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SYMPOSIUM

Novel Wearable Technology for Assessing Spontaneous Daily Physical Activity and Risk of Falling in Older Adults with Diabetes

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Abstract

Background:

As baby boomers age and their expected life span increases, there is an unprecedented need to better manage the health care of elders with diabetes who are at increased risk of falling due to diabetes complications, frailty, or other conditions. New clinical and research tools are needed to measure functioning accurately and to identify early indicators of risk of falling, thus translating into more effective and earlier intervention.

Methods:

The objective of this pilot study was to validate a significant change in hardware and algorithm to track activity patterns using a single triaxial accelerometer through validation of timed up and go and standard measures of balance and gait. We recruited a convenience sample of eight older adults with diabetes and peripheral neuropathy (age, 77 ± 7 years old) who were asked to wear the sensor for imposed daytime activity performed in our gait laboratory. Subjects were stratified into risk of falling categories based on Tinetti scores. We examined the accuracy of the suggested technology for discrimination of high- versus low-risk groups.

Results:

The system was accurate in identifying the number of steps taken and walking duration (random error <5%). The proposed algorithm allowed accurate identification and stratification of those at highest risk of falling, suggesting that subjects with high risk of falling required a substantially longer duration for rising from a chair when compared with those with low risk of falling ($p < .05$).

Conclusions:

Our new single triaxial accelerometer algorithm successfully tracked postural transition, allowing accurate identification of those at high risk of falling, and could be useful for intermittent or even continuous monitoring of older adults with diabetes. Other potential applications could include activity monitoring of the diabetes population with lower extremity disease and of patients undergoing surgical procedures or as an objective measure during rehabilitation.

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Abbreviations: (CI) confidence interval, (PT) postural transition, (SI-ST) sit-to-stand, (ST-SI) stand-to-sit, (TUG) timed up and go

Keywords: body-worn sensor, diabetes care, foot ulcer, home telemonitoring, physical activity monitoring, risk of falling, wearable technology

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Introduction

Physical activity level may correlate with the success or failure of treatment regimens instituted for diabetic foot disease and plays a significant role in the outcomes of many disparate maladies. Diabetic foot ulcers typically develop because of repetitive stress applied to the foot during weight-bearing activity.[1–3] A reliable measure of daily physical activity leads to better estimates of the cumulative stress applied to the foot as well as to a more accurate evaluation of the efficacy of various medical and surgical treatments.[4–7]

Traditionally, physical activity has been defined as the total number of steps per day. However, physical activity is a complex phenomenon, including different sequences of activities, including both static components such as resting body postures (sitting, standing, and lying) and dynamic components such as walking, climbing, and running.[6,7] The objective of physical activity monitoring is to quantify posture allocations during the period of monitoring. Even by focusing on static postures, however, in light of the highly articulated human anatomy, the number of distinct postures is very high. Thus a simpler model for body postures is needed to simplify the problem and to enable an accurate and objective analysis of body postures.. Several authors have used a rather simple model of four basic body postures to classify daily activities: sitting, standing, lying, and locomotion.[7,8] Most of our understanding about physical activity is only about the duration of walking or the number of steps per day. However, walking may encompass as little as 3–10% of a person's daily physical activity and may not be representative of natural activities of daily living.[5]

Past ambulatory measurements of physical activity have been based on various motion sensors, such as pedometers, actometers, and accelerometers strapped on the waist, wrist, or ankle.[6,9–13] These methods provide no information on the type of activity, however. New systems have been developed to identify the type of activity,[14–16] but these methods are cumbersome to use during activities of daily living as they require (1) multiple sites of attachment to the body (2) a cable for connecting between multiple sensors, or (3) uncomfortable methods of sensor attachment (e.g., using an elastic band to attach the sensor to the subject's thigh), thus reducing their usefulness for long-term monitoring of natural physical activity. This is because successful application of body-worn sensors for continuous daily physical activity monitoring requires that the subject carries the device during daily activities with no difficulty.[17] Naturally, if the device hinders the subject's movements because of the complexity of sensor attachments (e.g., multiple sensor units) or device management (e.g., limited battery life), subjects will be unwilling to carry or use it continuously during their daily lives.

The system proposed by Najafi and coauthors[7,18] can effectively overcome some of the key limitations of the systems mentioned here. This system is capable of detecting body postures (sitting, standing, and lying) as well as periods of walking using only one small kinematic sensor (one gyroscope and two accelerometers) attached to the chest. The validity of this approach has been established in three separate pilot studies and by benchmarking the results with independent analysis by an optical motion system.[7,18] This algorithm has a demonstrated overall sensitivity of 99% for detecting the time of various postural transitions [PTs; e.g., sit-to-stand (SI-ST) or stand-to-sit (ST-SI)], more than 87% sensitivity and specificity for identifying the transition type (i.e., SI-ST or ST-SI), and more than 95% sensitivity and specificity for estimating the duration of walking and lying postures. An important limitation of the developed algorithm, however, is its use of a gyroscope in estimating PTs (i.e., SI-ST or ST-SI). The high power-consumption rates of gyroscopes, however, severely limit the applicability of the algorithm for applications outside the laboratory (which include everyday life applications), because such a system has an autonomy of only a few hours, thus requiring frequent recharging or exchanges of the battery. While additional batteries increase the device's autonomy, they will also increase its size and weight and hinder the subject's natural movements. Here we suggest an innovative algorithm based on using accelerometer data in place of gyroscope data, enabling long-term, autonomous operability of the system.

We also aim to validate the application of the proposed system in assessing risk of falling in older adults. Our previous study has demonstrated that PT (i.e., SI-ST and ST-SI), quantified by duration of rising or sitting on chair, can identify older adults with high risk of falling from those with low risk of falling.[18] The previous study, however, used a gyroscope to identify and quantify PT. The current study aims to explore whether quantification of PT using a triaxial accelerometer may also allow for discriminating older adults with low and high risk of falling.

Methods

Instrumentation and Data Logger

Acceleration data were recorded by a small data logger named PAMSys™ (physical activity monitoring system) offered by BioSensics LLC (Cambridge, MA). This lightweight, small sensor unit (<24 g; 5.2 × 3.2 × 1.5 cm) can be integrated unobtrusively into a comfortable shirt (or directly to a patient's shirt; **Figure 1**) without hindering daily living activities. The sensor unit includes a triaxial accelerometer sensor (±2 g; FreeScale MMA7361LC; current consumption, 400 μA) measuring accelerations in three perpendicular directions to record accelerations in the frontal, vertical, and lateral directions, which are defined relative to the user (**Figure 1**). An embedded battery allows recording of data on a Micro SD (2 GB) memory unit with suitable sample-rate frequency (40 Hz), which is approximately more than 340 h of continuous measurement. The data can be transferred to a computer via a universal serial bus reader unit for offline analysis.

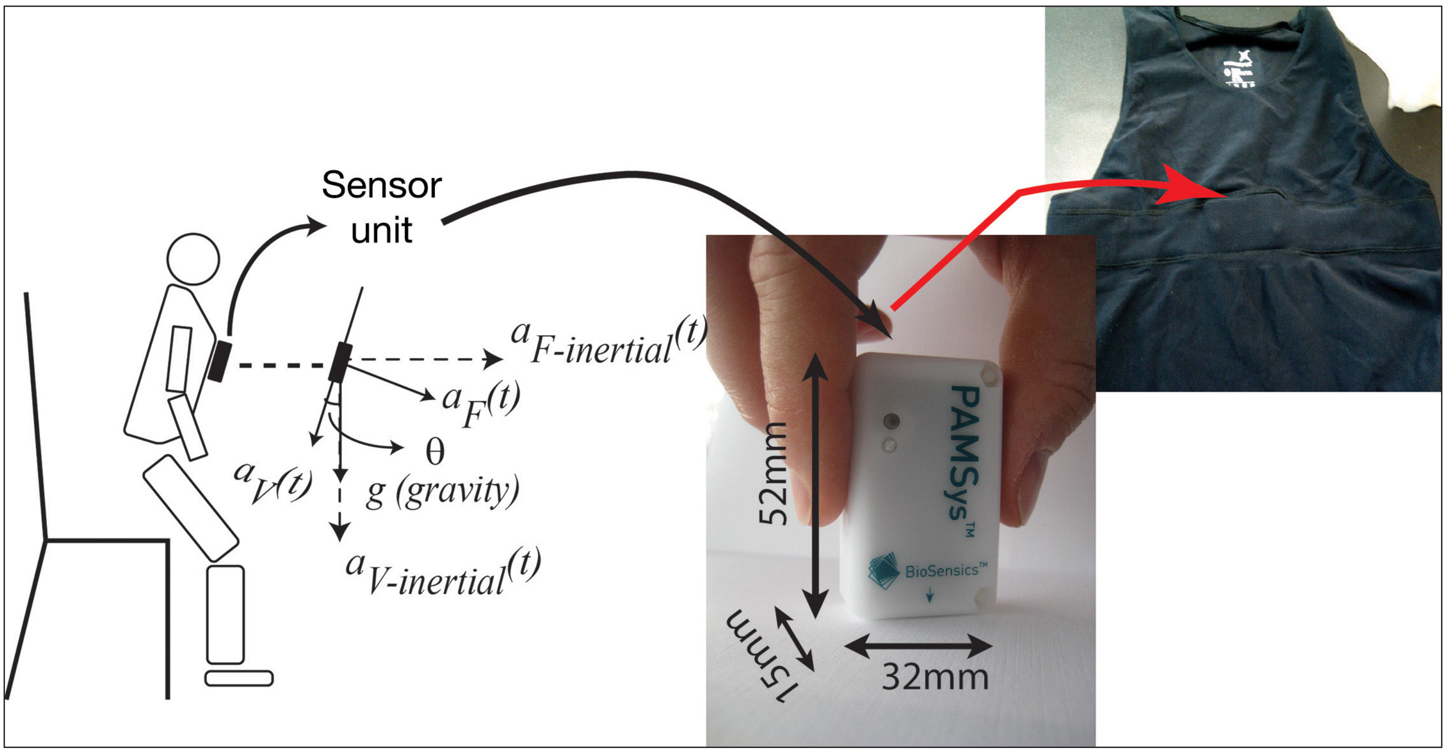

Figure 1. PAMsys is smaller than a business card, is based on a triaxial accelerometer, can be integrated unobtrusively into a comfortable shirt, and has an autonomy of approximately 6 days of continuous measurement with sample frequency of 50 Hz.

Algorithms

Monitoring the user's physical activity consists of monitoring, assessing, and quantifying the user's postures, movements, trunk tilt, as well as fall-related task parameters. To this end, the system computes various parameters associated with the subject's movement from the data recorded by the PAMSys unit attached to the subject's chest (see **Figure 1**). These parameters consist of (a) the subject's trunk tilt (specified in degrees, measuring the angle between the subject's trunk axis and the axis aligned with the gravitational force; **Figure 1**), (b) the type of the subject's PTs, (c) the time of the subject's PTs, (d) the duration of the subject's PTs, (e) the duration of the subject's locomotion, (f) characterization of the subject's locomotion (gait speed and number of step), and (g) the type of subject's postures (e.g., sitting, standing, lying). Use of accelerometers instead of gyroscopes allows for long-term autonomous operability of the system.

The associated challenges introduced by this replacement, however, consist of processing the resulting noisy accelerometer signals during everyday living activities.

Identifying the Types of Postural Transitions and Computing Their Durations and Occurrences

The flowchart in **Figure 2** and **Figure 3** demonstrate the operation of the algorithms used to continuously determine the type, time, and duration of the subject's PTs (in this case, SI-ST and ST-SI) during everyday movements. The algorithms use the frontal and vertical accelerometer signals, $a_F(t)$ and $a_V(t)$, respectively, in **Figure 3A.** The time-varying nature of the signals is shown explicitly by including the time variable t in the notation. In implementing the algorithms, the time variable t is necessarily discrete.

Figure 3A shows an example of the acceleration patterns recorded by the vertical and frontal accelerometers from an elderly subject with a high risk of falling [$a_V(t)$, green line; $a_F(t)$, black]. As identified on the plot, the pattern consists of a SI-ST PT followed by a period of walking and turning, followed by another PT (ST-SI; ST-SI). As shown in **Figure 3**, the algorithm performs the following steps on the frontal accelerometer signal to determine the occurrence, duration, and type of the PTs:

1. Segmenting, followed by wavelet filtering (box 1 in **Figure 3**) to remove signal artifacts induced by locomotion (e.g., walking, climbing or descending the stairs)—see also the red trace 5 in **Figure 3B**, an example of the resulting filtered signal $a_{F\text{-}filt}(t)$;

2. Locating the local maximum peaks (denoted by $a_{F\text{-}p}$ 6 in **Figure 3B**) in the filtered signal $a_{F\text{-}filt}(t)$ 5 through a peak-detection algorithm—this step corresponds to box 2 in **Figure 2**;

3. For each PT, corresponding to a particular $a_{F\text{-}p}$ 6, computing an initial estimate of the PT duration (ΔT_1) by (see boxes 3 and 4 in **Figure 2**)

    i. determining whether $a_{F\text{-}p}$ is greater than a predefined threshold *Th1*;

    ii. if yes, locating the local minima in $a_{F\text{-}filt}(t)$, within a specified time window, that precede and follow the particular maximum peak $a_{F\text{-}p}$—see **Figure 3B**;

    iii. computing ΔT_1 as the duration of the resulting time interval I_1, separating the local minima computed earlier.

These steps suppress and remove signal artifacts, such as the noisy peaks associated with shocks and other locomotion activities. Following the initial determination of the PT duration (ΔT_1), the system computes a more accurate estimate of the PT duration, ΔT_2, by applying additional filters to the frontal acceleration signal only within a time interval that is centered at I_1, but that is typically 10% to 30% longer in duration than ΔT_1. Such filtering of the frontal acceleration signal significantly decreases the requisite calculation costs, enabling real-time implementation of the algorithm. If the value ΔT_1 surpasses a defined threshold, Th_2 (box 5 in **Figure 2**), the following steps are performed on the frontal accelerometer signal $a_F(t)$ only during a time interval that is centered at I_1 but is typically 10% to 30% longer in duration:

1. as represented by box 6 in **Figure 2**, low-pass filtering of the $a_F(t)$ signal during the time interval I_1 by a wavelet;

2. as represented by box 7 in **Figure 2**, locating the maximum peak ($a_{F\text{-}p2}$) in the resulting filtered signal $a_{F\text{-}filt2}(t)$ during time interval I_1 (see **Figure 3C**);

3. within a specified time window, locating a local minimum in $a_{F\text{-}filt2}(t)$ closest to, and preceding, the particular maximum peak $a_{F\text{-}p2}$ (box 7 in **Figure 2**);

4. within a specified time window, locating a local minimum in $a_{F\text{-}filt2}(t)$ closest to, and following, the same maximum peak (box 7 in **Figure 2**);

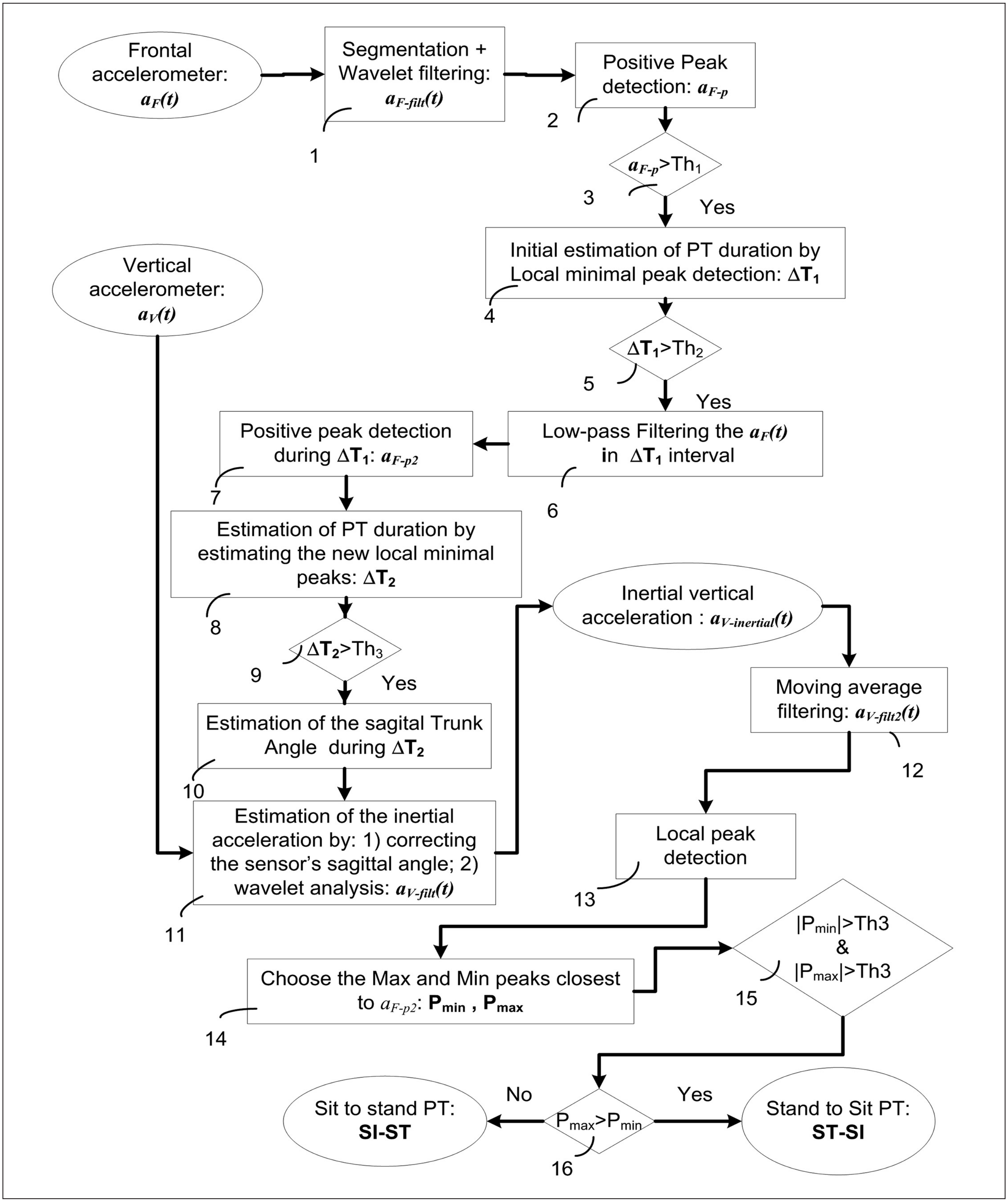

Figure 2. Flow chart diagram of the algorithm for identifying SI-ST and ST-SI PTs and the parameters associated with each transition.

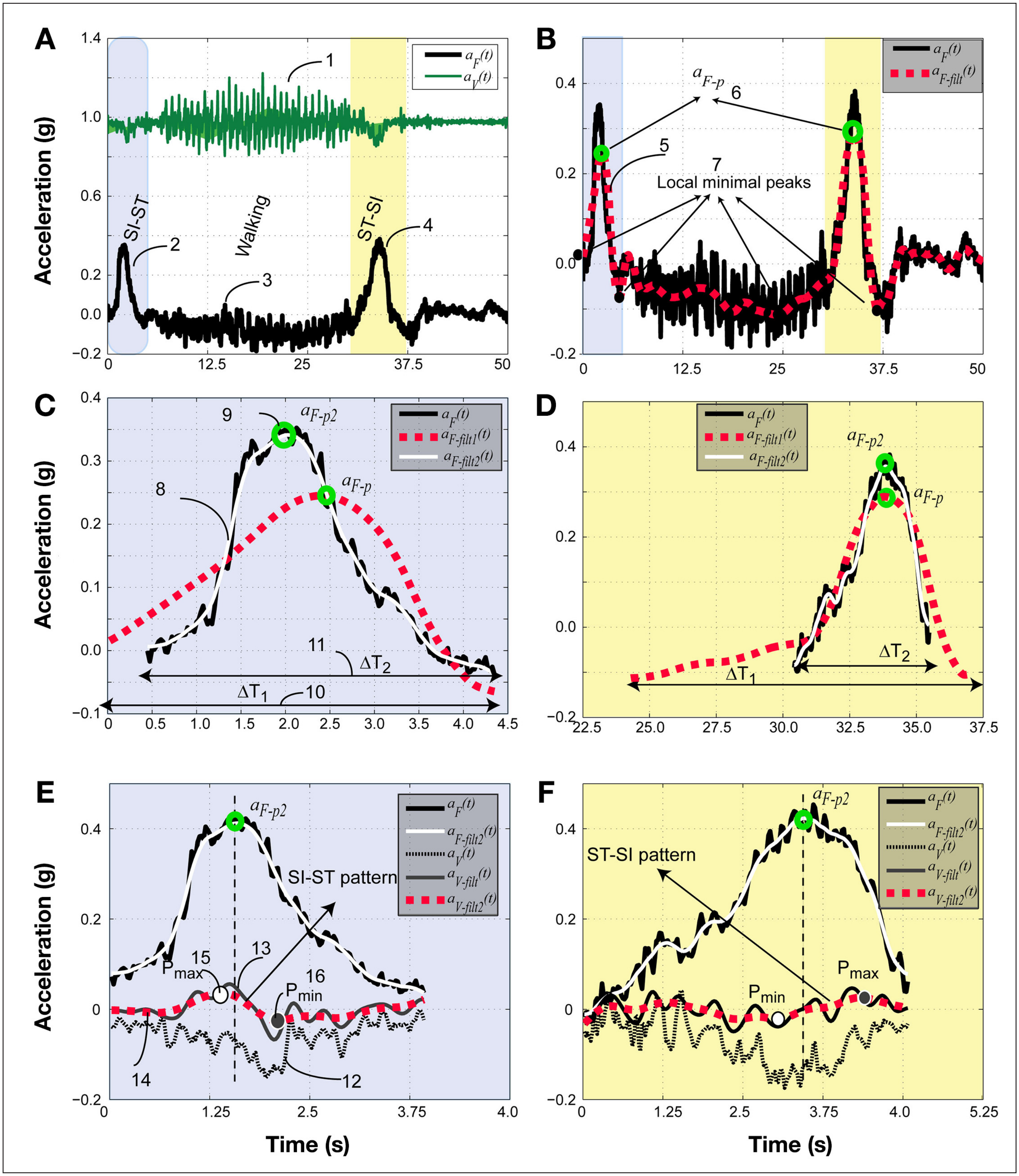

Figure 3. An example of identifying the SI-ST and ST-SI PTs and the parameters associated with each PT during a TUG test.

5. computing ΔT_2 (see **Figure 3C**) as the duration of resulting time interval I_2 separating the local minima computed earlier (box 7 in **Figure 2**).

The time of the maximum peak $a_{F\text{-}p2}$ represents the time of the PT, and ΔT_2 represents the estimate of the duration of the PT. For each PT, following the computation of its time of occurrence and its duration, the system uses the step-by-step algorithm described here to identify its type (e.g., ST-SI or ST-SI):

1. as represented by boxes 9 and 10 in **Figure 2**, for each PT, if ΔT_2 exceeds a predefined threshold Th_3, estimate the trunk tilt angle in the sagittal plane, θ, using a low-pass filtering of the $a_F(t)$ signal during corresponding time interval I_2. Because $a_F(t)$ consists of a θ-dependent gravitational component and a higher frequency, pure frontal-acceleration component, low-pass filtering removes the pure frontal-acceleration component, leading to a quantity proportional to sin (θ);

2. estimate time-varying inertial frontal and vertical accelerations $a_{F\text{-}interial}(t)$ and $a_{V\text{-}interial}(t)$ through the following coordinate transformation (see box 11 in **Figure 2**):

$$\begin{bmatrix} a_{F-inertial}(t) \\ a_{V-inertial}(t) \end{bmatrix} = \begin{bmatrix} \cos(\theta(t)) & -\sin(\theta(t)) \\ \sin(\theta(t)) & \cos(\theta(t)) \end{bmatrix} \begin{bmatrix} a_F(t) \\ a_V(t) \end{bmatrix} + \begin{bmatrix} 0 \\ g \end{bmatrix},$$

   where g represents the gravitational constant (9.81 m/s^2)—see also **Figure 1** for a free-body diagram showing the inertial acceleration components;

3. in parallel, apply an adequate, cascaded low-pass filter to remove the artifacts from $a_V(t)$, where the low-pass filter functions as follows:

   i. remove the gravitational component of $a_V(t)$ 12 (**Figure 3E**) using the following equations (see also box 11 in **Figure 2**):

$$a_F(t) = [a_{V-inertial}(t) + g]\sin(\theta(t)) + a_{F-inertial}(t)\cos(\theta(t)),$$

$$a_V(t) = [a_{V-inertial}(t) + g]\cos(\theta(t)) - a_{F-inertial}(t)\sin(\theta(t)),$$

$$\text{and } a_{V-filt}(t) = \sqrt{[a_F(t)]^2 + [a_V(t)]^2}\ ,$$

   ii. low-pass filtering of the resulting signal $a_{V\text{-}filt}(t)$, leading to $a_{V\text{-}filt2}(t)$; and

   iii. filtering this signal by a moving-average filter to obtain $a_{V\text{-}filt3}(t)$ (see also box 12 in **Figure 2**);

4. as exemplified in **Figure 3E** and **3F**, determine the local peaks in $a_{V\text{-}filt3}(t)$ using a peak-detection algorithm (box 13 in **Figure 2**); the resulting positive and negative peaks—P_{max} 15 and P_{min} 16, respectively—exceeding predefined threshold Th_4, are identified (boxes 14 and 15 in **Figure 2**);

5. classify the detected PT as SI-ST or ST-SI through the sequence by which P_{max} and P_{min} occur, e.g., a P_{max} followed by a P_{min} identifies the PT as a SI-ST pattern (box 16 in **Figure 2**; see also **Figure 3E** and **3F**);

6. apply a postprocessing algorithm to prevent misclassification of postures and PTs—for each PT, the classification as ST-SI or SI-ST will be corrected based on the preceding and subsequent sequences of PTs.

Analyzing Gait and Identifying the Corresponding Walking Periods and Number of Steps

Using data recorded by the accelerometers, an algorithm was developed to distinguish left and right gait steps, as well as estimate the gait cycle time and gait speed. The algorithm consists of the following steps:

1. remove from consideration data during time periods associated with PTs and lying;

2. compute the time-varying norm (i.e., time-varying magnitude) of the vertical and horizontal accelerometer signals as

$$a_F(t) = [a_{V-inertial}(t) + g]\sin(\theta(t)) + a_{F-inertial}(t)\cos(\theta(t)),$$

$$a_V(t) = [a_{V-inertial}(t) + g]\cos(\theta(t)) - a_{F-inertial}(t)\sin(\theta(t)),$$

$$\text{and } a_{V-filt3}(t) = \sqrt{[a_F(t)]^2 + [a_V(t)]^2}\ ,$$

where $\theta(t)$ represents the time-varying trunk angle and $a_{V\text{-}inertial}(t)$ and $a_{F\text{-}inertial}(t)$ represent the time-varying vertical and frontal acceleration components, respectively;

3. remove the gravitational component from the vertical acceleration signal in two steps: first, use formula stated in step 2 to compute $a_{V\text{-}filt3}(t)$, second, band-pass filter the result, leading to $a_{V\text{-}filt4}(t)$ (see **Figure 4C**);

4. identify gait steps as the peaks 4 (see, **Figure 4C**) in the $a_{V\text{-}filt4}(t)$ signal;

5. verify the sequence of the detected peaks according to predefined conditions for gait patterns;

6. distinguish left and right steps using the signal $a_L(t)$ from the lateral accelerometer—specifically, (i) the subject's lateral velocity $v_L(t)$ is computed by integrating $a_L(t)$ during the recognized walking periods and (ii) the relationship between the locations of the positive and negative peaks in $v_L(t)$ with the identified peak in the filtered vertical acceleration signal, $a_{V\text{-}filt4}(t)$, allows for left and right steps be distinguished.

This algorithm also enables both the recognition of undetected gait steps and the removal of false detected steps. Gait speed (i.e., stride velocity) is computed using information from the detected step time and the amplitude of acceleration during each gait cycle.

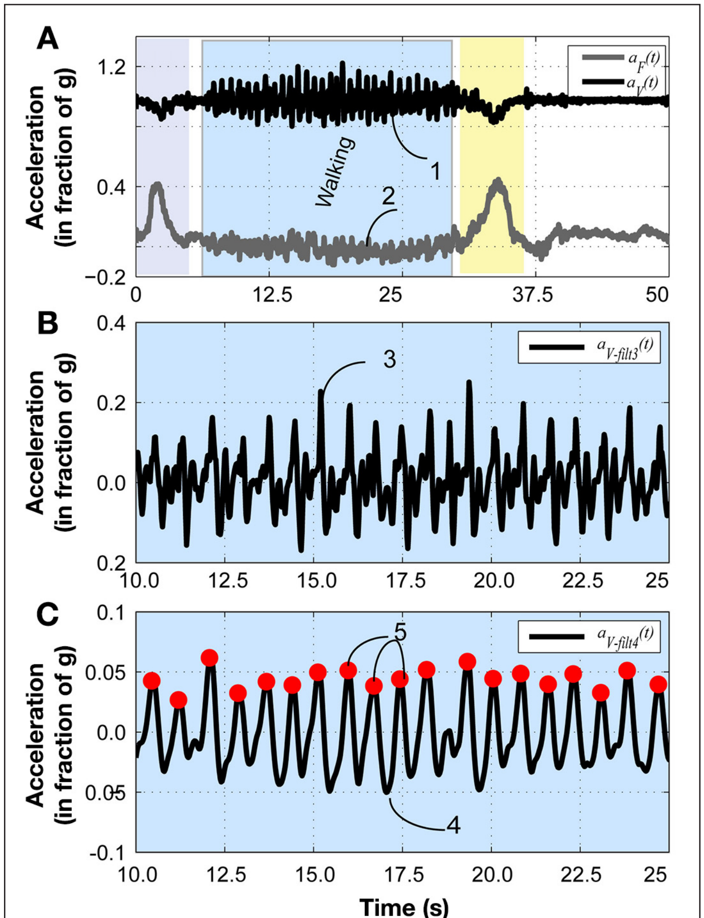

Figure 4. Illustration of an example of step detection using our suggested algorithm.

Detecting and Classifying the Lying Posture

The algorithm distinguishes lying from sitting and standing by comparing the orientation of vertical accelerometer signal $a_V(t)$ to that of the gravitational component. While the vertical accelerometer measures almost zero during lying periods, its value is significantly greater during sitting and upright postures—in some cases, the value is close to the gravitational constant.

Physical Activity Classification

The algorithms described here will classify the subject's physical activity and posture. In addition, several rules will be applied to improve the classifications performed by the discussed algorithms. These rules include the following:

1. If two contradictory states are detected (e.g., lying with walking or sitting with walking), preference is first given to lying, then to walking, and finally to PTs. This rule is based on the rationale that the lying posture is classified with the least amount of error. It should be noted that since the algorithms for different postural detections operate independently, two contradictory sets of activities may be identified.

2. Two successive PTs classified as the same type (e.g., SI-ST followed by SI-ST) are not possible—the classifications are modified according to the preceding and subsequent activities.

3. Elderly subjects cannot lean backward after an SI-ST transition with a high likelihood. The algorithm estimates the trunk lean angle based on the trunk angle before ($\theta_{PT\text{-}pre}$) and/or following ($\theta_{PT\text{-}post}$) the PT.

    i. Both $\theta_{PT\text{-}pre}$ and $\theta_{PT\text{-}post}$ are estimated based on the mean (E[.]) of the frontal acceleration by calculating the average of the signal over the rest period immediately before or after a PT, according to the following formulas:

    $$\theta_{PT-pre} = \sin^{-1}(E[a_F(t)|pre - PT - rest]),$$

    $$\theta_{PT-post} = \sin^{-1}(E[a_F(t)|post - PT - rest]),$$

    where $E[a_F(t)|pre - PT - rest]$ denotes the mean of the frontal acceleration signal during the rest period immediately before the PT and $E[a_F(t)|post - PT - rest]$ denotes the corresponding mean after the PT.

    ii. If the standard deviation of both frontal and vertical accelerations during a local interval before or after a PT were lower than a pre-defined threshold, the algorithm will classify that duration as a rest period.

    iii. Sensor inclination ($\theta_{initial}$) is computed from the average of the frontal accelerometer signal during a recognized walking episode containing at least 10 steps: $\theta_{initial} = \sin^{-1}(E[a_F(t)|\text{walking; 10 steps}])$.

    iv. The backward-leaning state is detected if subtracting $\theta_{initial}$ from $\theta_{PT\text{-}pre}$ (or $\theta_{PT\text{-}post}$) yields a value lower than a predefined threshold.

4. The duration of the lying posture should be more than a specified length (e.g., 30 s).

5. For an episode to be classified as "walking," it must include at least three successive steps within a predefined interval.

6. Since it is improbable for a person, especially an elderly subject, to stand for long periods without any movements, long standing periods without additional activity (e.g., more than 3 min) are interpreted as sitting. This rule applies if the standard deviations of both the vertical and frontal accelerations are below predefined thresholds.

Assessing Risk of Falling

Risk of falling was assessed based on the concept suggested by Najafi and coauthors[18] using the information extracted from PT. However, a new algorithm was design to quantify PT using the information from the accelerometer instead of the gyroscope, as described earlier. In summary, PT duration was defined by the interval initiated by the trunk leaning forward and terminated by the trunk leaning backward until reaching upright trunk posture. The average duration of PT as well as the number of unsuccessful attempts for rising from a chair were used for assessing the risk of falling. We assumed elderly subjects with a high risk of falling required a longer time to rise from a chair than elderly subjects with low risk of falling.

Experimental Setup

Eight elderly volunteers (older than 65 years, six females and two males, all diagnosed with diabetes with peripheral neuropathy) were recruited. Based on an evaluation of balance and gait (Tinetti score), four subjects were stratified to high risk (Tinetti score less than 21 over 28) or low risk of falling (Tinetti score >25 over 28).[19] Subjects were asked to perform a set of predefined activities based on classical timed up and go (TUG) test protocol using a single observer (**Figure 5**) while wearing the sensor, which was integrated in a comfortable shirt.

The exact time of each PT, as well as the duration of walking and number of taken steps, were recorded by an observer using an embedded program integrated into a personal digital assistant. These data were used to validate the accuracy of our algorithms for identifying PTs and their duration and type (i.e., SI-ST or ST-SI) and number of steps. Additionally, we examined whether our algorithm enables identification of older adults with high risk of falling.

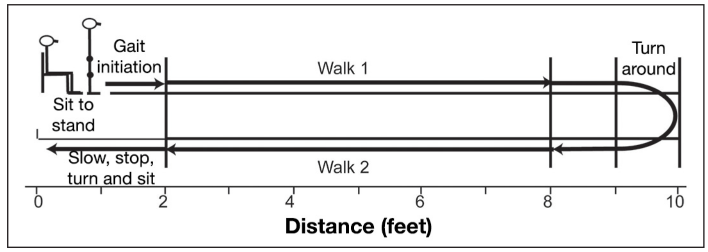

Figure 5. Illustration of the TUG test.

Statistical Analysis

To compare the reference system (observer report) with the suggested algorithm, systematic and random errors were calculated by calculating the average of errors and the standard deviation of errors, respectively. Additionally, the accuracy of the algorithm for classification of PT (SI-ST or ST-SI) was examined using sensitivity and specificity of the algorithm for PT classification. Considering the small sample size, we used nonparametric Mann–Whitney U-test to compare the duration of PT as well as TUG test scores between the two groups. Because the sample size was small, we used the "exact" method instead of the "approximate" method for estimating the p value. Finally, the correlation between PT duration and the Tinetti score or TUG test duration was evaluated using Pearson correlation of coefficient. For all tests, an alpha level of 0.05 was considered statistically significant. All calculations were made using MATLAB (MathWorks, Ver 7.4 (R2007a)).

Results

Overall, 16 PTs were gathered, including eight SI-ST and eight ST-SI transitions. All PTs associated with TUG test were correctly identified. Initially, two SI-ST and three ST-SI were misclassified. However, applying the physical activity classification rules described earlier, all misclassified PTs were correctly classified into SI-ST or ST-SI (100% sensitivity and specificity for PT classification to sitting or standing). Our algorithm accurately identified the duration of the TUG test. The systematic error for estimating TUG duration was 0.40 s (0.85%), and the random error was 0.70 s (3.6%). Our algorithm additionally enables an accurate measurement of the walking period (random error = 4.6%) and the number of taken steps (maximum number of missing steps = 1).

Table 1 summarizes the results related to the risk of falling assessment in the enrolled subjects. As expected, the duration of the TUG test was significantly higher in the group with a high risk of falling ($p = .028$). The average duration of the TUG test in the high-risk group was 62.0 ± 8.9 versus 26.1 ± 2.0 s in low risk of falling group. **Figure 6** illustrates the average SI-ST and ST-SI PT duration for the high and low risk of falling groups. Interestingly, the duration of SI-ST was significantly higher in the high-risk group ($p < .05$): the average duration for rising from a chair in the high-risk group was, on average, 124% higher than the low-risk group. Although the duration of ST-SI was, on average, 80% higher in the high-risk group, the observed increase was not significant ($p = .34$). In both groups, the duration of sitting on the chair was moderately higher than rising from a chair. This observed tendency was not significant for both groups, however ($p > .05$).

Figure 7 illustrates the relationship between SI-ST duration and Tinetti score (**Figure 7A**) as well as TUG test duration (**Figure 7B**) for all subjects. The relationship between TUG duration and Tinetti score has been illustrated in **Figure 7C**.

Table 1.
Assessing Risk of Falling in Elderly Adults by Measuring Postural Transition Duration

		Age	Gender	Tinetti score	TUG duration	SI-ST	ST-SI
Low risk of falling	Subject 1	76	Female	28	24.47	2.18	2.16
	Subject 2	75	Female	26	24.35	1.70	3.0
	Subject 3	77	Female	28	27.25	1.88	3.47
	Subject 4	66	Female	26	28.38	2.06	2.32
	Mean ± standard deviation	73.5 ± 5.0		27.0 ± 1.2	26.1 ± 2.0	1.95 ± 0.22	2.73 ± 0.61
High risk of falling	Subject 5	71	Male	21	69.60	5.39	5.39
	Subject 6	91	Female	19	50.30	5.70	8.48
	Subject 7	84	Female	17	59.82	3.92	4.52
	Subject 8	76	Male	18	68.20	2.4	0.91
	Mean ± standard deviation	80.5 ± 8.8		18.8 ± 1.7	62.0 ± 8.9	4.37 ± 1.53	4.92 ± 1.55

Results suggest a relatively high correlation was observed between SI-ST and the Tinetti score (r = -0.65; 95% confidence interval [CI], -0.92, 0.09; p = .08) as well as TUG test duration (r = 0.67; 95% CI, -0.06, 0.93; p = .07). In addition, results demonstrate an excellent correlation between the Tinetti score and TUG test duration (r = -0.89; 95% CI, -0.98,-0.51; p = .003).

Discussion

For comorbidly ill elders, geriatric syndromes are often more important considerations in maintaining independence and functioning than are diseases, *per se*. Remaining physically active is a key feature in the function and quality of life of the elderly; physical activity is an important indicator of wellbeing, and changes in activity are important early indicators of changes in health state (as occurring with increasing frailty and risk of falling, for example). This is especially true in cases of (1) posthospitalization in-home reconditioning, (2) medication regimen changes requiring careful monitoring, (3) fall monitoring, (4) prescriptive daily acitivity monitoring

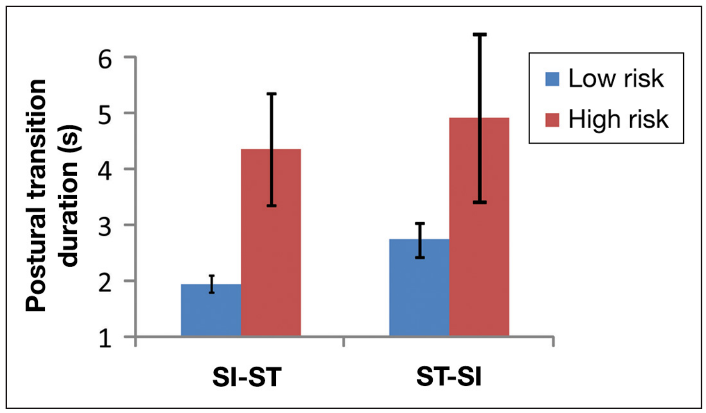

Figure 6. Comparison of PT duration between older adults with low and high risk of falling.

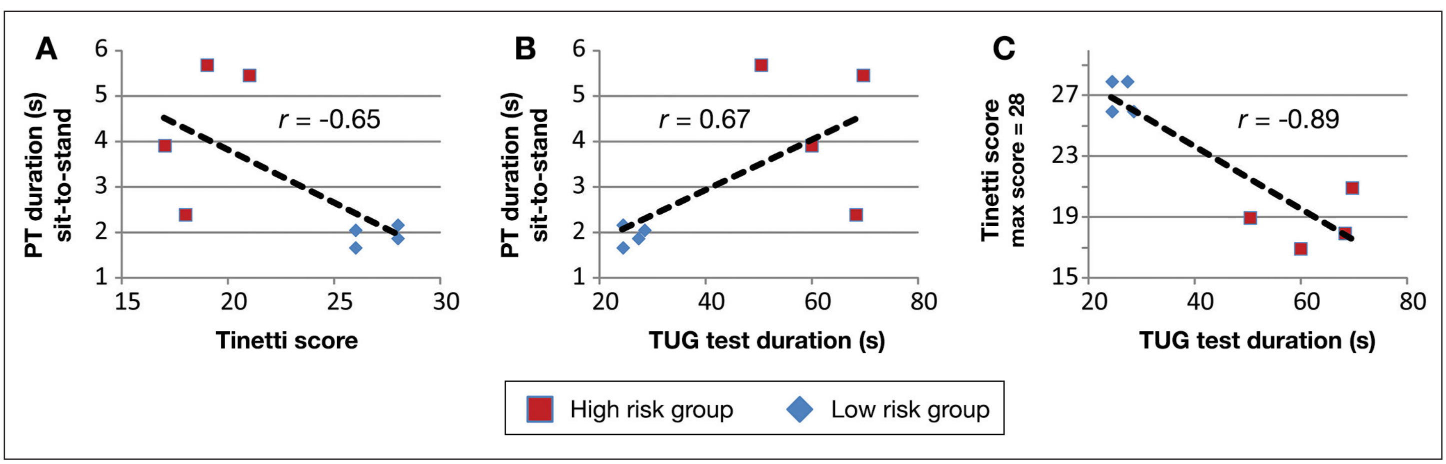

Figure 7. Comparison between **(A)** SI-ST duration and Tinetti score, **(B)** SI-ST duration and TUG test duration, and **(C)** TUG test duration and Tinetti score.

to sustain conditioning in prefrail patients, and (5) insomnia and nightime activity. Activities of daily life, perceived disability, and quality of life are currently assessed by validated tools, which are mostly questionnaire based. While these methods have been shown to be reliable, have become generally accepted, and are increasingly used, they rely on the patients' subjective assessments, are time-consuming to complete, and provide episodic cross-sectional data rather than just-in-time information targeted to critical clinical triggers. A reliable and valid method for the measurement of long-term spontaneous physical activity in daily life will provide an instrument of unprecedented objectivity, with far-reaching scientific applications and the ability to evaluate the efficacy of various medical, surgical, and psychosocial treatments and management strategies.

Physical activity has been traditionally defined as the total number of steps per day. However, as previously discussed, walking may comprise little of a person's total daily physical activity and is an important but minor component of total daily activity.[20] Several systems have been developed to identify the type of physical activity,[14–16] but these methods are cumbersome, as they require two or more different sites of sensor attachment to the body and hence are less suitable for elderly care applications. Indeed, to be most useful for long-term monitoring of the elderly and telecare applications, the user must be able to carry on with his/her natural daily activities, unhampered. If the device poses any hindrance to the subject's movements, due to either the complexity of sensor attachments (e.g., multiple sensor units) or device management (e.g., limited battery life), elderly people may be unable or unwilling to carry it continuously during their daily lives.

Najafi and coauthors[7] suggested an algorithm for monitoring daily physical activity that is capable of detecting body postures (sitting, standing, and lying) as well as periods of walking using only one small kinematic sensor (one gyroscope and two accelerometers) attached to the chest. An important limitation of the developed algorithm, however, is the necessity of using a gyroscope for estimating PTs (i.e., SI-ST or ST-SI). The sensor's resulting high-energy consumption rate significantly limits the autonomy of the system. Additionally, the current algorithm is ill suited for real-time and remote telemonitoring applications because its calculation costs are too high due to the incorporation of complex filtering schemes.

The results of this study demonstrate that a single wearable sensor attached to the chest and based on only a triaxial accelerometer performed very well in monitoring activities and in assessing the risk of falling in older subjects. This system was able to identify PT, sitting, standing, lying, and walking as well as the number of steps taken. Substituting an accelerometer for a gyroscope allows economization in power consumption by a factor of more than three. The suggested cascade filters used in place of the complex filtering scheme used in the initial algorithm additionally lowered the calculation cost by a factor of more than two. Specifically, the current algorithm does not require any integration and drift removal algorithms, which were used in the previous study for identifying the PT using gyroscope sensor. Additionally, instead of using a very complex filter for estimating the duration of PT and its classification, several low-cost moving average filters were used. This facilitates the direct implementation of the suggested algorithms in a low-power microcontroller for real-time application purposes.

Our results also confirmed the initial finding reported by Najafi and coauthors[18] in which they demonstrated that the duration of rising from a chair in older adults with high risk of falling is longer than older adults with low risk of falling. This can be explained by the fact that elderly people who fall have slower movements due to reduced peak hip extension and increased pelvic tilt as well as higher postural during PT.[21–23] Despite an observed increase in the duration of PT from sitting to standing in the high-risk group, this increase was not significant in our study. This could be partially explained by the limited sample size in our study. Alternatively, a relatively high variation observed for intersubject PT duration for sitting down on a chair can be explained by the usual weakening of the hamstring in the high-risk group, causing a fast transition to sitting down or falling on a chair.

This new monitoring device minimally interferes with the usual activity of the subjects because it is lightweight and wireless. Monitoring the subject in his/her usual environment with minimal interference is, therefore, possible, in contrast with other systems that can be used only in laboratory settings. The current autonomy of the system allows continuous recording for up to 2 weeks. Where necessary, the battery could be easily recharged for extended monitoring. Alternatively, a more powerful battery could be used to improve the battery life.

The results of this study have some limitations. First, we used a small number of subjects, and these results would need to be confirmed with a larger sample. Second, these subjects were a convenience sample and may not be representative. Third, the device was assessed during short-term monitoring and an imposed set of activities (TUG test). Another study should validate the device in the home environment and over longer periods of monitoring. Finally, although the subjects were encouraged to move as usual for them, we cannot exclude the possibility that their activity was influenced by the fact they were participating in a study while confined to a gait laboratory. Despite these limitations, we believe this system has the potential for extended clinical as well as research applications. In particular, this system could help better document subject mobility, an important component of the quality of life. An objective method for clinically relevant remote monitoring of activity organization inclusive of clearly communicated individualized targets and triggers by noninvasive physical activity telemonitoring has not yet been developed. Such technology would enable remote and continuous screening during daily life, supporting independence, functioning, and quality of life while providing important clinical triggers for "just-in-time" clinical intervention.

Additionaly, the suggested technology could assist health care providers in diabetic foot ulcer prevention as well as clinical management of the diabetic foot disease via controlling the foot loading condition as well as the organization of activity. The most common reason for hospitalization among diabetes patients is foot ulceration. The repetitive trauma associated with physical activity is responsible for a majority of these ulcers. Although several studies have utilized commercially available pedometers to better understand this etiology,[24–28] those devices can only track the number of steps taken per day. During standing, the foot is also under considerable stress, therefore likely increasing ulceration and/or reulceration risks. The suggested system measures both periods of walking and standing, thus assessing foot loading in diabetes patients at risk of foot ulceration as well those who already developed diabetic foot ulcers during daily living. Furthermore, a study performed by Armstrong and coauthors[26] led to the hypothesis that when assessing ulceration risk, the absolute volume of physical activity may be less important than the daily variability. It would therefore stand to reason that furthering the role of physical activity fluctuation over several days could hugely benefit the clinical management of the diabetic foot disease. Thus, the suggested system could be beneficial for smart management of diabetic foot disease and for foot ulcer prevention.

Conclusion

Here we proposed a novel technology based on a single wearable sensor, housing only an accelerometer that allows monitoring of all three main postures (i.e., sitting, standing, and lying), PTs (SI-ST and ST-SI), their durations, and the duration of walking and the number of steps taken. In addition, the proposed algorithm enables quantifying PT via measuring its duration, which is initiated by the trunk leaning forward and terminated by the trunk leaning backward to achieve upright posture. The results suggest that the postural-transition duration for rising from a chair increases with increased risk of falling. Thus daily monitoring of PT could offer an objective assessment of the risk of falling in older adults using a single wearable sensor based on a triaxial accelerometer.

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References:

1. Wu SC, Crews RT, Armstrong DG. The pivotal role of offloading in the management of neuropathic foot ulceration. Curr Diab Rep. 2005;5(6):423–9.
2. Brand PW. The diabetic foot. In: Ellenberg M, Rifkin H, eds. Diabetes mellitus, theory and practice. 3rd ed. New York: Medical Examination Publishing; 1983:803–28.
3. Wrobel JS, Najafi B. Diabetic foot biomechanics and gait dysfunction. J Diabetes Sci Technol. 2010;4(4):833–45.
4. Najafi B, Wrobel JS, Grewal G, Menzies RA, Talal TK, Zirie M, Armstrong DG. Plantar temperature response to walking in diabetes with and without acute charcot: the Charcot Activity Response Test. J Aging Res. 2012;2012:140968.
5. Najafi B, Crews RT, Wrobel JS. Importance of time spent standing for those at risk of diabetic foot ulceration. Diabetes Care. 2010;33(11):2448–50.
6. Aminian K, Najafi B. Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications. Computer Animation Virtual Worlds. 2004;15(2):79–94.
7. Najafi B, Aminian K, Paraschiv-Ionescu A, Loew F, Bula CJ, Robert P. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. IEEE Trans Biomed Eng. 2003;50(6):711–23.
8. Najafi B, Wrobel J, Armstrong D. A novel ambulatory device for continuous 24-h monitoring of physical activity in daily life (abstract #586). In: Ashton-Miller JA, Hughes RE, Andrews D, eds. North American Congress on Biomechanics (NACOB). Ann Arbor: NACOB; 2008.
9. Patterson SM, Krantz DS, Montgomery LC, Deuster PA, Hedges SM, Nebel LE. Automated physical activity monitoring: validation and comparison with physiological and self-report measures. Psychophysiology. 1993;30(3):296–305.
10. Ng AV, Kent-Braun JA. Quantitation of lower physical activity in persons with multiple sclerosis. Med Sci Sports Exerc. 1997;29(4):517–23.
11. Meijer GA, Westerterp KR, Verhoeven FM, Koper HB, ten Hoor F. Methods to assess physical activity with special reference to motion sensors and accelerometers. IEEE Trans Biomed Eng. 1991;38(3):221–9.
12. Bouten CV, Koekkoek KT, Verduin M, Kodde R, Janssen JD. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE Trans Biomed Eng. 1997;44(3):136–47.
13. Bouten CV, Westerterp KR, Verduin M, Janssen JD. Assessment of energy expenditure for physical activity using a triaxial accelerometer. Med Sci Sports Exerc. 1994;26(12):1516–23.
14. Aminian K, Robert P, Buchser EE, Rutschmann B, Hayoz D, Depairon M. Physical activity monitoring based on accelerometry: validation and comparison with video observation. Med Biol Eng Comput. 1999;37(3):304–8.
15. Chen KY, Sun M. Improving energy expenditure estimation by using a triaxial accelerometer. J Appl Physiol. 1997;83(6):2112–22.
16. Tamura T, Fujimoto T, Sakaki H, Higashi Y, Yoshida T, Togawa T. A solid-state ambulatory physical activity monitor and its application to measuring daily activity of the elderly. J Med Eng Technol. 1997;21(3-4):96–105.
17. Najafi B. Physical activity monitoring and risk of falling evaluation in elderly people, Ph.D. dissertation. Lausanne: Electrical Engineering Department, Ecole Polytechnique Federale de Lausanne (EPFL); 2003.
18. Najafi B, Aminian K, Loew F, Blanc Y, Robert PA. Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. IEEE Trans Biomed Eng. 2002;49(8):843–51.
19. Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly persons living in the community. N Engl J Med. 1988;319(26):1701–7.
20. Najafi B, Crews RT, Wrobel JS. Incorporating standing time into physical activity assessment of patients at risk of diabetic foot ulceration. Proceedings of the 70th American Diabetes Association Scientific Sessions (ADA '10), Orlando, FL, June 2010.
21. Laughton CA, Slavin M, Katdare K, Nolan L, Bean JF, Kerrigan DC, Phillips E, Lipsitz LA, Collins JJ. Aging, muscle activity, and balance control: physiologic changes associated with balance impairment. Gait Posture. 2003;18(2):101–8.
22. Lee LW, Kerrigan DC. Identification of kinetic differences between fallers and nonfallers in the elderly. Am J Phys Med Rehabil. 1999;78(3):242–6.
23. Lee LW, Zavarei K, Evans J, Lelas JJ, Riley PO, Kerrigan DC. Reduced hip extension in the elderly: dynamic or postural? Arch Phys Med Rehabil. 2005;86(9):1851–4.
24. Crews RT, Armstrong DG, Boulton AJ. A method for assessing off-loading compliance. J Am Podiatr Med Assoc. 2009;99(2):100–3.
25. Crews RT, Bowling FL, Boulton AJ. Controversies in off-loading: should big brother be watching? Curr Diab Rep. 2009;9(6):417–9.
26. Armstrong DG, Lavery LA, Holtz-Neiderer K, Mohler MJ, Wendel CS, Nixon BP, Boulton AJ. Variability in activity may precede diabetic foot ulceration. Diabetes Care. 2004;27(8):1980–4.
27. Armstrong DG, Abu-Rumman PL, Nixon BP, Boulton AJ. Continuous activity monitoring in persons at high risk for diabetes-related lower-extremity amputation. J Am Podiatr Med Assoc. 2001;91(9):451–5.
28. Armstrong DG, Boulton AJ. Activity monitors: should we begin dosing activity as we dose a drug? J Am Podiatr Med Assoc. 2001;91(3):152–3.