0.25	0.47
Lying									
Lying during 24 hours, %	30.6±15.6	26.1±13.5	25.8±15.6	.191	.997	.433	0.31	0.02	0.31
Lying bouts mean duration, sec	1837±1321	2661±2365	1559±1384	.065	.115	.990	0.43	0.57	0.21
Longest lying bout duration, sec	11366±11491	9266±6440	7592±5865	.437	.926	.362	0.23	0.27	0.41
Lying bouts duration variability, SD, sec	3098±2491	3136±2180	2355±1806	.992	.630	.631	0.02	0.39	0.34
Transfers									
Sit-stand duration, 90 percentile, sec	3.87±0.68	4.09±0.72	4.46±0.78	.258	.188	.023	0.31	0.49	0.81
Stand-sit duration, 90 percentile, sec	3.87±0.68	4.20±0.92	4.73±0.93	.096	.104	.004	0.41	0.57	1.06

Displayed are results of each derived PA parameter (mean±SD) for different frailty status groups.

[a]Games-Howell contrasts due to unequal group sizes and in some cases unequal variances.

[b]Effect sizes have been calculated as Cohen's d.

SD= standard deviation

Table 4

Most Sensitive Pre-Frailty Screening Variables From Sensor-Based Gait, Balance and Physical Activity Assessment

	Unadjusted model			Age-adjusted model		
Variables	**OR**	**(95% CI)**	**AUC**	**OR**	**(95% CI)**	**AUC**
Gait: speed, single-task, per 10cm/s	.53	(.40 – .71)	.797	.56	(.41 – .76)	.802
Balance: hip sway, deg^2	1.12	(1.05 – 1.20)	.647	1.11	(1.03 – 1.19)	.734
PA: Steps during 24 hours, per 100	.97	(.95 – .98)	.712	.97	(.96 – .99)	.763

AUC = area under curve derived from logistic regression analysis; OR= odds ratio; PA= physical activity

Table 5

Most Sensitive Parameters for Discriminating Three Frailty Levels (Non-Frail, Pre-Frail, Frail)

Variables	Unadjusted model					Age-adjusted model[a]				
	Pre-frail vs. non-frail		Frail vs. pre-frail			Pre-frail vs. non-frail		Frail vs. pre-frail		
	OR	(95% CI)	OR	(95% CI)	AUC	OR	(95% CI)	OR	(95% CI)	AUC
Gait: stride length, single-task, per 10cm	.52	(.36 – .74)	.65	(.50 – .86)	.853	.57	(.39 – .83)	.63	(.44 – .92)	.857
Gait: double support, single-task, %	1.22	(1.11 – 1.34)	1.11	(1.02 – 1.20)	.776	1.21	(1.10 – 1.34)	1.10	(1.003 – 1.20)	.841
Gait: speed, single task, per 10cm/s	.59	(.43 – .80)	.71	(.54 – .94)	.796	.63	(.46 – .87)	.71	(.50 – 1.007)	.830
PA: walking bout duration variability (SD), sec	.96	(.93 – .99)	.91	(.83 – .99)	.814	.97	(.93 – 1.002)	.90	(.83 – .99)	.818

Multinomial logistic regression with pre-frail group as reference. Inverse ORs presented for Pre-frail vs. Non-frail.

[a]Adjustment for age did not appreciably alter significance, except for gait speed (frail vs. pre-frail, p= 0.055) walking bout duration variability (pre-frail vs. non-frail, p= 0.065).

AUC = area under curve derived from multinomial regression analysis; OR= odds ratio; PA= physical activity; SD= standard deviation.