Ambulatory System for Human Motion Analysis Using a Kinematic Sensor: Monitoring of Daily Physical Activity in the Elderly

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***Abstract*—A new method of physical activity monitoring is presented, which is able to detect body postures (sitting, standing, and lying) and periods of walking in elderly persons using only one kinematic sensor attached to the chest. The wavelet transform, in conjunction with a simple kinematics model, was used to detect different postural transitions (PTs) and walking periods during daily physical activity. To evaluate the system, three studies were performed. The method was first tested on 11 community-dwelling elderly subjects in a gait laboratory where an optical motion system (Vicon) was used as a reference system. In the second study, the system was tested for classifying PTs (i.e., lying-to-sitting, sitting-to-lying, and turning the body in bed) in 24 hospitalized elderly persons. Finally, in a third study monitoring was performed on nine elderly persons for 45–60 min during their daily physical activity. Moreover, the possibility-to-perform long-term monitoring over 12 h has been shown. The first study revealed a close concordance between the ambulatory and reference systems. Overall, subjects performed 349 PTs during this study. Compared with the reference system, the ambulatory system had an overall sensitivity of 99% for detection of the different PTs. Sensitivities and specificities were 93% and 82% in sit-to-stand, and 82% and 94% in stand-to-sit, respectively. In both first and second studies, the ambulatory system also showed a very high accuracy ($>$ 99%) in identifying the 62 transfers or rolling out of bed, as well as 144 different posture changes to the back, ventral, right and left sides. Relatively high sensitivity ($>$ 90%) was obtained for the classification of usual physical activities in the third study in comparison with visual observation. Sensitivities and specificities were, respectively, 90.2% and 93.4% in sitting, 92.2% and 92.1% in "standing + walking," and, finally, 98.4% and 99.7% in lying. Overall detection errors (as percent of range) were 3.9% for "standing + walking," 4.1% for sitting, and 0.3% for lying. Finally, overall symmetric mean average errors were 12% for "standing + walking," 8.2% for sitting, and 1.3% for lying.**

***Index Terms*—Ambulatory system, elderly people, kinematic sensor, long-term monitoring, physical activity, postural transition, wavelet transform.**

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I. Introduction

Quantification of daily physical activity is a key determinant in evaluation of the quality of life of subjects with limited mobility, such as elderly persons [1]. The aging of the population and the related increase in the burden of chronic diseases have already had a major impact on most western health care systems [2], and will likely have an increased effect these systems in the future. Indeed, projections in industrialized nations suggest a continuing mortality decline in the next decades [3] with a dramatic increase in the number of disabled persons requiring support. For example, in the USA it is estimated that by 2050 the number of elderly persons living in their own home but requiring assistance will triple (from 0.8 to 2.6 million), as will the number of those institutionalized in nursing homes (from 1.3 to 4.5 million) [4], [5]. Similar trends have been observed in the last decades in Switzerland [6], [7].

Chronic diseases such as arthritis, cardiovascular, or neurodegenerative diseases result in limitation of mobility and physical activity of the affected persons. A reliable measure of the physical activity in daily life would allow a better assessment of activities of daily living and the effects of numerous medical conditions and treatments. Continuous 24-h recording of posture and motion can also be useful in behavior assessment [8]. Transitions between postures such as the sit-to-stand (SiSt) transition may also be regarded as a physiologically essential function in man and a prerequisite for gait [9]. The quantitative assessment of daily activity in humans requires an objective and reliable technique that can be used under conditions of daily living. Currently, measurement of energy expenditure is widely accepted as the standard measurement of physical activity [10], but this is impractical under normal conditions and not feasible outside of a laboratory environment. Thus, interest in the use of direct and indirect measures of energy expenditure, using measurement techniques such as observations, questionnaires, heart rate recordings, or motion capture is growing. Motion capture with body-fixed sensors offers an appropriate alternative for assessment of daily physical activity. In the past, ambulatory measurement of physical activity was based on various motion sensors such as pedometers, actometers [11], or accelerometers strapped onto the waist, wrist, or ankle [12]–[18]. However, these methods provide no information on the type of activity. Recently, new systems have been developed to identify the type of activity [19]–[22], but these methods are cumbersome because they used two or more different sites of attach-

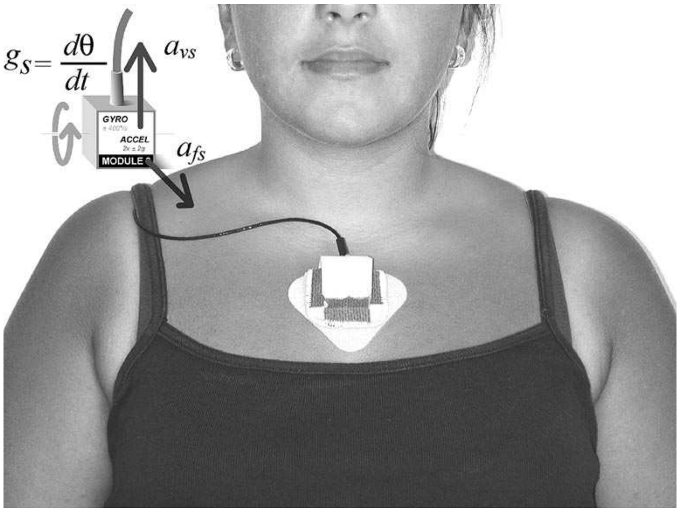

Fig. 1. Sensor attachment. Vertical and frontal acceleration (a_{vs} and a_{fs}) as well as angular velocity (g_s) are measured using a kinematic sensor attached to the subject's chest.

ment to the body and cable connection, reducing their applicability for long-term monitoring of physical activity, and in fact interfering with activities.

The purpose of this study was to test the performance of a new ambulatory measurement system, based on only one miniature kinematic sensor, in categorizing body postures (sitting, standing, and lying) and locomotion (walking). Specifically, we hypothesized that the information provided by a single kinematic sensor attached to the chest will accurately detect postural transitions (PTs) between standing, sitting, and lying, as well as locomotion activity when standing. Once identified, PTs will result in categorizing the type of activity and also to better understand problems occurring during daily activity (e.g., difficulty during rising from a chair, falling, etc.) [23], [24]. Furthermore, the device might offer an option to express fall incidence/walked distance and, hence, gives a very different perspective in this area.

II. Methods

A. Experimental Design

Three different studies were conducted with subjects older than 65 years. The first study was performed in a laboratory setting, the second in a clinical center, and the third in a free living environment. For all three, subjects wore an ambulatory system that included a kinematic sensor attached to their chest and a light portable datalogger (Physilog®, BioAGM, CH) carried on the waist. The kinematic sensor is composed of one miniature piezoelectric gyroscope (*Murata*, *ENC-03J*, $\pm 400^{\circ}/\mathrm{s}$) which measures trunk angular velocity (g_s) in the sagittal plane, and two miniature accelerometers (*ADXL202*, $\pm 2g$), which measure vertical (a_{vs}) and frontal trunk accelerations (a_{fs}), respectively. The principle operation of the gyroscope is the measurement of the Coriolis acceleration, which is generated when a rotational angular velocity is applied to the oscillating piezoelectric bimorph. These battery-operated sensors can be have low energy consumption (4.6 mA at 5 V), and are appropriate for ambulatory monitoring. The signal from the gyroscope and accelerometers were amplified and low-pass filtered (cutoff frequency: 17 Hz) to remove electronic noise. Signals were digitized at 40-Hz sampling rate and recorded by the datalogger. At the end of the recording, the data were transferred to a computer for analysis. The gyroscope, two accelerometers and their conditioning electronics were packaged in a very small box ($25 \times 25 \times 15$ mm) and strapped with an elastic belt in front of the sternum (Fig. 1).

TABLE I
Set of Tests Performed by Each Subject During the First Study

Test number	Type of Activity	
1	sit + lying + sit + stand + walk	Bed (Desired Height for each subject)
2	sit-to-stand + walk + stand-to-sit	Upholstered chair without armrest (Seat height: 48 cm)
3	sit-to-stand + stand-to-sit	Armchair with armrest (Seat height: 46 cm)
4	sit-to-stand + stand-to-sit	Wooden chair without armrest (Seat height: 46 cm)
5	sit-to-stand + stand-to-sit	Upholstered chair without armrest (Seat height: 48 cm)
6	sit-to-stand + stand-to-sit	Wooden Chair with armrest (Seat height: 46 cm)

Written informed consent was obtained from all the subjects, and the protocol of the studies was approved by the ethics committee of the Faculty of Medicine of Geneva or the University of Lausanne.

1) First Study: Eleven community-dwelling elderly subjects (six females, five males, age: Mean $= 79$, SD $= 6$ years old) were enrolled. Each subject performed six different tests including lying down, walking, as well as SiSt and stand-to-sit (StSi) transitions using different types of chairs (standard wooden chair, armchair, and upholstered chair), with and without armrests (Table I). Each test was repeated two to three times, depending on the subject's ability level. Three subjects used a walking aid (e.g., cane). As the reference system to detect body posture and activities, we used five cameras and four retro reflective markers placed on the trunk (Vicon™, Oxford Metrics, U.K.). This optical system enabled accurate three dimensional measurements of chest movements as described in our previous publication [24]. Sensitivities and specificities of the ambulatory system in detecting body postures, transitions, and activity (e.g., walking) were determined using as standard criterion the information provided by the reference system.

2) Second Study: The accuracy of this ambulatory system was further assessed by identifying lying positions, transition from one lying position to another, and transfer in or out of bed (i.e., sitting-to-lying or lying-to-sitting). Participants were 24 elderly persons (Mean $= 81$ years, SD $= 7$) hospitalized in a rehabilitation unit. They were asked to change their position in bed two to three times (according to their ability), and to transfer in or out of bed. For both sets of movements the head of the bed was placed at their desired usual incline. The time corresponding to each movement was measured by an observer using a stopwatch.

3) Third Study: The ambulatory system was carried by nine subjects (Mean $= 66$ years, SD $= 14$) to record 45 or 60 min of daily physical activity, depending on their ability. During recording, subjects performed different activities at their usual pace without any external supervision. Using simple software loaded in a laptop, an observer concurrently recorded the nature of each activity undertaken, as well as the timing of each PT.

These data were used as reference to calculate the performance of the system in identifying these events (sensitivity, specificity, and accuracy).

B. Signal Processing: Wavelet Transform

A time-frequency analysis (wavelet transform) [25] was used to detect PT) from the kinematic sensor attached on the chest. Body postures are identified by estimating the nature of the movement transitions between the postures. Traditional spectral analysis methods such as the Fourier transform tell us about frequency components contained in a signal. However, they do not provide the time at which those frequency components occurred [26], [27]. This information is important in analyzing nonstationary signals, where the frequency content changes over time. In contrast, wavelet processing provides good frequency resolution at both low and high frequencies. An example of nonstationary signals includes the acceleration pattern during PTs such as SiSt or StSi transitions, and walking with varied velocity, where sharp high-frequency transients are present. In these situations, the information of interest is often a combination of features that are well localized in time and frequency domains. In practical terms, drift in a signal can be isolated while desired high frequency transients are preserved. Several investigators have already shown the advantages of wavelet transform for the analysis of kinematic signals [23], [28]–[30]. Wachowiak *et al.* compared the performance of wavelet-based noise removal technique with four automatic conventional noise removal techniques used in biomechanics [28] for the analysis of biomechanical signals (i.e., velocity and acceleration). They showed that wavelet transform techniques are very effective in removing noise from signals with sharp transients while leaving these transients intact. In other words, the most important information of these signals is often carried by transients and abrupt changes, where the irrelevant information is highlighted by irregular structures such as peaks. Fourier transform is a global tool providing a description of the overall regularity of a signal. However, it is not suited to characterize the temporal distribution of singularities and transient events. In contrast, the wavelet transform is an optimal technique for describing the local regularity of signals [31]. Moreover, instead of using sinusoidal signals, wavelet transform uses a suitable basic function, which is more similar to the patterns of accelerations and trunk tilt during PT [26], [27].

We used a similar technique based on multiresolution discrete wavelet transform (DWT) to approximate the signal with different resolutions [27]. It consists of splitting a signal into high-scale components (low-frequency components) called the approximation, and low-scale components (high-frequency components) called the detail. By considering the original signal $s(n)$ (e.g., acceleration), the approximation of the signal at scale $j = 0$ is $A_{2^0}s$ which corresponds to the signal $s(n)$. At scale j the $A_{2^j}s$ represents approximation of $s(n)$ with a resolution of one sample for every 2^j samples of the original signal. Mallat showed a recursive algorithm for decomposition and reconstruction of approximated signal. He showed that using a suitable low-pass filter h, and a high-pass filter g, the approximate signal can be further presented based on approximated and detailed signals in higher or lower resolutions

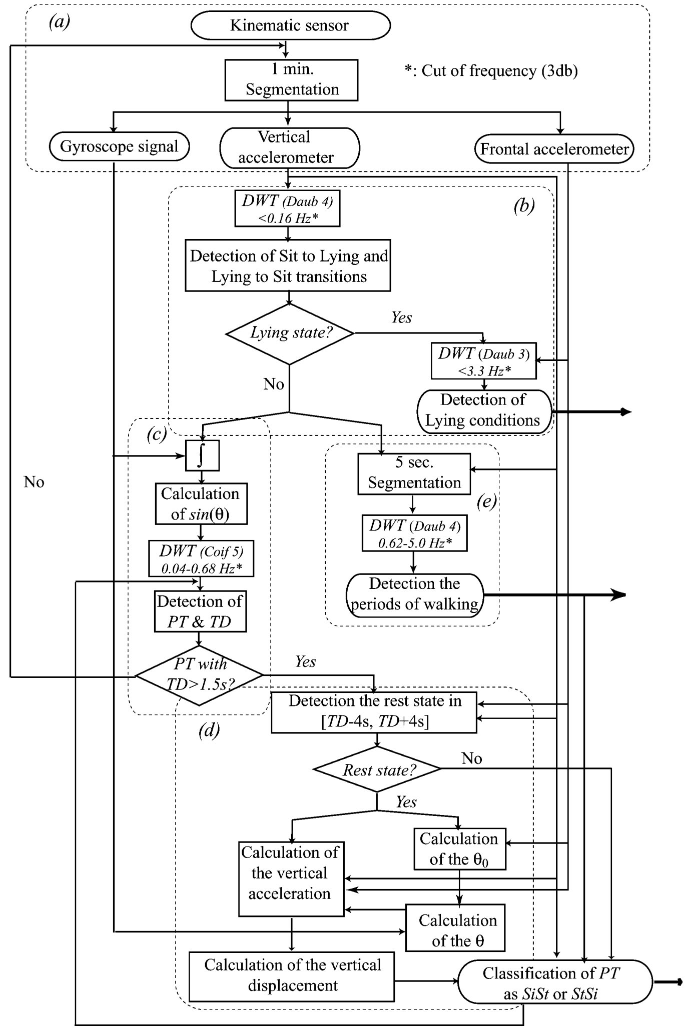

Fig. 2. Algorithm flow chart. (a) Kinematic sensor signal was divided to 1-min segment. (b) Lying state was detected using the vertical accelerometer signal (see the text). Different positions of lying were detected using frontal accelerometer signal. (c) SiSt and StSi were detected in absence of lying state. The gyroscope signal was integrated and drift and other movement artifact were canceled by DWT. PT and its duration (*TD*) were estimated from the pattern of $\sin(\theta)$. (d) Using the frontal accelerometer signal, initial trunk tilt (θ_0) as well as the rest state in interval of $[TD - 4\text{ s}, TD + 4\text{ s}]$, were detected. Trunk tilt angle (θ) during PT was calculated, using the gyroscope signal. Vertical displacement was calculated from θ and trunk accelerometer signals as described in the text. (e) Periods of walking were detected, using the vertical acceleration. Considering the periods of walking and vertical displacement; PT lasting more than 1.5 s was classified as SiSt or StSi. In the absence of any rest period, the vertical acceleration pattern was used instead of vertical displacement to classify PT as described in the text.

(i.e., scales) [27], [32]. The coefficients of the h and the g filters are associated with the shape of wavelet used for the analysis. Furthermore, the signal can be reconstructed from the approximate and the detail signals. In this study, we used the same method. However, in order to have the same number of samples as $s(n)$, $A_{2^j}s$ was reconstructed (i.e., $RA_{2^j}s$) by setting the detail signals (from scale j until scale 1) to zero

$$RA_{2^j}s = A_{2^0}s \Big|_{D_{2^l}|_{l=1,\ldots,j}=0}\,. \tag{1}$$

In this way, only the desired frequency band (in scale j) of the original signal is reconstructed and the other frequency components are rejected. This method was applied to enhance patterns

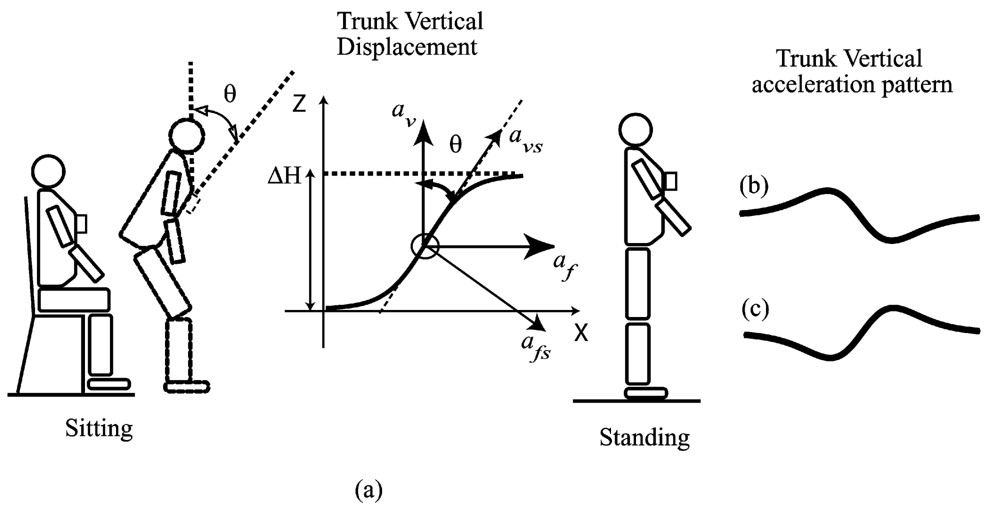

Fig. 3. (a) Trunk vertical displacement during SiSt transition. Vertical acceleration (a_v) can be calculated using the vertical and frontal accelerometers signals. (b) Second derivative of trunk vertical displacement during SiSt transition. (c) Second derivative of trunk vertical displacement during StSi transition.

belonging to PTs, lying down and walking. Different scales of decomposition and reconstruction were considered depending on the nature of physical activity. In Sections II-C–II-F, the features of DWT used for each activity are presented. The wavelet toolbox of MATLAB 6 (The Math Works, Inc., Natick, MA) was used to calculate the different wavelet transformations used in this study.

C. Lying Detection

Distinguishing the lying posture from sitting and standing was performed by considering the orientation of the accelerometer with respect to the direction of gravitational acceleration [13], [19]. In the lying, the vertical accelerometer measures almost zero g, while in sitting and standing the value is approximately $1g$. A flowchart of our algorithm is summarized in Fig. 2(b). Vertical acceleration (a_{vs}) was segmented every 1 min and additional peaks having different frequency components than lying transition (e.g., walking) were canceled using the DWT. The approximated wavelet signal, $\mathrm{DWT}(a_{vs})$, in scales seven ($RA_{2^7}a_{vs}$) was considered. A Daubechies mother wavelet with order four was applied (*db4*) [33]. The corresponding h and g filters are finite impulse response (FIR) filters with lengths of seven. The frequency band corresponds to less than 0.16 Hz. After reconstruction, the transitions between sitting-to-lying versus lying-to-sitting were detected using a defined threshold. Each transition was confirmed if, during 1 s before and after transition, the mean value of a_{vs} was greater, respectively, less than a fixed threshold (i.e., $> 0.6g$, respectively, $< 0.4g$).

Body posture on the back (supine), sides, and ventral were detected using the frontal trunk acceleration (a_{fs}). For this purpose, DWT was applied on a_{fs}. Daubechies mother wavelet in scale three and order three (*db3*) was chosen ($RA_{2^3}a_{fs}$) [33]. The corresponding h and g filters are FIR filters with lengths of five and the chosen frequency band is lower than 3.3 Hz. After DWT, the magnitude of a_{fs} during the lying state was analyzed to find periods corresponding to back ($a_{fs} \cong 1g$), ventral ($a_{fs} \cong -1g$), or side positions ($a_{fs} \cong 0g$). If the number of successive samples close to each threshold showed a time duration greater than 10 s, then these samples were chosen as sides (right or left), ventral, or back position, respectively.

D. Sitting and Standing Detection

Sitting occurs at the end of an StSi transition, while standing occurs at the end of an SiSt transition. As a result, the identification of these two transitions is sufficient to recognize sitting and standing postures. These PTs were detected based on the change of trunk tilt in the sagittal plane (θ) which was computed from the integral of the gyroscope signal (g_s) [24].

As shown in Fig. 2(c), to detect the PT, the gyroscope signal (g_s), was first segmented into 1-min intervals. Then, g_s was integrated and $\sin(\theta)$ was calculated. In order to cancel the drift and to eliminate noise from other sources such as movement artifact noise, the DWT with decomposition into nine scales by "Coiflet order five (*Coif5*)" mother wavelet was used [33]. The corresponding h and g filters were *FIR* filters with length of 30. For each PT, the wavelet approximation corresponding to ($RA_{2^5}\sin(\theta) - RA_{2^9}\sin(\theta)$) was chosen. The scales of five and nine provide the best approximation of StSi and SiSt transitions [23], [24]. The frequency band corresponding to these scales is 0.04–0.68 Hz. The minimum peak of $\sin(\theta)$ was considered as the time of PT, which its duration (*TD*) was determined from $\sin(\theta)$ as described in our previous publications [23], [24]. Considering the frequency band of 0.04–0.68 Hz, selected PTs lasting more than 1.5 s ($TD > 1.5$ s) were chosen as "candidate" for true PT.

Fig. 3 illustrates the nature of the vertical displacement during SiSt and StSi transitions, as well as the accelerations pattern corresponding to the second derivative of the vertical displacement. As shown, a SiSt transition generates an initial acceleration peak (positive) followed by a deceleration peak (negative) while the reverse occurs during a StSi transition. Thus, the comparison of the peak values of vertical acceleration (a_{vs}), occurring during transition allowed identifying SiSt and StSi events. In this study, vertical accelerometer, approximated between scales five and six ($RA_{2^5}a_{vs} - RA_{2^6}a_{vs}$) with frequency band: 0.34–0.68 Hz, was used for SiSt or StSi classification. These frequency bands were compared to the information provided by the Vicon reference system in order to confirm the choice of this frequency band.

The critical issue in using the above method to discriminate between SiSt and StSi transitions is the choice of an appropriate threshold to select the correct peaks in vertical acceleration. Additional peaks, unrelated to PTs, could be present in the acceleration signal, even though DWT decreases substantially these artifacts. A more powerful method to discriminate between SiSt and StSi transitions consists of estimating the vertical displacement during the interval of PT ($[P_1, P_2]$). Vertical displacement ΔH during a time period $[t_1, t_2]$ can be calculated from the vertical velocity (V_v)

$$\Delta H = \int_{t_1}^{t_2} V_v dt. \tag{2}$$

V_v can be obtained from vertical acceleration relative to the room reference a_v according to (3)

$$V_v = \int_{t_1}^{t_2} a_v dt + V_0. \tag{3}$$

V_0 is the initial value of the vertical velocity at time t_1. As shown in Fig. 3(a), vertical acceleration (a_v) can be calculated from vertical and frontal accelerations (relative to the subject)

$$a_v = a_{vs} \cos\theta - a_{fs} \sin\theta + g. \tag{4}$$

Where a_{vs} and a_{fs} correspond to the signals measured, respectively, by the vertical and frontal accelerometers.

The trunk tilt angle θ is the only unknown value in the (4), which can be calculated from the following equation:

$$\theta = \int_{t_1}^{t_2} g_s dt + \theta_0 \tag{5}$$

where θ_0 stands for the initial value of trunk tilt at time t_1. θ_0 was estimated by searching the nearest "1-s period" of "a_{fs}," where its variance was around zero. In general, it was assumed that this period corresponded to a rest state. During rest, both frontal and vertical accelerations are close to zero. According to this hypothesis, the initial value of θ_0 can be calculated from the following equations at each 1-s rest period ($T = 1$, $a_f \approx 0$ and $a_v \approx 0$):

$$a_{fs} = a_f \cos\theta - a_v \sin\theta + g \sin\theta \tag{6}$$

$$\theta_0 = \arcsin\left(\frac{1}{T.s_f} \sum_{n=1}^{T.s_f} \frac{a_{fs}(n)}{g}\right) \tag{7}$$

where s_f is the sampling frequency. V_0 in the (3) was supposed to be null, since during rest, vertical velocity is close to zero.

The interval $[t_1, t_2]$ was found from the rest period detected in $[TD{-}4\text{ s}, TD{+}4\text{ s}]$. If the rest period preceded the PT, t_1 and t_2 were chosen as the end of rest and transition periods, respectively. For a rest period after PT, t_2 was chosen as the beginning of the rest period and t_1 as the beginning of the PT, respectively. Fig. 2(d) shows the summary of the algorithm mentioned above for estimation of the vertical displacement during the PT.

In practice, the most important limitation of the above method is the integration drift in (2), (3) and (5) due to dc component present in the acceleration (a_{vs}). To reduce this drift, the interval for integration must be as small as possible. So, the rest period was searched in the interval $[TD - 4\text{ s}, TD + 4\text{ s}]$ and the dc component removed before integration. In the absence of any rest period during $[TD - 4\text{ s}, TD + 4\text{ s}]$, the previous method based on vertical acceleration pattern was used. In the case of several peaks, it was assumed that the nearest maximum and minimum peaks to t_{PT} belonged to PT.

E. Walking Detection

Walking state was identified by analyzing a_{vs} every 5 s [Fig. 2(e)]. Wavelet decomposition was also used to enhance the walking pattern and to reduce noise and drift arising from other activities such as PTs and turning. The approximated wavelet signal, $\mathrm{DWT}(a_{vs})$, between scales two and five ($RA_{2^2}a_{vs} - RA_{2^5}a_{vs}$) was considered. A Daubechies mother wavelet with order four (*db4*) was applied [33]. The corresponding h and g filters were FIR filters with the length of seven. The frequency band corresponds to 0.62–5.00 Hz. To identify the walking signature, negative peaks in $\mathrm{DWT}(a_{vs})$ beyond a fixed threshold were detected. Successive peaks with intervals of 0.25–2.25 s were chosen as possible walking steps. A walking period was defined as an interval with at least three successive steps.

F. Physical Activity Classification

Using the above algorithms, physical activity can be categorized as lying, sitting, standing, and walking (Fig. 2). In order to improve this classification the following rules were added.

- If two contradictory states were detected (e.g., lying with walking or sitting with walking), preference was given first to lying then to walking and finally to StSi or SiSt transitions. This decision was based on the rationale that error was more improbable to occur in lying position.
- Two successive SiSt, respectively StSi, transitions were not considered possible. These transitions were modified according to the previous and/or subsequent activities (e.g., new PT or walking state).
- Leaning backward during a standing state was considered unlikely for the elderly subjects. The trunk angle θ was estimated using (5) at the beginning of the measurement while each subject was asked to remain in quiet standing during 5 s. Leaning backward was defined when θ varied more than 15° from the angle in quiet standing.
- Quiet standing periods longer than 200 s were interpreted as sitting if the variance of a_{vs} (during each 1-s interval) was inferior to a defined threshold (i.e., $0.0007g^2$). This decision was based on the rationale that it is improbable that an elderly person would stay standing for such a long period ($>$ 3 min) without any movement.

In order to estimate the performance of the system's classification, sensitivity (defined as the ability of the system to

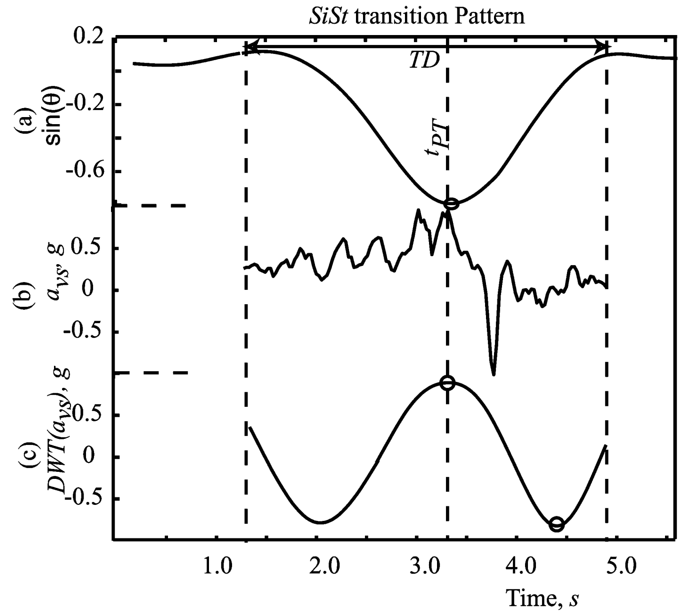

Fig. 4. (a) $\sin(\theta)$ estimated by gyroscope after applying DWT for SiSt transition, (b) Original vertical accelerations (a_{vs}) during SiSt transition, (c) "a_{vs}" after applying DWT. Applying DWT on a_{vs} allows a better detection of the type of transition. "o" shows the peaks selected by the algorithm (nearest maximum and minimum peaks to the $t_{\rm PT}$).

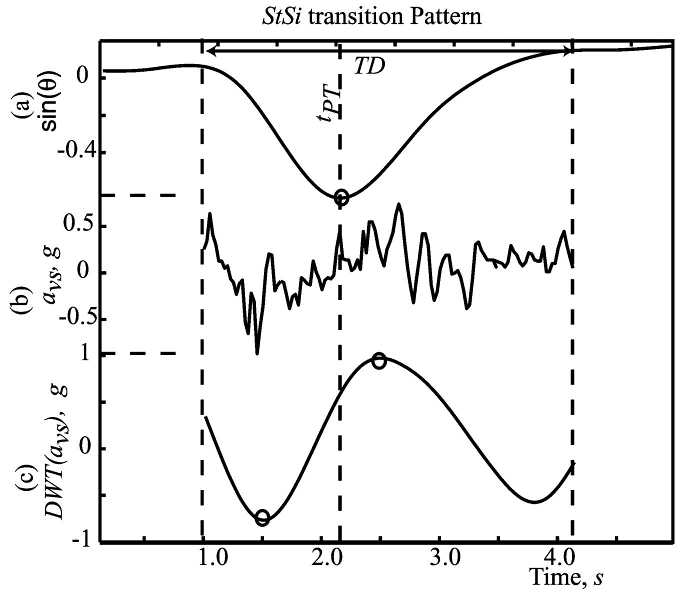

Fig. 5. (a) $\sin(\theta)$ estimated by gyroscope after applying DWT for StSi transition, (b) Original vertical accelerations (a_{vs}) during StSi transition, (c) "a_{vs}" after applying DWT. Applying DWT on "a_{vs}" allows a better detection of the type of transition. "o" shows the peaks selected by the algorithm (nearest maximum and minimum peaks to the t_{rmPT}).

correctly identify the true PTs) and specificity (defined as the ability of the system not to generate false detection) were estimated. Sensitivity and specificity are calculated as follow:

Sensitivity is the "true positives" divided by ("true positives" + "false negatives") multiplied by 100.

Specificity is the "true negatives" divided by ("true negatives" + "false positives") multiplied by 100.

For example, in case of SiSt, the above parameters are defined as follows.

- True positives equal the number of true SiSt detection by the system.
- False negatives equal the number of undetected and misclassified SiSt.
- True negatives equal the number of other type PTs (in this example = StSi) detected by the system, which are not true SiSt.
- False positives equal the number of false detection as SiSt.

Errors have been reported in forms of percentage of range (PRE) and symmetric mean average percentage error (SMAPE).

$$\text{PRE} = \frac{|\text{measured value} - \text{actual value}|}{\text{monitoring duration}} \times 100 \quad (8)$$

$$\text{SMAPE} = \frac{|\text{measured value} - \text{actual value}|}{\frac{(\text{measured value}+\text{actual value})}{2}} \times 100. \quad (9)$$

III. Results

A. First Study

Figs. 4 and 5 show the efficiency of the DWT for SiSt and StSi detection, respectively. As illustrated, for both type of transition the chosen peaks (i.e., nearest maximum and minimum peaks to the local minimum point of $\sin(\theta)$) in DWT(a_{vs}) closely corresponded to our model (see Fig. 3). An initial positive peak was followed by a negative peak during SiSt transition [Fig. 4(c)], while the reverse occurred during StSi transition [Fig. 5(c)].

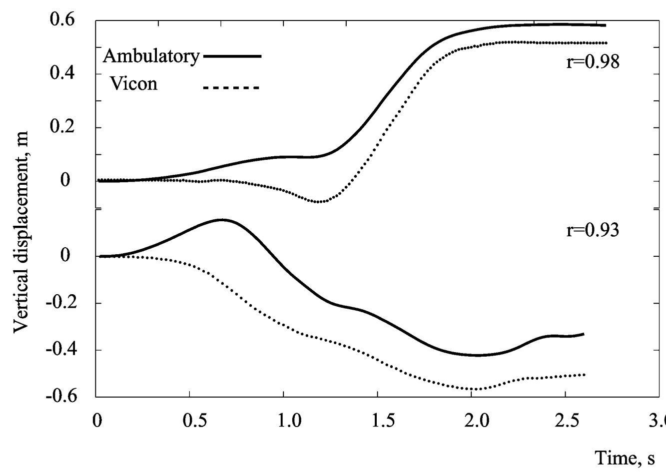

Fig. 6. Comparison between the patterns of vertical displacement of trunk during PT estimated by the ambulatory (solid line) and the Vicon system (dotted line). (a) Typical pattern of SiSt. (b) Typical pattern of StSi. The estimated patterns of vertical displacement of the trunk are high correlated with the actual patterns measured by the Vicon reference system.

Fig. 6 compares the estimation of trunk vertical displacement obtained from the ambulatory and the Vicon reference system for typical SiSt and StSi transitions. Although both measures were highly correlated ($r > 0.93$), vertical displacement estimated by the ambulatory system is slightly shifted compared to the Vicon reference system. However, this shift does not preclude a correct classification of PTs as SiSt or StSi. When considering all 349 PTs performed by the study subjects, overall sensitivity was 99%. Sensitivity and specificity were 93% and

TABLE II
OVERALL SENSITIVITY AND SPECIFICITY OF TRANSITION DETECTION FOR THE 11 ELDERLY (FIRST STUDY)

# Test	Total PT*	Sensitivity, %					Specificity, %	
		PT	SiSt**	StSi	Lying	Walking	SiSt	StSi
1	40	100	100	100	100	95±4	100	100
2	66	98±5	100	97±10	-	97±3	95±12	100±0
3	58	100	97±10	63±29	-	-	63±29	97±10
4	58	100	88±25	75±29	-	-	75±29	88±25
5	64	96±9	89±18	86±19	-	-	86±19	94±13
6	57	100	85±19	72±24	-	-	72±24	85±19
Mean	**57±9**	**99±2**	**93±7**	**82±15**	**100**	**96±1**	**82±15**	**94±6**

* PT: Postural transition.
** SiSt: sit-to-stand transition.
† StSi: stand-to-sit transition.

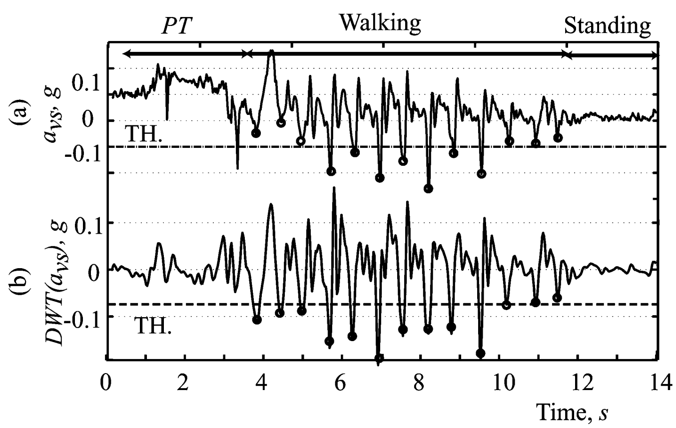

Fig. 7. (a) Raw signal of vertical acceleration during walking (dc of signal has been removed). (b) The same signal after DWT. "o" shows peaks corresponding to the actual walking steps.

82% for SiSt transition, and 82% and 94% for StSi transition, respectively (Table II). When considering data from the first and second tasks, these figures (i.e., sensitivity and specificity) were even increased to 100% and 94% for SiSt transitions, and 97% (for both sensitivity and specificity) for StSi transitions.

The effectiveness of DWT for walking sequence enhancement is shown in Fig. 7, where all peaks belonging to walking steps detected by the reference system (Vicon) are marked. It can be seen that the drift in a_{vs} signal is reduced in $\mathrm{DWT}(a_{vs})$, while the actual walking peaks are enhanced. These advantages of the DWT also make unnecessary to calibrate the system (i.e., chosen a threshold) for each subject. The sensitivity and specificity for walking period detection were more than 95% (Table II).

B. Second Study

Fig. 8 shows a typical pattern of trunk acceleration for different positions when lying. Subjects were asked to change their position by turning in bed. The efficacy of DWT in suppressing noisy peaks from the original signal [Fig. 8(a)] is shown in Fig. 8(b) and (d). In the analysis of 144 PTs to back, right and left sides, there was no detection error (sensitivity and specificity of 100%). Results were similar for 30 transfers in or out of bed. Together with the findings of the first study (test 1) where no detection errors occurred in the analysis of 32 transfers in or out of bed (Table II), these results confirm an especially high accuracy of the ambulatory system for this purpose.

C. Third Study

Fig. 9 shows a typical classification of physical activity obtained during 1 h of recording in an elderly person. This figure further compares, the distribution of the different activities (sitting, standing, lying and walking) performed over 1 h according to the ambulatory system [Fig. 9(a) and (b)] and to the observer [Fig. 9(c)]. Close agreement was found between activity identified by the ambulatory system and the actual activity reported by the observer.

Relatively high accuracy was obtained for the classification of usual physical activities in comparison with visual observation. Sensitivities and specificities were, respectively, 90.2% and 93.4% in sitting, 92.2% and 92.1% in standing and walking, and, finally, 98.4% and 99.7% in lying (Table III). Table IV shows the relative duration of specific activity (in percentages) for nine elderly subjects monitored during 45 or 60 min as obtained by the ambulatory system, and compares this duration to those obtained by an observer. Overall PRE was 3.9% for "standing + walking," 4.1% for sitting, and 0.3% for lying detection. Overall *SMAPE* was 12% for "standing + walking," 8.2% for sitting, and 1.3% for lying detection.

IV. DISCUSSION AND CONCLUSION

Our results demonstrate that a new system, based on only one kinematic sensor attached to the chest, performs very well in monitoring activities in elderly subjects. This system was able to identify accurately activities ranging from PTs (SiSt and StSi), to turning on the bed, transferring in or out of bed, walking, or remaining still. In all these tasks, this ambulatory system was highly correlated with the reference systems that were used. Finally, when used for prolonged recording, the system proved also reliable and valid in monitoring daily life activities. The sensor's low power consumption (4.6 mA), battery's lifetime (900 mAhr) and the memory card (up to 8 Mb) permit monitoring for up to 12 h. If necessary, the datalogger can be recharged quickly and memory card replaced for a new recording. An example of 12-h continuous monitoring of daily physical activity is shown in Fig. 10, where a diary report performed by the nurse is also provided.

Although several systems have been proposed in the past to monitor physical activities, this system appears especially promising in several regards. First, its performance compares favorably with previously proposed systems [19], [17], [21], [34]. For example, Aminian *et al.* showed an overall misclassification of 10.7% using two kinematic sensors (attached to the chest and thigh) [19]. Busser *et al.* used a similar configuration and found an overall validity ranging between 76% and 92% [34]. More recently, Morlock *et al.* used an ambulatory system based on three sites of sensor (an electro-goniometer attached on the knee and two inclinometers attached to the thigh and shank) [35]. Although their system had a good accuracy in classifying sitting and standing postures (overall error less than

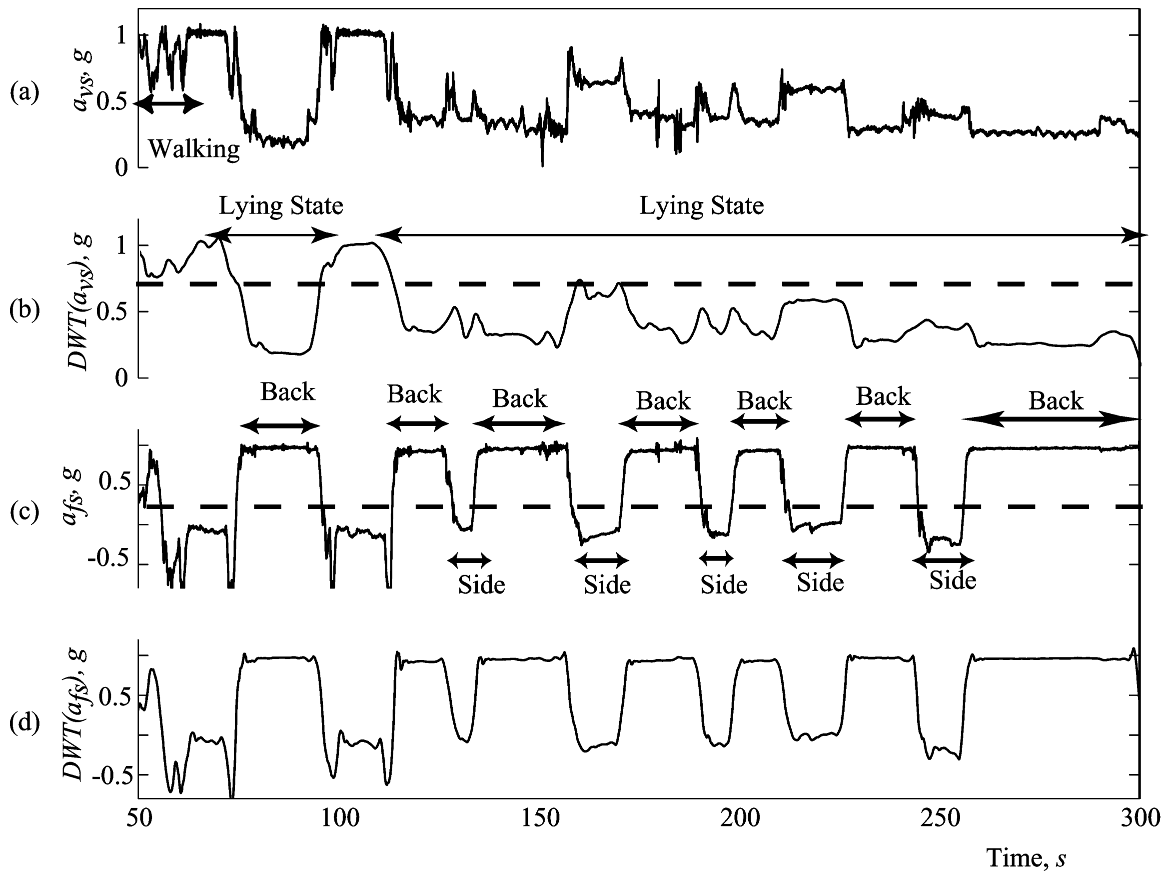

Fig. 8. Typical acceleration pattern obtained from an elderly person asked to change her position when lying. Based on two accelerometers in vertical and frontal directions and using wavelet transform, the transition from sit to lying and different positions on the bed (lying on back or sides) are detected. (a) Signal of the vertical accelerometer (a_{vs}). (b) Wavelet transform of the vertical accelerometer signal. (c) Signal of the frontal accelerometer (a_{fs}). (d) Wavelet transform of the frontal accelerometer. (b) and (d) Show how the wavelet transform is able to cancel the artifact peaks from the vertical and frontal accelerometer signals arisen from walking or other movements.

3%), lying posture detection was poor (overall error of 19%). Moreover, the use of three sites of attachment makes prolonged monitoring more cumbersome and likely introduces biases in observation.

Second, this system is based on several innovative features of kinematic signal (or biomechanics) analysis. This study confirms the efficacy of using wavelet-based techniques for the analysis of kinematic signal reported by other investigators [28], [29], [36]. Our results show that DWT is a powerful technique to detect PT, as well as walking period even in subjects using walking aids such as a cane or walker. DWT also facilitate the identification of frontal and vertical acceleration components during PT in the range of [0.04 Hz -0.68 Hz] and [0.35 Hz -0.68 Hz], respectively, implying a duration of PT greater than 1.5 s. According to this observation, only the transitions lasting more than 1.5 s were considered as true transition, allowing canceling noise from other movements such as leaning forward. Although these frequency bands were obtained from elderly persons, a similar rule could be derived from observation of younger population. Similarly, for lying transition detections (i.e., transfer or rolling out of bed and turning the body position during lying) DWT use helps to reduce noisy peaks caused by the moments when the subject attempts to change position or is rolling out of bed (Fig. 8). DWT is particularly appropriate when studying elderly persons with mobility impairment and difficulties in changing their position in bed because noisy peaks that could cause faulty detections in lying transitions are suppressed. Using different DWT packages for PT detection (*coif5* with 30 coefficients), walking detection (*db4* with seven coefficients), and lying transfer or rolling from the bed (db4 with seven coefficients), lying position such as lying on back or sides (*db3* with five coefficients), makes it possible to select the minimum filter coefficients needed to extract the effective information.

From a methodological standpoint, our results also demonstrate that the new method of SiSt and StSi detection, based on estimation of vertical displacement (see Section II-D) rather than vertical acceleration pattern only [37], results in improved accuracy. This is particularly striking in SiSt and StSi transitions, where overall sensitivity and specificity were 93% and 82% compared with 63% and 84% in the previous method. However, even in our analysis, reliance only on the pattern of vertical acceleration was still necessary in some circumstances. In fact, one limitation of this new method is that its accuracy depends on the existence of a resting period to estimate the initial values. Although only 4 s of monitoring are necessary before or after a transition to calculate the variance of frontal acceleration to find the resting period value, these seconds could be lacking when the subjects walks immediately after or before a PT. In addition, very fast or very slow PTs are not well handled by this new method because of the limited number of samples or simi-

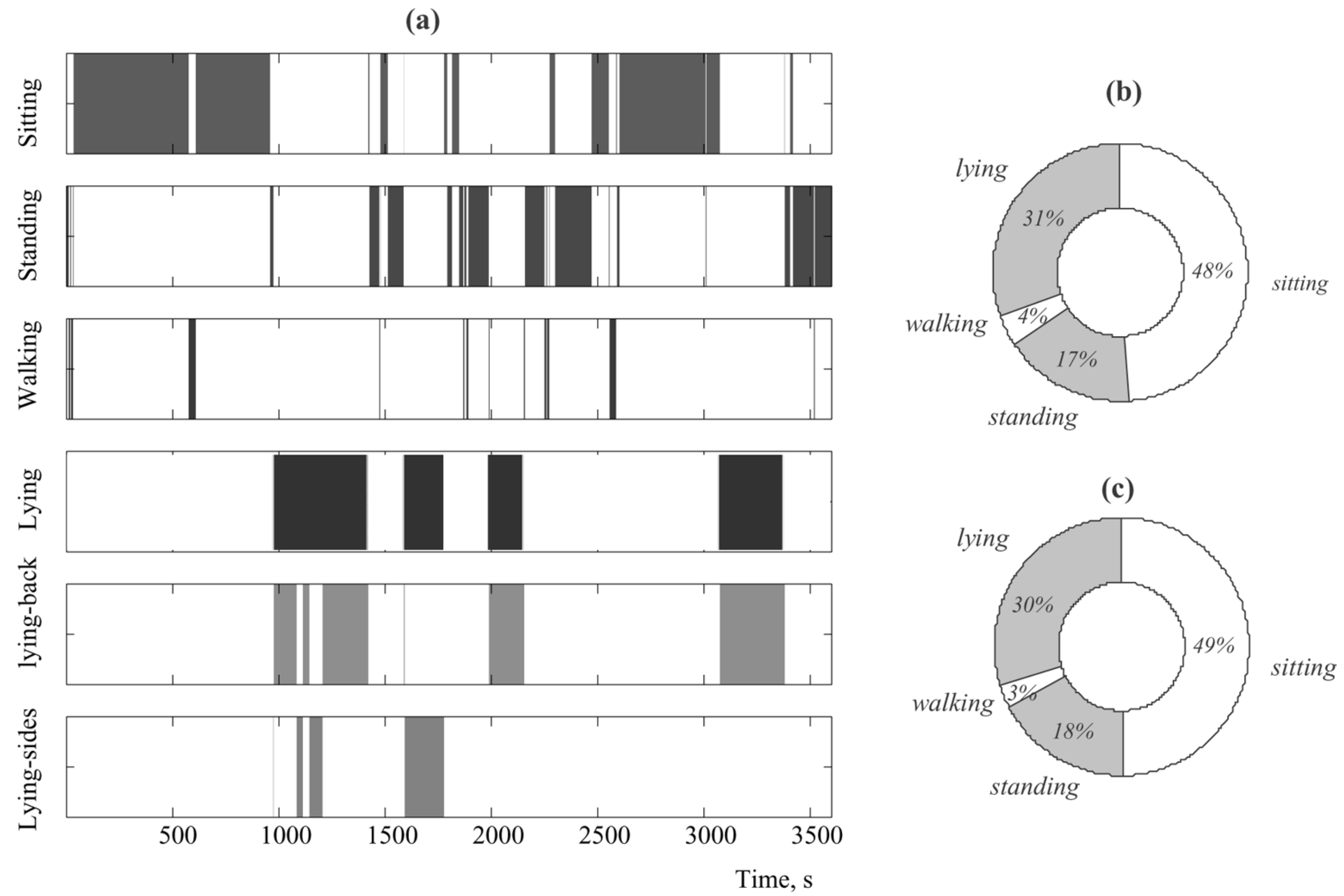

Fig. 9. Typical classification of a subject's physical activity during a 1-h recording. (a) Activities classified by the ambulatory system, and (b) their relative distribution. (c) Same activities obtained from an observer. The classification by the ambulatory system is in close agreement with the observation.

TABLE III
OVERALL SENSITIVITIES AND SPECIFICITIES OF THE USUAL PHYSICAL ACTIVITIES FOR THE NINE ELDERLY SUBJECTS (THIRD STUDY)

# Subject		1	2	3	4	5	6	7	8	9	*Mean SD**
Duration of monitoring **(minutes)**		*60*	*60*	*60*	*60*	*60*	*45*	*45*	*45*	*45*	
Sensitivity (%)	*Sitting*	100	79	96	92	76	100	79	100	90	**90.2±9.9**
	Standing+walking	95	97	94	82	100	94	98	85	85	**92.2±6.5**
	Lying	100	100	-†	-†	100	99	94	100	96	**98.4±2.4**
Specificity (%)	*Sitting*	93	99	94	82	100	98	98	92	85	**93.4±6.3**
	Standing+walking	94	87	96	92	79	100	81	100	100	**92.1±8.1**
	Lying	100	99	100	100	100	100	100	98	100	**99.7±0.7**

*: Standard deviation
†: No lying state was observed.

TABLE IV
RELATIVE DURATION OF EACH ACTIVITY (RELATED TO THE TOTAL TIME OF OBSERVATION) FOR 9 ELDERLY SUBJECTS (THIRD STUDY), MONITORED DURING 45 OR 60 MIN. PRE AND SMAPE HAVE BEEN REPORTED FOR EACH SUBJECT. ALL VALUES ARE IN %

Subject		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Average Error**
Duration of monitoring (minutes)		60	60	60	60	60	45	45	45	45	
Walking + standing (%)	Actual	39.9	20.3	37.0	17.8	25.6	26.1	39.4	36.9	46.2	
	Measured	46.4	20.4	38.8	23.0	35.1	25.9	37.2	30.7	49.5	
	*PRE**	*6.5*	*0.1*	*1.8*	*5.2*	*9.5*	*0.2*	*2.2*	*6.2*	*3.3*	**3.9±3.2**
	*SMAPE***	*15.1*	*0.5*	*4.7*	*25.5*	*31.3*	*0.8*	*5.7*	*18.3*	*6.9*	**12.0±11.7**
Sitting (%)	Actual	50.7	49.7	62.9	82.1	68.4	48.3	55.4	27.4	45.6	
	Measured	44.1	49.0	61.1	77.0	58.7	49.4	57.8	33.6	42.5	
	*PRE**	*6.6*	*0.7*	*1.8*	*5.1*	*9.7*	*1.1*	*2.4*	*6.2*	*3.1*	**4.1±3.0**
	*SMAPE***	*13.9*	*1.4*	*2.9*	*6.4*	*15.3*	*2.3*	*4.2*	*20.3*	*7.0*	**8.2±6.7**
Lying (%)	Actual	9.4	30.0	0.0	0.0	6.1	25.7	5.2	36.0	8.2	
	Measured	9.4	30.6	0.0	0.0	6.1	24.7	5.0	35.7	8.1	
	*PRE**	*0.0*	*0.6*	*0.0*	*0.0*	*0.0*	*1.0*	*0.2*	*0.3*	*0.1*	**0.3±0.3**
	*SMAPE***	*0.0*	*2.0*	*0.0*	*0.0*	*0.0*	*4.0*	*3.9*	*0.8*	*1.2*	**1.3±1.6**

* Percentage of range error.
** The symmetric mean average percentage error

larity of signal with drift and dc components. In these situations, vertical acceleration pattern were used.

The improved accuracy of the system is also related to the application of explicit decision rules to classify contradictory states in preferential order (lying down, walking, and, finally, transitions) based on the assumptions described in Section II-F. This is particularly true for lying posture for which sensitivity reached 100% with only a small error (1%) during long-term monitoring. Sensitivity and specificity for sitting and standing classification were lower, especially for the tests three and four of the first study that did not include walking and lying periods. This is essentially due to the correction made in physical activity classification based on walking and lying state detection (see Section II-F). Moreover, for some subjects, rising from the armchair (test 3) or making PT without using armrest (test 4), were difficult. Consequently, for these tests, more jerky movements and artifacts were superimposed on the measured signals.

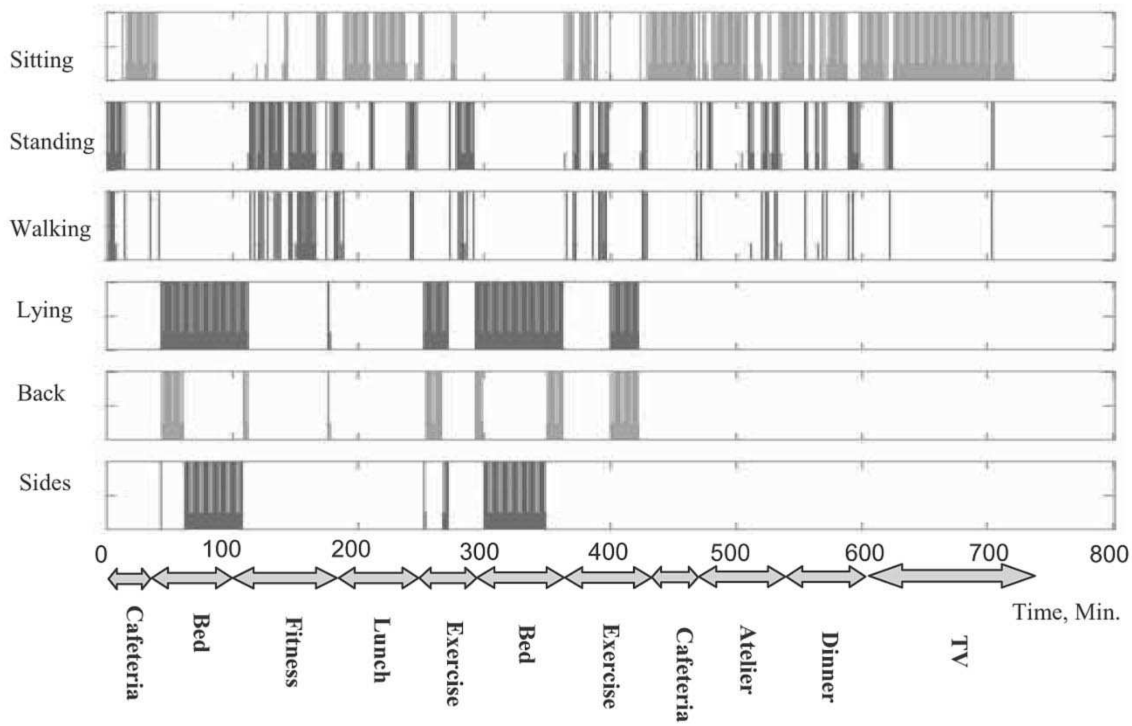

Fig. 10. Duration of each activity extracted from the diary recorded by an observer in comparison with the ambulatory system. A close agreement is found between the two results.

These situations were the major sources of lower sensitivity and higher error for some subjects in the third study (Tables III and IV). Since the observer could over-or under-estimate the actual walking state, defined as three successive steps, the sensitivity, specificity, and errors corresponding to standing and walking ("standing + walking") in Tables III and IV were reported altogether. It is clear that when the number of distinct walking periods increases, this over-or under-estimation will increase too. For example, in Fig. 9 the duration of walking is only 3% of the total observation duration. Therefore, even a 1% error seems high in this configuration. However, this error is in the accuracy range of observation.

Third, another unique feature of this system is its potential for real-time processing of information. Because vertical and forward acceleration are analyzed during PTs only (and not through the entire signal), this method drastically simplifies the amount of calculation required. The real-time processing would be useful in several applications such as an alarm system detecting attempts of confused elderly patients to get out of bed or to rise from a chair [38] or the monitoring of mobility in bed for patients at increased risk for pressure sores. It could also be applied in the rehabilitation setting, where the patterns of PT could be analyzed and trained with more accuracy [39]–[41].

Finally, this new system expands our capabilities of activity monitoring. Prolonging calculation of the variance of the accelerometers signals every 1 s provides additional information about the activities' intensities. Fig. 11 shows typical frontal and vertical accelerations obtained during a 50-s recording of different activities such as sitting, walking, and standing. In order to identify rest and low- and high-activity periods, frontal accelerations were divided into 1-s intervals. Based on the variance of the signal, rest can be easily discriminated from activity. The comparison of the amplitude of frontal variance [Fig. 11(c)] with a fixed threshold makes it possible to classify activities according to their intensity. This possibility opens to numerous potential applications such as estimating the intensity of an activity (e.g., rising from a chair) or estimating energy expenditure.

This new monitoring device interferes minimally with the usual activity of the subjects because it is light weight and portable. The cable between sensor and datalogger is short and does not hinder the subject's motion. Monitoring the subject in their usual environment with minimal interference is, therefore, possible, in contrast with other systems that require laboratory settings. Integrating the sensor and recorder is suggested for wireless and telemetry applications. To minimize the interference and maintain optimal performance of the system, the site of attachment of the kinematic sensor is an important issue [42]. The kinematic and gravitational components of accelerometer output depend on the sensor location. Because of the use of the gyroscope technology, the PT detection is not influenced by the gravitational component (for other advantages to use gyroscopes for detection of the PT see our previous work [24]), but the detection of walking period and discrimination between SiSt and StSi could be influenced by this component. Attaching the kinematic sensor to the chest (Fig. 1) not only minimize discomfort and avoid interference with usual activities, but provides the opportunity to further integrate other physiological measurement such as heart and respiration rates. However, further research should address whether other sites might be more appropriate and evaluate the influence of different types of attachments on the performance of the system.

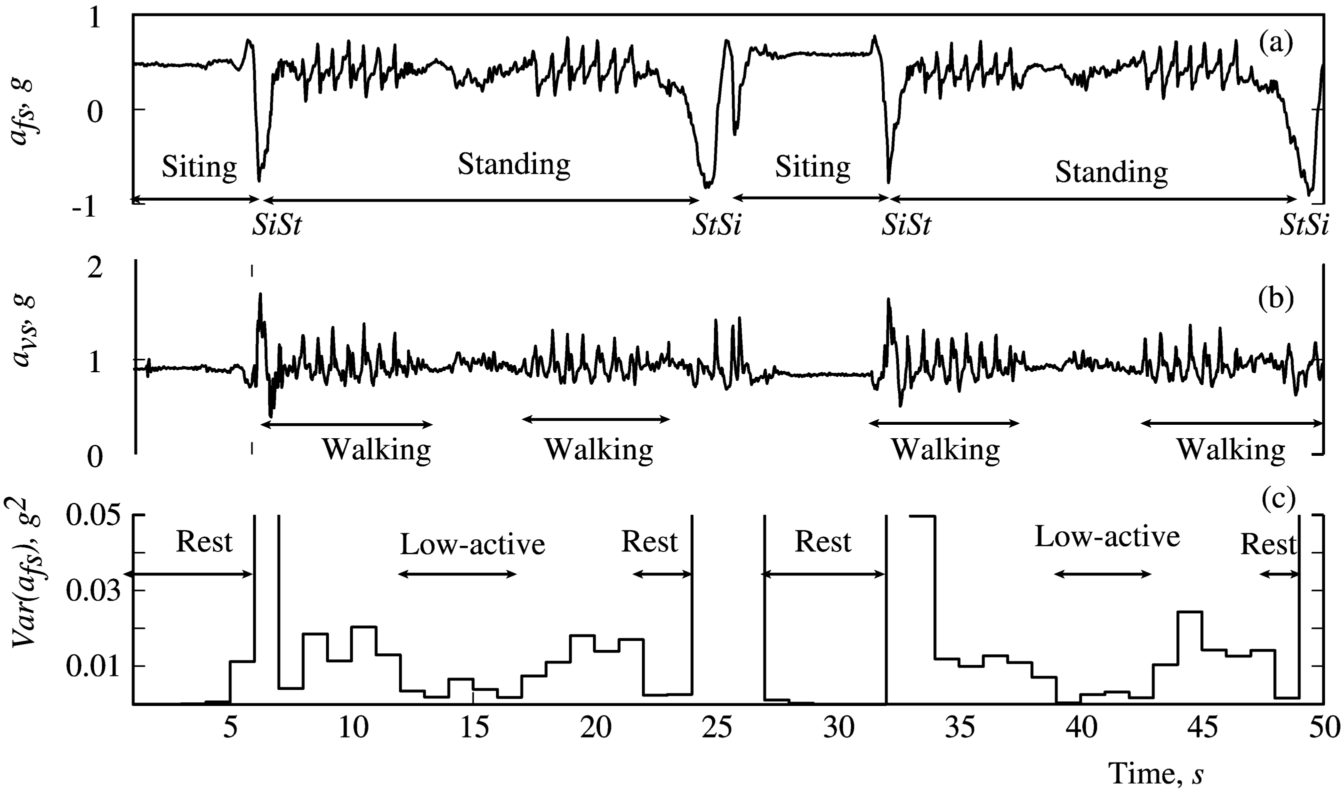

Fig. 11. (a) Frontal and (b) vertical accelerations (a_{fs} and a_{vs}) during different activities and rest state. (c) Variance of a_{fs} estimated during each second. By using a suitable threshold, rest and low- and high-activity periods can be discriminated from other activities.

There are several limitations of this study. First, we used a small number of subjects, and these results would need to be confirmed with larger population. Second, these subjects were volunteers and probably not representative of all elderly subjects. However, when we used subjects from various settings (community, hospitalized in rehabilitation) for the different studies, the performance of the system was not substantially altered. Finally, although the subjects were encouraged to move as usual for them, we cannot exclude that their activity was influenced by the fact they were participating in a study.

Despite these limitations, we believe this system has the potential for extended clinical as well as research applications. In particular, this system could contribute to better document subjects' mobility, an important component of their quality of life. The proposed methodology could also be useful in some telemedicine applications such as in-home health care for elderly persons or other persons with reduced mobility.

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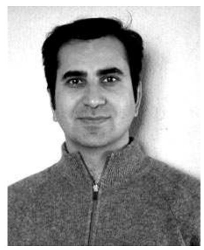

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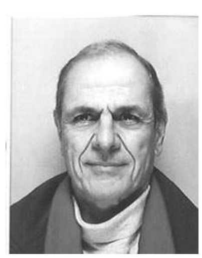

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