Posture and Movement Classification: The Comparison of Tri-Axial Accelerometer Numbers and Anatomical Placement

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Patient compliance is important when assessing movement, particularly in a free-living environment when patients are asked to don their own accelerometers. Reducing the number of accelerometers could increase patient compliance. The aims of this study were (1) to determine and compare the validity of different accelerometer combinations and placements for a previously developed posture and dynamic movement identification algorithm. Custom-built activity monitors, each containing one tri-axial accelerometer, were placed on the ankles, right thigh, and waist of 12 healthy adults. Subjects performed a protocol in the laboratory including static orientations of standing, sitting, and lying down, and dynamic movements of walking, jogging, transitions between postures, and fidgeting to simulate free-living activity. When only one accelerometer was used, the thigh was found to be the optimal placement to identify both movement and static postures, with a misclassification error of 10%, and demonstrated the greatest accuracy for walking/fidgeting and jogging classification with sensitivities and positive predictive value (PPVs) greater than 93%. When two accelerometers were used, the waist-thigh accelerometers identified movement and static postures with greater accuracy than the thigh-ankle accelerometers (with a misclassification error of 11% compared to 17%). However, the thigh-ankle accelerometers demonstrated the greatest accuracy for walking/ fidgeting and jogging classification with sensitivities and PPVs greater than 93%. Movement can be accurately classified in healthy adults using tri-axial accelerometers placed on one or two of the following sites: waist, thigh, or ankle. Posture and transitions require an accelerometer placed on the waist and an accelerometer placed on the thigh. [DOI: 10.1115/1.4026230]

Keywords: accelerometer, movement analysis, posture detection, monitor placement

1 Introduction

Developing tools to accurately assess posture and movement in a free-living environment is of great importance. However, many studies have reported patient compliance issues using activity monitors to assess physical activity in free-living environments [1–4]. One of the main issues which can affect patient compliance in assessments are requesting them to wear multiple sensors [5] which can be too cumbersome for long-term use [6]. Using numerous activity monitors per subject can provide information on the movement of a greater number of body segments. For more complex postural orientation and movement classifications, this can generate results of superior accuracy [2]. However, reducing the number of activity monitors would increase the user-friendliness of such assessments. This could increase participation willingness in activity assessments and reduce the possibility of user error [5] as instructions would be simpler.

In addition, patients may find some activity monitor placements to be uncomfortable which could further hinder patient compliance [5]. Optimal activity monitor placement and the number of activity monitors required depend greatly on the research question [7]. For whole body movement, locations on the waist, sternum and lower back have been shown to be optimal, whereas thigh and ankle locations have been used to measure leg movement [8]. For more complex movement classification systems, higher numbers of activity monitors (up to 36) have been used [9,10]. Many different studies have demonstrated postural orientation and movement identification using varying numbers of activity monitors (from 1 to 7) and different locations [6,11–24]. However, only a few studies have investigated how the robustness of any of these postural and movement identification algorithms would change with different activity monitor numbers and locations [5,25,26]. Studies using one activity monitor for posture and movement identification utilize simplified protocols and whether or not the algorithms would perform as accurately for protocols involving fidgeting of the feet while sitting or standing has not been tested. Recently, a posture and movement classification algorithm was developed by the authors, which is capable of accurately identifying standing, sitting, and lying postures as well as walking, jogging, and transitional movement using two tri-axial accelerometers (one on the waist and one on the thigh) [27]. The study included a range of gait velocities from 0.1 m/s to 4.8 m/s and fidgeting of the legs while sitting and standing. An accurate posture and movement classification algorithm using either one or two accelerometers in a number of different locations would allow for user preferences of wear location and accelerometer numbers to be taken into consideration while providing a safeguard against missing data such as from malfunctioning devices.

The aim of this study were to determine and compare the validity of different accelerometer (1) placements and (2) combinations

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Table 1 Mean signal magnitude area and corresponding walking/fidgeting and jogging thresholds for different monitor locations

Variables	Ankle monitor	Thigh monitor	Waste monitor
Mean SMA for 5 min protocol (g)	0.584	0.355	0.296
Walking/Fidgeting threshold (g)	0.246	0.175	0.135
Jogging threshold (g)	1.46	1.04	0.8

for a previously developed posture and dynamic movement identification algorithm [27]. Three static postures and four dynamic tasks were recorded. The validity of the posture and dynamic movement identification algorithm for different accelerometer locations and combinations was evaluated in a simulated free-living environment by comparison to video recordings.

2 Methods

2.1 Experimental Design. The data used in this study was collected in a previous study [27] and reanalyzed for this study. Accelerometer and video data were acquired from 12 (3 M, 9 F) healthy adults as they performed an approximately 5 min protocol of static postures and dynamic movements involving standing, sitting, lying, walking, stair climbing and jogging in the laboratory [27]. Additionally, subjects were asked to make small movements of their body to simulate changing body position or fidgeting during selected sitting and standing tasks [27]. All activities were performed at self-selected speeds. At the time of evaluation, the median (range) age and average (SD) body mass index (BMI) of the subjects were 31 (25–55) years, and $24.7 \pm 5.5\,\mathrm{kg\,m^{-2}}$, respectively. Exclusion criteria were a history of musculoskeletal deficits, neurological impairment or lower extremity surgery. The study protocol was approved by the Mayo Clinic Institutional Review Board and each subject provided written informed consent before participating.

2.2 Data Collection. Accelerometer data were captured from each subject using custom built activity monitors developed at the Mayo Clinic [27]. Each activity monitor incorporated a tri-axial MEMS accelerometer (analog, ± 16 g, Analog Devices), microcontroller (12 bit ADC, Texas Instruments), power source (Tadiran battery, semiconductor voltage regulator), and onboard data storage (NAND flash memory, 4 Gbit memory chip, Micron). Monitors weighed 22 gs with dimensions of $4.7\,\mathrm{cm} \times 2.8\,\mathrm{cm} \times 1.2\,\mathrm{cm}$. Prior to data collection, all four accelerometers were calibrated to record $+1$ g, 0 g and -1 g when placed in orthogonal orientations.

Subjects wore four activity monitors on the waist at the midpoint of the ASIS, on the lateral midpoint of the right thigh and bilateral ankles above the lateral malleoli. Activity monitors were secured with straps and were programmed to sample each axis at 100 Hz. Video data were simultaneously acquired using a hand-held camera which collected data at 60 Hz. Video data were synchronized to the accelerometer data by asking all subjects to perform three vertical jumps prior to and following the described protocol. The four accelerometers were also synchronized to each other based on the onset of jumping. The onset of jumping was set as time zero for both video and accelerometer data. The time point for the onset of jumping was selected visually by a rater from the video data and manually from the acceleration data based on the onset of change in vertical acceleration of all the monitors. Three accelerometer placements and one accelerometer combination were analyzed in this study: (1) single waist, (2) single thigh, (3) single ankle, and (4) thigh and ankle (right side only) accelerometers. These configurations were compared to the previously analyzed and validated waist and thigh accelerometer combination [27]. The combination of the waist and ankle monitors was not investigated in this study as it would not enable the separation of sitting and standing postures or the identification of sit to stand and stand to sit transitions. Therefore, this accelerometer combination would provide no additional information on postural and movement detection compared to using either the waist or ankle accelerometers alone apart from separating lying and sitting with legs straight, i.e., sitting up while in bed.

2.3 Signal Processing. All post processing and analysis of accelerometer data were performed offline using MATLAB (Version 7.11.0, Mathworks, Natick, MA, USA). The raw accelerometer data were calibrated and a median filter, with a window size of three, was applied to each of the orthogonal raw calibrated acceleration signals to remove any high-frequency noise spikes [15]. The resulting filtered signal was separated into its gravitational component by using a third-order zero phase lag elliptical low pass filter, with a cut-off frequency of 0.25 Hz, 0.01 dB passband ripple and -100 dB stopband ripple. Subtracting the gravitational component from the original median filtered signal provided the bodily motion component [15].

2.4 Movement Detection. Dynamic movement was detected by calculating when the signal magnitude area (SMA) of the bodily motion component of the accelerometer data exceeded the dynamic movement threshold (Table 1) for each 1 s interval [27]. In order to allow the identification of movement at lower frequencies (i.e., walking at gait velocities less than approximately 0.5 m/s) which are often missed when looking at SMA alone, a continuous wavelet transform (CWT) using a Daubechies 4 Mother Wavelet was applied to the acceleration signal over the frequency range of 0.1–2.0 Hz [28] for those seconds of data identified as nonmovement using SMA. The energy contribution for each data point was calculated from the coefficients returned from the CWT using a scalogram. If the average energy contribution for a 1 s interval exceeds 1.5, that 1 s interval is classified as dynamic movement. The value of 1.5 was determined based on observations made on a single random subject (as it gave the greatest agreement of detected seconds of movement with video-observed seconds of movement at slow gait velocities) prior to complete testing on the remaining subjects. The wavelet toolbox from MATLAB was used to calculate the wavelet transforms in this study. Movement was characterized as jogging when the SMA exceeded the jogging threshold (Table 1) and as walking (including stair climbing and fidgeting of the feet while standing) when the SMA was between the threshold for dynamic movement and jogging. The threshold of 0.135 g for dynamic movement detection from waist accelerations was obtained from Ref. [29] and the threshold of 0.8 g for jogging detection for waist accelerations was obtained from Ref. [27]. The thresholds for detecting dynamic movement and jogging from acceleration data recorded from the thigh and ankle were calculated as ratios of the waist acceleration thresholds (Eq. (1)) as both thigh and ankle accelerations were consistently larger than waist accelerations during movement (Fig. 1). These ratios were determined from the mean of the signal magnitude area (SMA) from each monitor location from the 5 min simulated free-living protocol for all subjects (Table 1).

$$th_{\text{monitor location}} = \frac{\text{mean}(\text{SMA}_{\text{monitor location}})}{\text{mean}(\text{SMA}_{\text{waist}})} \times th_{\text{waist}} \tag{1}$$

where $th_{\text{monitor location}}$ is the threshold for either movement or jogging at a specified accelerometer location, i.e., thigh or ankle.

2.5 Postural Orientation. When using a single waist or ankle accelerometer, lying down was determined when the waist or ankle angle was between 50 and 130 deg, with undefined orientations for waist or ankle angles greater than 130 deg and upright postures between 0 and 50 deg (Fig. 2(*a*)) [30]. When using only

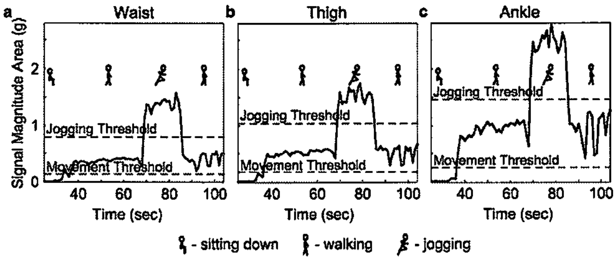

Fig. 1 Mean signal magnitude area per second and corresponding movement and jogging thresholds for (*a*) waist, (*b*) thigh, and (*c*) acceleration data from one subject chosen at random during the simulated free living protocol

the thigh accelerometer, standing and sitting/lying were differentiated based on the thigh angle, in relation to gravity, of less than 45 deg or greater than 45 deg, respectively [30] (Fig. 2(*b*)). To differentiate lying conditions between supine, prone, left and right positions, the angles in transverse plane were portioned into four equal 90 degree segments [15]. When using both the thigh accelerometer with the ankle accelerometer, the ankle accelerometer was used to detect movement and to determine if the posture was upright or lying down while the thigh accelerometer was used to determine if upright postures were standing or sitting (Fig. 2(*c*)). Rolling over while lying down was classified as a transition, specifically a lying to lying transition. To identify sit to stand, stand to sit, lying to upright and upright to lying transitions, all beginning and ending segments of lying and sitting were identified. When a postural change was detected 2 s prior to and 2 s after the beginning and ending points, respectively, transitions (of either upright to lying, lying to upright, sit to stand, or stand to sit depending on the identified postures) were classified as the active seconds for postural change. Among upright movement, sitting while fidgeting was identified by the thigh angle.

2.6 Validity. Video data were imported into Windows Movie Maker (Microsoft, Seattle, WA). Two raters, each with greater than one year of gait analysis experience, manually determined start and end times of each postural orientation and movement. The video data were considered the gold standard for all validation analysis. Video classification and accelerometer data were organized into one second windows for a second-by-second comparison. In this study, we are using the term validity to mean the "agreement between two efforts to measure the same thing with different methods" with one of those methods being the gold standard [31]. Validity of the accelerometer algorithm to properly identify different postures and movement was assessed with sensitivity and positive predictive value (PPV). Specificity was not used as the number of true negatives would depend largely on the time duration of the protocol (as more time was spent not performing each task than performing each task during the protocol) and specificity would; therefore, not provide a valuable measure in regards to accuracy in this study. Sensitivity described the percentage of an observation category which was correctly detected by the activity monitors, or the ratio of true positives to the sum of true positives and false negatives. PPV provided the percentage of true positives that was identified when compared to the total number of true positives and false positives determined by the activity monitor. Misclassification error was also calculated as the percentage of disagreement between the algorithm and the video analysis for detecting all movement and static postures of standing, sitting and lying across the total protocol time [12]. There are no defined acceptable levels of sensitivity or PPV for posture and movement detection. Similar to previously published guidelines for κ values [32], sensitivity, and PPV were divided into three levels in this study: less than 60%, between 60% and 80%, and $\geq$80% [27]. Comparably, 70–80% is defined as acceptable levels for sensitivity and specificity for developmental screening tools by the American Academy of Pediatrics. In [33], a sensitivity of 71.7% and a specificity of 67.8% were deemed to be acceptable for detecting sitting postures in healthy children. In Ref. [12], a misclassification error of approximately 11% was considered as acceptable for most clinical applications. The overall accuracy of a single accelerometer or an accelerometer combination, in the present study, was determined to be acceptable at detecting a specific posture or movement if both sensitivity and PPV were greater than 60%. Acceptable accuracy was further classed as either 'moderate' or "high" with the criteria for high accuracy being that both sensitivity and PPV are $\geq$80%. The Bland-Altman method was utilized to compare the total time spent in upright movement as determined by both the algorithm and video observation [34].

3 Results

All twelve participants completed the protocol as prescribed. For one individual, the waist accelerometer came loose during the laying down transitions, and therefore all subsequent analyses during the protocol for this subject were not utilized for any accelerometer combinations or placements. The total time to complete the protocol averaged 359 ± 42 s. Reliability of video observation between the two raters was high for all postures and activities (ICC(A,1) > 0.92) except for transitions (ICC(A,1) of 0.47) [27]. All further analyses were performed comparing accelerometer identification to a single rater.

3.1 Standing. Thigh-ankle and single thigh accelerometers identified standing with moderate accuracy (median sensitivities and PPVs > 75%; Tables 2 and 3, and Figs. 3 and 4).

3.2 Standing/Sitting. The single waist identified standing/sitting with moderate accuracy (median sensitivity and PPV > 71%; Table 2, Figs. 3 and 4). However, the single ankle demonstrated unacceptable accuracy with only 53% in median sensitivity.

3.3 Sitting. The thigh-ankle accelerometers identified sitting with moderate accuracy (median sensitivity and PPV > 69%; Tables 2 and 3, Figs. 3 and 4).

3.4 Sitting/Lying. The single thigh accelerometer detected sitting/lying with high accuracy (median sensitivity and PPV > 84%; Tables 2 and 3, and Figs. 3(*b*) and 4(*b*)).

3.5 Lying. The single waist accelerometer identified lying with high accuracy (median sensitivity and PPV > 97%), while thigh-ankle and single ankle accelerometers demonstrated

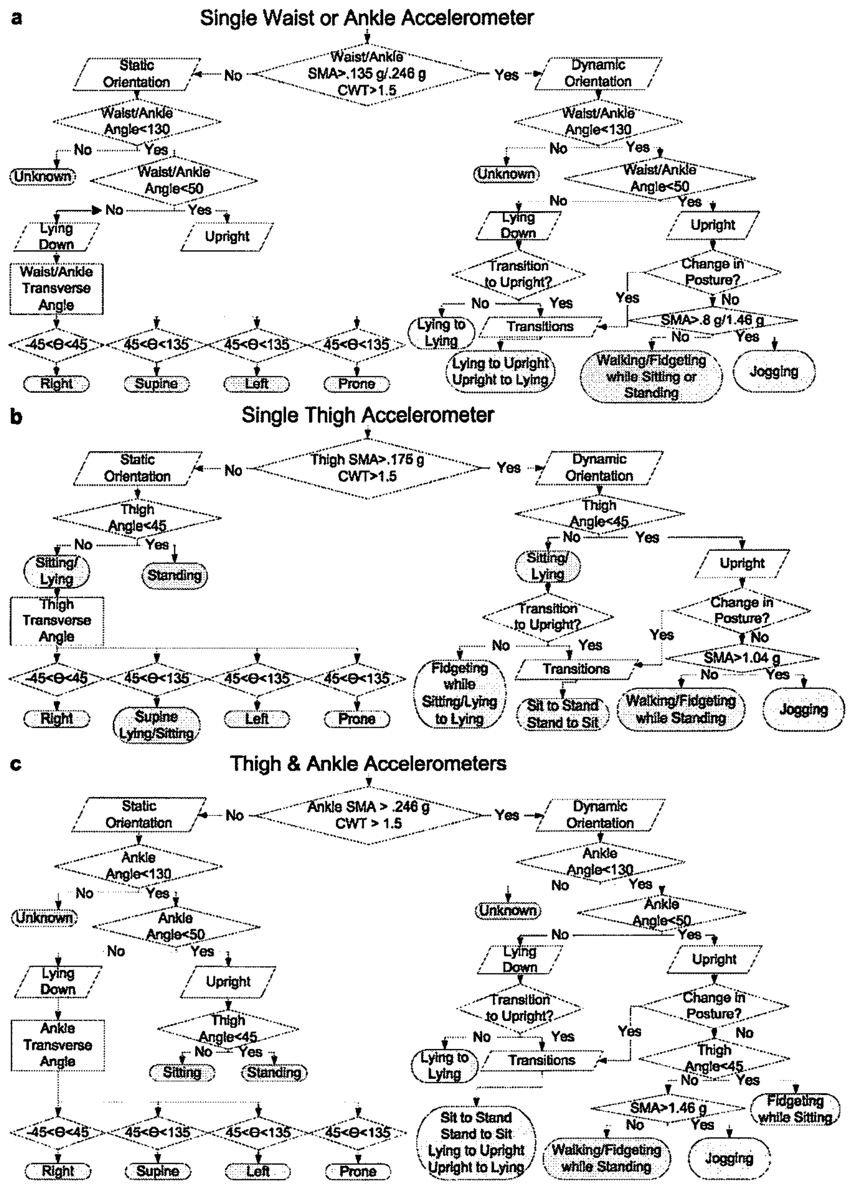

Fig. 2 Decision algorithm for the possible posture and movement classifications determined from the accelerometer data when using (*a*) single waist or ankle, (*b*) a single thigh, and (*c*) thigh and ankle accelerometers. SMA is signal magnitude area and CWT is continuous wavelet transform

moderate accuracy (median sensitivities and PPVs > 67%; Tables 2 and 3, and Figs. 3 and 4).

3.6 Transitions. Transitions between sitting and standing, and lying to lying were identified for the thigh-ankle and single thigh accelerometers with moderate accuracy (sensitivities and PPVs > 77%; Tables 2 and 3, and Figs. 3 and 4). Transitions were detected with unacceptable accuracy with median sensitivity < 47% for single waist and single ankle accelerometers as only transitions between upright and lying, and lying to lying

Table 2 Median sensitivity and PPV and overall misclassification error (SD) for different monitor locations. Bold indicates highest value in each row (lowest for misclassification error), red indicates poor accuracy (≤ 60% [32]). The Waist and Thigh column data is taken from [27] for comparison

Sensitivity (%)	Waist and thigh	Thigh and ankle	Waist	Thigh	Ankle
Standing	86	75	79[a]	75	53[a]
Sitting	97	43		98[b]	
Lying	98	98	98		98
Walking/Fidgeting	87	94	91	94	95
Jogging	97	99	97	99	93
Transitions	87	81	46	81	43
PPV (%)					
Standing	75	87	71[a]	87	71[a]
Sitting	69	54		84[b]	
Lying	97	69	97		67
Walking/Fidgeting	95	93	76	93	79
Jogging	100	99	100	99	98
Transitions	71	77	86[a]	77[b]	82[a]
Misclassification Error (%)	11(2)	17(3)[c]	12(3)[a]	10(2)[b]	16(3)[a]

[a]Standing cannot be separated from sitting.
[b]Lying cannot be separated from sitting.
[c]Transitions between sitting with legs straight cannot be separated from lying.

Table 3 Static orientation and movement identification accuracy levels based on sensitivity and PPV for varying accelerometer locations. White: unacceptable, light grey: moderate, dark grey: high.

Accuracy:	Waist-thigh	Thigh-ankle	Waist	Thigh	Ankle
Standing			A		A
Sitting				B	
Lying					
Walking/Fidgeting					
Jogging					
Transitions		C	A	B	A

Note: A:A standing cannot be separated from sitting; B: lying cannot be separated from sitting; and C: transitions between sitting with legs straight cannot be separated from lying.

transitions could be detected, not sit to stand or stand to sit. Sensitivity values were higher for the single thigh accelerometer as only sit to lie and lie to sit transitions could not be detected. Sit to lie and lie to sit transitions also could not be detected using the thigh-ankle accelerometers as only transitions between sitting on a bed with legs straight and lying down were investigated.

3.7 Walking/Fidgeting. Among dynamic orientations, walking/fidgeting was identified with high accuracy (median sensitivities and PPVs > 87%) for the thigh-ankle and single thigh accelerometers (Tables 2 and 3, and Figs. 3 and 4). Single waist and ankle accelerometers demonstrated moderate accuracy (median sensitivities and PPVs > 91% and 76%, respectively).

3.8 Jogging. Jogging was identified with high accuracy (median sensitivities and PPVs > 93%) for all combinations and placements tested (Tables 2 and 3, and Figs. 3 and 4).

The amount of time spent moving while upright demonstrated good agreement, when utilizing the Bland-Altman method to compare the accelerometer combinations and placements to video observation (Fig. 5). The single thigh accelerometer and thigh-ankle accelerometers showed approximately 1% of mean error in identifying how many seconds dynamic movement occurred across all subjects (Figs. 5(*b*) and 5(*d*)) while the single waist accelerometer showed 12% (Fig. 5(*a*)). The ankle showed the worst agreement with 17% (Fig. 5(*c*)). Overall misclassification error between movement and static postures of standing, sitting and lying were less than 17% in all cases (Table 2).

4 Discussion

The aim of this study was to test and compare movement and posture classification schemes using different accelerometer combinations and placements. Reducing the number of accelerometers required for postural and movement assessments in free-living environments and care settings is of high importance for patient compliance [5,6]. Requesting the user to don too many devices can be cumbersome and lead to overly complicated wear instructions [5]. In addition, patients may find some accelerometer placements to be uncomfortable which could further hinder patient compliance. The waist is often the preferred location as accelerometers can easily be attached to belts. However, for subjects who spend most of their time in bed or do not wear a belt or trousers, the waist placement may be uncomfortable [5]. Furthermore, missing acceleration data due to failed devices and subject compliance issues often cause problems with data analysis [35]. Therefore, reducing the number of accelerometers required for analysis and using algorithms which are robust to a variety of accelerometer locations may increase patient compliance and also provide alternative analysis options. It is important to note that while it is important for patient compliance that the number of accelerometers is kept low, redundant accelerometers should be used whenever possible in case of device failure or corrupt data.

Misclassifications occurred with all accelerometer combinations and placements to some degree.

4.1 Standing. When the single thigh accelerometer or the thigh-ankle accelerometers were used, false negatives were caused by misclassification of standing as walking/fidgeting when standing still occurs between activity segments of fidgeting while standing (Table 2, and Figs. 3(*b*) and 3(*d*)).

4.2 Standing/Sitting. When the single ankle accelerometer was used, a large number of false negatives (Table 2, Fig. 3(*c*)) resulted from subjects sitting with legs straight (i.e., on the floor or on a bed). When the single ankle accelerometer was used, false positives were due to parts of sit to stand and stand to sit transitions being misclassified as static sitting/standing when the ankle acceleration was too low to be detected as movement. When the single waist accelerometer was used, false positives were due to fidgeting of the feet while standing and sitting being misclassified as static standing/sitting when there was very little waist movement. These findings are consistent with previous studies, showing that the waist location is optimal for detecting whole body movement, while the ankle or thigh are optimal for detecting limb movement [8].

4.3 Sitting. When the thigh-ankle accelerometers were used, a large number of false negatives (Table 2, Fig. 3(*d*)) resulted from subjects sitting with legs straight (i.e., on the floor or on a bed). When the thigh-ankle accelerometers were used, false positives were caused by the misclassification of sitting while fidgeting as static sitting (Table 2, Fig. 4).

4.4. Sitting/Lying. When the thigh accelerometer was used, false positives (Table 2, Fig. 4(*b*)) were due to the start and end of lying transitions being misclassified as static sitting/lying.

4.5 Lying. When the single ankle accelerometer and the thigh-ankle accelerometers were used, a large number of false positives (Table 2, Figs. 4(*c*) and 4(*d*)) resulted from subjects sitting with legs straight (i.e., on the floor or on a bed).

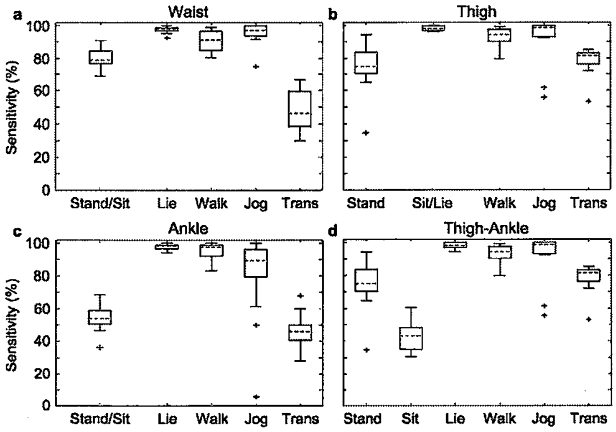

Fig. 3 Sensitivity when identifying static orientations and dynamic movements compared to video identification using (*a*) a waist accelerometer, (*b*) a thigh accelerometer, (*c*) an ankle accelerometer, and (*d*) the central line (dashed) represents the median, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to ±1.5 of the interquartile range. Outliers beyond this range are labeled as +. Trans: Transitions.

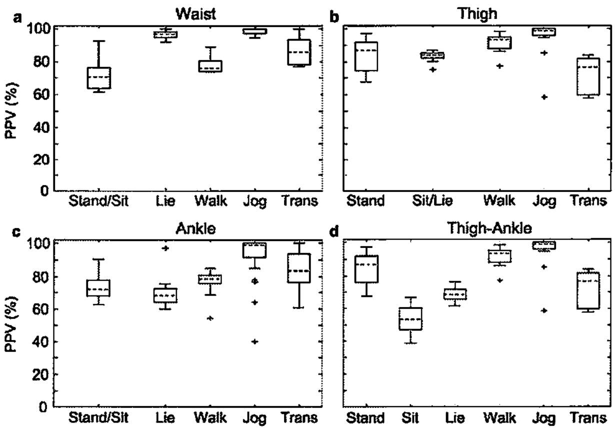

Fig. 4 Positive predictive value (PPV) when identifying static orientations and dynamic movements compared to video identification using (*a*) a waist accelerometer, (*b*) a thigh accelerometer, (*c*) an ankle accelerometer, and (*d*) thigh and ankle accelerometers. The central line (dashed) represents the median, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to ±1.5 of the interquartile range. Outliers beyond this range are labeled as +. For the PPV of jogging in (*a*), the median value and the 75th percentile are equal to 100%.

4.6 Transitions. A thigh accelerometer was needed for accurate sit to stand transition detection, and a thigh accelerometer in combination with a waist accelerometer was needed for accurate postural detection, consistent with previous studies [2,14,36]. When the single waist and single ankle accelerometers were used, false negatives occurred mostly due to transitions between sitting and standing being misclassified as walking/fidgeting, as sitting could not be separated from standing.

In this study, the thigh-ankle accelerometers were found to detect postures less accurately than the waist-thigh accelerometers in Ref. [27], however, the results were still comparable to those from other studies involving two accelerometer locations [12] and could still provide beneficial information in the event of waist accelerometer failure or if it is not feasible for a patient to wear a waist accelerometer. While some studies have investigated posture identification using only one accelerometer on the waist

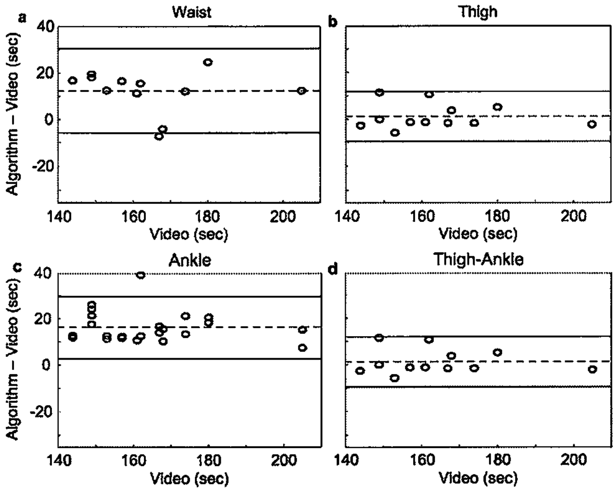

Fig. 5 Bland-Altman plots demonstrating error in identifying walking/fidgeting and jogging activities when using accelerometer compared to video identification for (*a*) a waist accelerometer, (*b*) a thigh accelerometer, (*c*) an ankle accelerometer, and (*d*) thigh and ankle accelerometers. The dashed line represents the mean, while the solid lines represent the repeatability coefficients (± 1.96 SD). ICC(A,1) values are also presented.

[15,17] or lower back [16], the protocols used to test the algorithms validities did not include fidgeting of the feet during standing or sitting postures which could possibly reduce the accuracy. Furthermore, difficulties in differentiating between standing and sitting using an accelerometer located on the waist have been reported [8]. Studies involving ActivPal placed on the thigh report combined results for sitting and lying [14,37]. In this study, the single waist accelerometer identified upright and lying postures with greater accuracy than the single ankle accelerometer.

4.7 Walking/Fidgeting. In this study, the thigh accelerometer identified walking/fidgeting with the most accuracy for single accelerometer use, while the waist accelerometer produced the least accuracy due to missed fidgeting steps. Another study reported that the ankle accelerometer demonstrated the most accurate results for walking detection with single accelerometer use between waist, thigh, and ankle location [25]. However, in this study, as sitting orientations were included in the protocol, and sitting and standing could not be separated using single waist and single ankle accelerometers, false positives occurred when fidgeting of the feet while sitting was misclassified by the algorithm as walking.

4.8 Jogging. The thigh accelerometer also identified jogging with the most accuracy for single accelerometer use, consistent with Ref. [5]. Median sensitivities and PPVs for jogging were slightly lower at 93% and 98% for the single ankle accelerometer than the other combinations and placements due to the correlation of increasing amplitude variation with increasing movement resulting in some jogging seconds being misclassified as walking and vice versa. However, despite some accelerometer locations producing more accurate results than others, all tested accelerometer combinations and placements in this study detected walking/fidgeting with moderate to high accuracy (median sensitivities and PPVs from 76% to 95%) and jogging with high accuracy (median sensitivities and PPVs from 93% to 100%; (Table 3)) which were comparable to other studies [12,16]. While both thigh-ankle and waist-thigh accelerometers produced results of high accuracy for walking and jogging detection, the thigh-ankle accelerometers had higher sensitivity values than the waist-thigh accelerometers and only slightly lower PPVs (Table 2) consistent with a previous study on level walking, stair ascent, and descent detection [25]. The single thigh accelerometer and thigh-ankle accelerometers identified upright movement with the most agreement using Bland-Altman (Fig. 5). The misclassification errors for detecting postures and movement using the waist-thigh, single waist, and single thigh accelerometers were similar to Ref. [12] which reported a misclassification error of 11% and involved a much simpler protocol with no fidgeting of the feet or jogging. The higher misclassification errors for the single ankle and thigh-ankle accelerometers were due to errors in identifying between upright and lying postures. The single thigh accelerometer demonstrated the lowest misclassification error for single monitor use. Without fidgeting of the feet, the misclassification errors (SD) were 4% (1%), 7% (2%), and 6% (2%), 11% (1%), and 15% (3%) for the waist-thigh, single waist, single thigh, thigh-ankle, and single ankle accelerometers, respectively.

There are a number of limitations in this study which are important to consider. The disadvantage of using only one accelerometer is that in the case of device failure or corrupt data, there is no source of redundant data that can be used instead. Movement and jogging thresholds could possibly be refined in accuracy with a higher number of subjects. It is important to note that only healthy subjects were included in this study. Further investigation would be needed before using the method examined in this study on unhealthy subjects as changes in accelerometer orientations due to body shape, skeletal deformities, and skin movement artifacts could result in posture and movement classification errors. However, the healthy subjects tested in this study had a range of body types with a BMI range of 19.9–40.1 kg/m^2. Furthermore, the algorithm was originally designed for use with waist and thigh accelerometers and therefore the results may be biased towards the waist-thigh accelerometers. However, while the waist-thigh accelerometers produced the most accurate results overall, all accelerometer combinations and placements detected jogging and walking/fidgeting with sufficient accuracy. For single accelerometer use, thigh accelerometer placement demonstrated optimal results as it can most accurately identify standing postures and movement and can detect transitions from sitting/lying to standing.

5 Conclusion

The results from this study show that there is a trade-off between reducing the number of accelerometers per subject, choosing their locations and accuracy. The data suggests that researchers should carefully choose accelerometer numbers and their locations depending on the information required while considering patient preferences. For posture-related tasks, we recommend using a waist and thigh accelerometer combination. For redundancy, an extra thigh accelerometer should be added. For eddynamic tasks, we recommend using a thigh accelerometer. For redundancy, an ankle accelerometer should be added. While this study involves a simulated protocol conducted in a laboratory environment, the results suggest that the proposed analysis methods are suitable for posture and movement classification in healthy adults in a free-living environment.

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