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Reliability of Recurrence Quantification Analysis Measures for Sit-to-Stand and Stand-to-Sit Activities in Healthy Older Adults Using Wearable Sensors

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Abstract: Standing up and sitting down are prerequisite motions in most activities of daily living scenarios. The ability to sit down in and stand up from a chair or a bed depreciates and becomes a complex task with increasing age. Hence, research on the analysis and recognition of these two activities can help in the design of algorithms for assistive devices. In this work, we propose a reliability analysis for testing the internal consistency of nonlinear recurrence features for sit-to-stand (Si2St) and stand-to-sit (St2Si) activities for motion acceleration data collected by a wearable sensing device for 14 healthy older subjects in the age range of 78 $\pm$ 4.9 years. Four recurrence features—%recurrence rate, %determinism, entropy, and average diagonal length—were calculated by using recurrence plots for both activities. A detailed relative and absolute reliability statistical analysis based on Cronbach's correlation coefficient (α) and standard error of measurement was performed for all recurrence measures. Correlation values as high as α = 0.68 (%determinism) and α = 0.72 (entropy) in the case of Si2St and α = 0.64 (%determinism) and α = 0.69 (entropy) in the case of St2Si—with low standard error in the measurements—show the reliability of %determinism and entropy for repeated acceleration measurements for the characterization of both the St2Si and Si2St activities in the case of healthy older adults.

Keywords: sit-to-stand; stand-to-sit; recurrence quantification analysis; reliability; wearable sensors; activities of daily living

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1. Introduction

Standing up (Si2St) from and sitting down (St2Si) [1–3] on a chair or a bed constitute two primary motions in most of the activities encountered in daily living (ADLs) [4,5] and require adequate biomechanical muscle strength [6]. Sufficient muscle power, healthy balance, and strong coordination during body movements are required for a successful completion of transitional Si2St and St2Si activities [7,8]. Particularly, with the older population, with increasing age, physiological functioning deteriorates and the mobility of joints is reduced due to acute health problems or the inevitable process of sarcopenia (i.e., loss of muscle mass and muscle strength due to aging) [9–11], and hence, the capacity to perform different ADLs, such as bathing, dressing, or independently walking, becomes complex [12], making assistance from caregivers necessary. Research specific to older adults shows that most of the falls at homes, hospitals, and elderly care centers [13–15] occur while getting out of bed or getting off a chair [16,17], especially at night, when there is less assistance. Monitoring the body movements of older adults in their daily living environment and detecting the level of risk for occurrence of a fall event provides a chance for caregivers to intervene and provide instant help and attention. Recognizing intent rather than recognizing the fall event itself using intelligent devices and techniques can allow timely and reliable assistance to be provided [18]. Even with best practices in hospitals to prevent falls, the fall rates are very high.

In recent years, technology has played an important part in recognizing high-risk body movements that might lead to a fall [19,20]. One important approach to reducing falls in hospitals is camera surveillance so that the patients at high risk of falling are provided assistance while getting out of bed or getting up from chairs and vice versa. A second dominant approach is the use of pressure sensors [3]. Both of these approaches are highly computational and incur latency and privacy violations. Novel wearable sensing devices, such as inertial measurement units and accelerometers [19–22], are popular choices as body-motion sensors—the reason is partly due to their capability of extracting information that is useful for automatically inferring the physical activity in which the human subject is involved, in addition to the low cost, ease of use, light weight, and fast processing of biomechanical input parameter estimators. Several studies have used Si2St and St2Si activities as primary recognition movements in order to assess the risk of falls in older people [23–27]. In particular, by using acceleration data from wearable sensors as body-movement-capturing signals, multiple studies reported different types of features—for example, the frequency domain [28], autoregressive [28,29], statistics [30,31], correlation, energy, and maximum and approximate entropy [31] were extracted and used for activity and intent recognition algorithms.

Recently, recurrence quantification analysis (RQA) has emerged as a competitive nonlinear signal analysis [32] technique, as nonlinear representative features are better able to represent the complex trends in a signal. RQA has been applied to the extraction of the nonlinear dynamics of human body movements by quantifying the system repeatability, complexity, and local dynamics through different variables [32–35]. The computation of these variables requires the selection of suitable embedding parameters for state-space reconstruction (i.e., the time delay and embedding dimension). Four RQA measures were used to characterize the dynamics of a system: (1) Recurrence rate (%RR) is a measure of the density of recurrence points in the recurrence plot (RP); (2) determinism (%DET) is a measure of the system's predictability, and is the ratio of recurrence points that form diagonal structures of a chosen minimal length to all recurrence points; (3) entropy (ENT) is the Shannon entropy of the probability of finding a diagonal line of a specific length in the RP; (4) average diagonal line length (L) is a measure of the average time for which two trajectory segments stay close to each other [34]. RQA has previously been used in multidimensional research areas—for example, to predict COP fluctuations in older adults with and without a history of falls [36] and to analyze complex eye movements [37,38], traffic data [39], etc. However, the measurement reliability of these nonlinear RQA variables in defining a system dynamic or, in our case, human body movements during Si2St and St2Si activities has not been investigated enough. Statistically reliable measures allow researchers and clinicians to discriminate measurement features between subjects and provide the capacity to detect changes in studied test data [40–42]. Internal consistency reliability is the extent to which multiple trials performed by single or multiple subjects (raters or observers in statistical terms) agree. It addresses the issue of the consistency of the implementation of a rating system. In this study, we used the split-half reliability method and reported the findings in terms of the Cronbach's correlation coefficient (α) [43,44] within the confidence interval of 95%, the standard error of measurement (SEM), the minimal metrically detectable change (MMDC), and the coefficient of variation (CV), and thus showed clinically different variations.

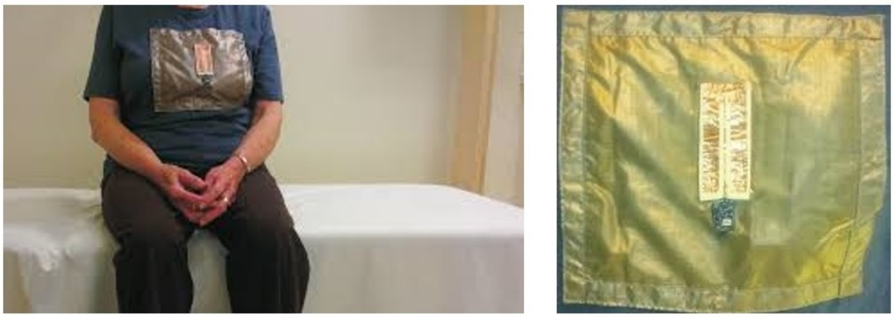
A few related studies had high human activity recognition (HAR) capabilities by using recurrence parameters [25–27], but they did not perform a reliability analysis of the measurement changes in the RQA feature values during the performance of human body movements for the Si2St and St2Si activities while considering healthy older groups, multiple subjects, and multiple experimental conditions. The authors of [2] performed HAR, but there was not a reliability analysis of the RQA features, and the dataset used for the study was not open access. As such, the performance of the RQA features for the HAR was not reliably validated. Instead of performing RQA, the authors of [25] used different sliding-window techniques to segment signals and detect activity. The dataset used was the same as that in this work. High accuracy values were obtained, but the work lacked a validation of the reliability of the technique for varied structures of activity types. HAR using recurrence analysis on a dataset of accelerometer sensor recordings could also be achieved by applying visual segmentation. The research in [26] used recurrence plots as visual descriptors instead of RQA features and reached 80% accuracy. Different recurrence features have been used in various works; for example, postural fluctuations in older adults were assessed with two RQA measures, %DET and ENT [36], while in some cases, such as in [37], additional features, such as the laminarity and center of recurrence mass, were been analyzed. Moreover, neither study performed a reliability assessment to select the most useful features. By using a subset of features instead, the authors of [27] were able to offer an improvement in the HAR task. The reliability of RQA on the center of pressure signal from subjects with musculoskeletal disorders and in a standing posture was evaluated for the %RR, %DET, ENT, and trend [45,46]; these authors also assessed the reliability of the RQA features of %DET and laminarity for postural sway, but instead focused on the determination of the optimum recurrence threshold. However, a reliability analysis helps one focus on the best features for individual tasks and applications. In the current work, a statistical study was performed to assess the internal consistency reliability of the dynamic RQA features calculated for the nonlinear analysis of the acceleration data acquired by wearable sensors for changes in human body movements that occurred in older adults while performing Si2St and St2Si activities in order to provide timely help and aid for the prevention of falls in older adults at home and in hospitals and elderly care institution.

2. Materials and Methods

2.1. Data

The "Activity recognition with healthy older people using a batteryless wearable sensor" dataset [47,48] was made publicly available by the UC Irvine Machine Learning Repository [49] and was used for experimental analysis of the currently proposed research. The data were acquired with a flexible, batteryless, and wearable wireless identification and sensing platform (W^{2}ISP) [25,47,50] that was attached above the clothing of the participants at the sternum level, as shown in Figure 1. The W^{2}ISP contains a 3-axis accelerometer (ADXL330) and a microprocessor (MSP430F2132), and it records acceleration signals in the x-, y-, and z-axes with respect to the device's and subject's pose. We obtained the frontal ($\mathbf{a}_f$), lateral ($\mathbf{a}_l$), and vertical ($\mathbf{a}_v$) acceleration, which was measured with respect to the sensor's position on body. The data were collected in two clinical room settings, *RoomSet1* and *RoomSet2*, which differed with respect to the RFID antenna placement and the number of antennas deployed. The setting of *RoomSet1* uses 4 RFID reader antennas around the room (one on the ceiling level and 3 on the wall level) for the collection of data, whereas the room setting *RoomSet2* used 3 RFID reader antennas (two at the ceiling level and one at the wall level) for the collection of motion data. The sensor settings were designed to investigate the living conditions in hospitals and elderly care institutions. The room settings, however, did not differ with respect to the sensor's placement on the subject's body and the sequence of scripted activities to be performed. Hence, the acceleration signal recorded by W^{2}ISP was unaffected by the room RFID antenna settings. The component of acceleration along the vertical axis $\mathbf{a}_v$ showed a clear change in the signal value as the position of the human body changed while performing the two activities under consideration, Si2St and St2Si. Hence, we used the $\mathbf{a}_v$ signal for calculating the RQA parameters in this study [29,46,51–54].

Fourteen healthy older subjects aged 78 ± 4.9 years performed different ADLs: walking to the chair, sitting on the chair, getting off the chair, walking to the bed, lying on the bed, getting off the bed, and walking to the door. Hence, the possible class labels assigned (provided with each signal) for every sensor observation were: sitting on the bed (labeled 1), sitting on the chair (labeled 2), lying on the bed (labeled 3), and ambulating (labeled 4), where ambulating included standing and walking around the room. Out of 14, 9 subjects performed the scripted activities in *RoomSet1* and 5 subjects performed the scripted activities in *Roomset2*. The sequence of movements carried out for Si2St and St2Si by the subjects during the data collection is shown in Figure 2. Based on the labels provided with each recorded sample, the occurrence of Si2St was identified as sequence 1-4 (sitting on a chair to standing) and 2-4 (sitting on a bed to standing). The occurrence of the St2Si movement was identified as 4-1 (standing to sitting on a chair) and 4-2 (standing to sitting on a bed). A total of 34 and 54 transitions were identified as Si2St and St2Si, respectively, for *RoomSet1*. A total of 18 and 10 transitions were identified as Si2St and St2Si, respectively, for *RoomSet2*. The number of instances for the Si2St and St2Si activities recorded in *RoomSet1* and *RoomSet2* was in agreement with the frequency of activities reported in [28] for the current dataset. Based on the labels provided with each recorded sample, the occurrence of Si2St was identified as sequence 1-4 (sitting on a chair to standing) and 2-4 (sitting on a bed to standing). The occurrence of St2Si movement was identified as 4-1 (standing to sitting on a chair) and 4-2 (standing to sitting on a bed). For Si2St, the point of change in the sequence of labels from (1,2) to 4 was identified as the transitional point, and an interval of 10 s before and 10 s after the transitional point was used to identify a complete Si2St transition. For St2Si, the point of change in the sequence of labels from 4 to (1,2) was identified as the transitional point, and an interval of 10 s before and 10 s after the transitional point was used to identify a complete Si2St transition. The complete signal consisted of more continual points before and after the cut points selected here. Due to the anonymity of the available records, there is no way of knowing which trials came from the same subject, and hence, a within-subject reliability study was not possible. Therefore, a partially standardized within-trial reliability study that would still be feasible for clinicians to follow is presented in this work [55].



(a) (b)

Figure 1. Wearable sensor settings during data acquisition: (**a**) positioning of the W^{2}ISP sensor on the subject's body, (**b**) the W^{2}ISP sensor attached to the subject's clothing with isolating silver fabric [47].

The data were sparse, meaning that the time intervals for recording inter-sensor observations were variable. When a W^{2}ISP sensor has adequate power supply, an upper-bound frequency of 40 Hz is achieved, as reported in [28]. Hence, using the timestamp provided with the data, we used cubic polynomial interpolation to attain the final signal frequency of 40 Hz (maximum), as suggested in [28]. The interpolated $\mathbf{a}_v$ signal obtained at this point was noisy because the power for sampling the embedded physical sensor was inadequate. A linear polynomial smoothing filter with a span of 0.1 (a span of 0.1 means that 10% of the data points are used to calculate the smoothed output) was applied to smooth out any noisy spikes. A sample of the Si2St and St2Si signals acquired in raw, interpolated, and filtered forms is shown in Figure 3.

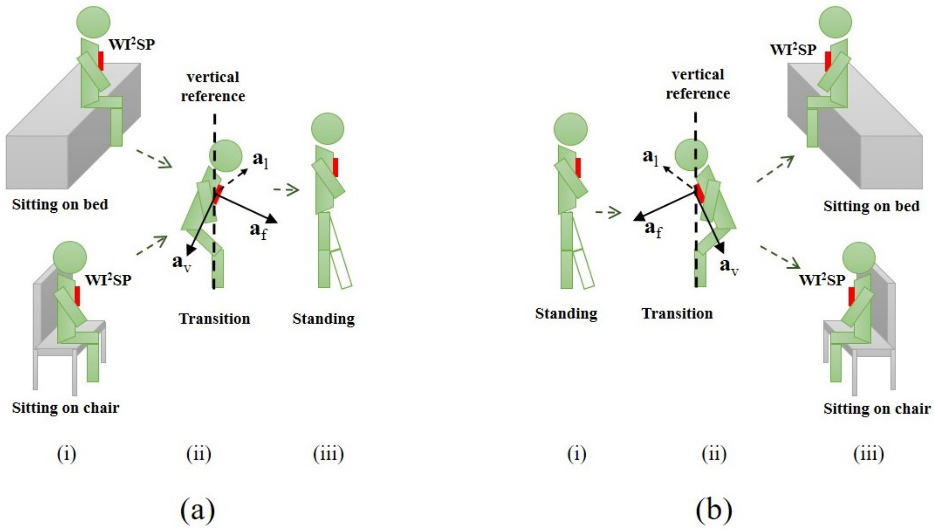


Figure 2. Experimental setting for data collection using W^{2}ISP during activities: (**a**) sit-to-stand (Si2St); (i) sitting on the bed/chair, (ii) transition, (iii) standing; (**b**) stand-to-sit (St2Si); (i) standing, (ii) transition, (iii) sitting on the bed/chair.

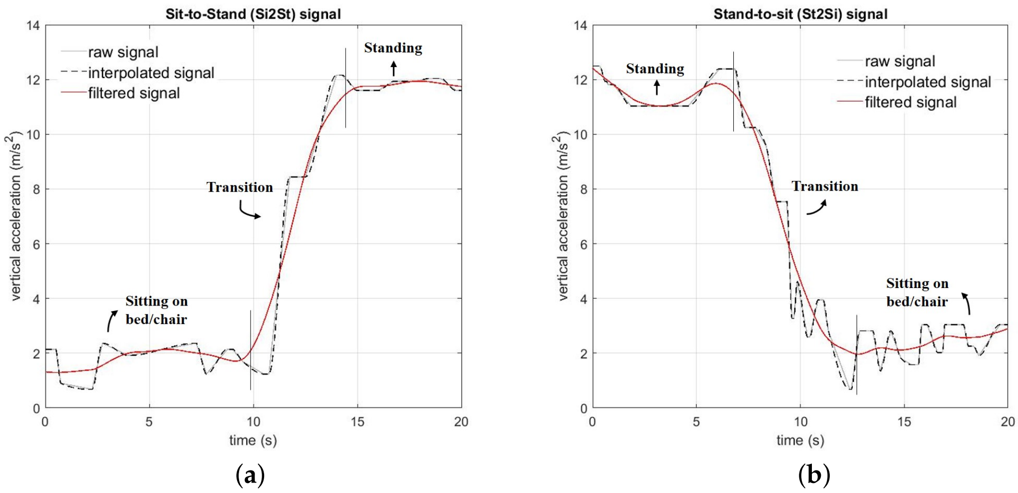


Figure 3. Raw, interpolated, and filtered vertical acceleration signal $\mathbf{a}_v$ acquired from W^{2}ISP while performing (**a**) Si2St and (**b**) St2Si.

2.2. Methodology

The proposed procedure included two steps: (1) RQA feature extraction and (2) reliability analysis. These are explained in detail below.

2.3. RQA Feature Extraction

The value of the embedding dimension (m) and delay (τ) affects the computed RQA feature values heavily [32]; hence, an optimized upper bound, m = 5, was first calculated and set by using the false nearest neighbors method proposed by [56], and an optimized τ for each Si2St and St2Si was calculated by using the average displacement method proposed by [57] for all $\mathbf{a}_v$ signal records. A recurrence matrix was created by first determining the Euclidean distances between all embedded vectors, which is called a distance matrix. A threshold (ρ) that was computed as 20% of the mean distance was applied, and all points in the normalized distance matrix with values below this threshold were identified as recurrent points; the resulting matrix of 1s and 0s was called a recurrence matrix (**R**), and it was calculated by using Equation (1).

$$\mathbf{R}_{i,j}^{m,\rho} = \Theta(\rho - \|\mathbf{a}_v(i) - \mathbf{a}_v(j)\|) \quad (1)$$

where $\mathbf{a}_v(i), \mathbf{a}_v(j) \, \epsilon \, \mathbb{R}$, $i, j = 1, 2, 3, ..., N$, and N is the number of states. In this case, every new incoming sample in the time-series signal represents the next state, and hence, N also represents the length of the signal for which the recurrence is plotted. m is the embedding dimension, $\Theta(.) : \mathbb{R} \rightarrow (0, 1)$ is the Heaviside step function, $\|(.)\|$ is the norm, and ρ is a distance threshold calculated as $0.2 \cdot \text{mean}(\|\mathbf{a}_v(i) - \mathbf{a}_v(j)\|$.

Figure 4a,b show the sample distance matrices and Figure 4c,d show the corresponding recurrence matrices **R** calculated for the St2Si and Si2St activities.

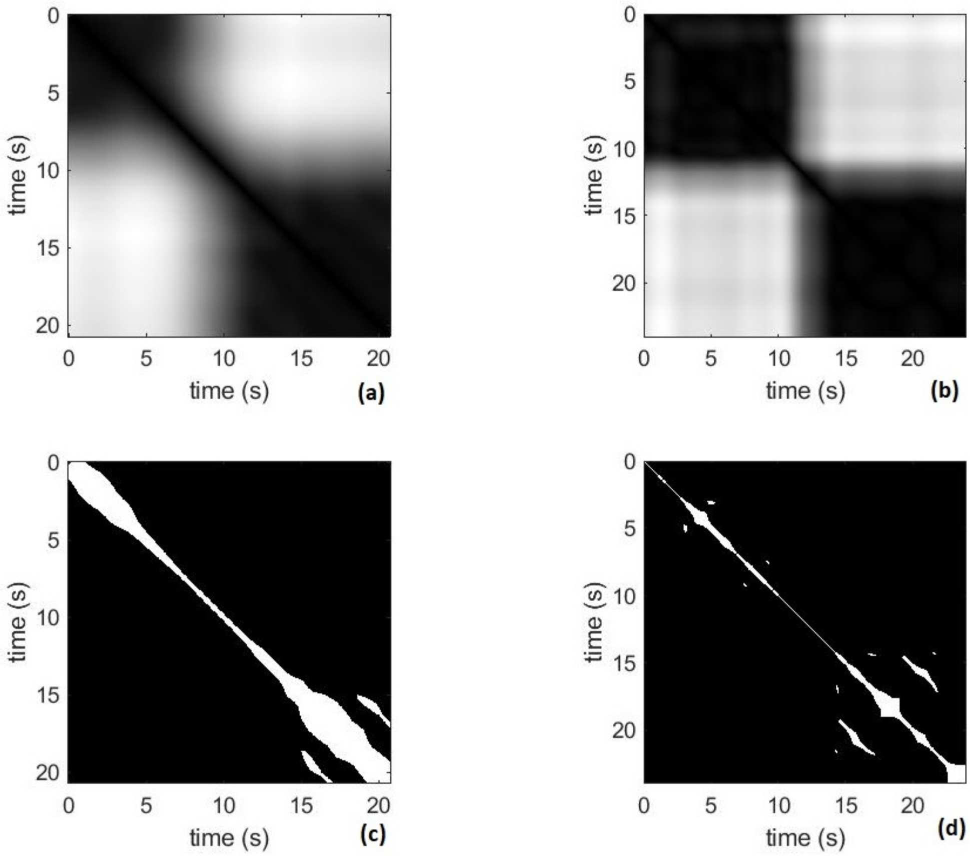


Figure 4. Recurrence matrices for the activities: (**a**) Si2St (m = 5, τ = 15, ρ = 0.01); (**b**) St2Si (m = 5, τ = 18, ρ = 0.04) before the step function; (**c**) Si2St; (**d**) St2Si after the step function.

Several variables were used to quantify the structure present in the recurrence matrix. The percent recurrence (%RR) signifies how often a trajectory visits similar locations in the state space and is computed as the percentage of recurrent points in the recurrence matrix, as shown in Equation (2):

$$\%RR = \frac{1}{N(N-1)} \sum_{i \neq j = 1}^{N} \mathbf{R}_{i,j}^{m,\rho} \quad (2)$$

The percent determinism (%DET) is quantified as the fraction of recurrent points that form diagonal lines (at least three consecutive points in length) parallel to the main diagonal and is computed as shown in Equation (3):

$$\%DET = \frac{\sum_{l=d_{min}}^{N} l H_D(l)}{\sum_{i,j=1}^{N} \mathbf{R}_{i,j}^{m,\rho}} \tag{3}$$

Entropy (ENT) is the Shannon entropy of the frequency distribution of the diagonal line lengths and measures the complexity of the system. The entropy of the probability distribution of the diagonal lines' lengths $p(l)$ of $\mathbf{R}_{i,j}^{m,\rho}$ is calculated as shown in Equation (4):

$$ENT = -\sum_{l=d_{min}}^{N} p(l) l(p(l)), \quad where\ p(l) = \frac{H_D(l)}{\sum_{l=d_{min}}^{N} H_D(l)} \tag{4}$$

The average diagonal line length (L) is the average time for which two segments of the trajectory are close to each other. In this case, L can be interpreted as the mean prediction time and is calculated as shown in Equation (5):

$$L = \frac{\sum_{l=d_{min}}^{N} l H_D(l)}{\sum_{l=d_{min}}^{N} H_D(l)} \tag{5}$$

where $i, j = 1, 2, 3, ..., N$, N is the number of states, $H_D(l)$ is the histogram of the frequency of occurrence of different diagonal line lengths l in $\mathbf{R}_{i,j}^{m,\rho}$, and d_{min} is the minimum number of consecutive points considered as a diagonal. In this case, $d_{min} \geq 3$.

2.4. Reliability Analysis

There are multiple statistical methods that can be used to measure the reliability of a parameter—for example, split half, test–retest, parallel forms, etc. Test–retest means administering the same test to the same group of individuals in two different time periods and correlating the first set of scores with the second. Parallel forms implies administering two alternate forms—say, A and B—of a test to the same group of individuals and correlating the scores on form A with the scores on form B. The split-half method implies administering a test to a group of individuals and splitting the test in half. This method treats the two halves of a measure as alternate forms. The correlation between these two split halves is used to estimate the reliability of the test. Due to the nature of the data collection procedure used in the current experiment, we used the split-half method to assess and analyze the degree of reliability of the RQA parameters in the case of the Si2St and St2Si movements. To assess the relative reliability, an internal consistency analysis was performed by using the split-half method for *RoomSet1* and *RoomSet2* while considering the environmental and physiological conditions to be individually and internally consistent for the *RoomSet1* and *RoomSet2* data. Split-half reliability statistics were calculated for the RR, DET, ENT, and L for the data from *RoomSet1* (Si2St (n = 34) and St2Si (n = 54)) and for the data from *RoomSet2* (Si2St (n = 10) and St2Si (n = 18)), where n is the number of recognized transitions. The split-half reliability was reported in terms of Cronbach's alpha (α) [43,58] with a 95% confidence interval (95% CI), as shown in Equation (6), to show how closely related the RQA measures were for Si2St and St2Si. A paired t-test was performed on the two randomly split halves of the RQA parameters to verify the effect of systematic bias, and the result was reported in terms of the p-value. To assess the degree of reliability achieved, Munro's criterion was applied, which ranks the reliability range according to the value of α': very low: 0–0.25, low: 0.26–0.49, moderate: 0.50–0.69, high: 0.7–0.89, and very high: 0.9–1.00 [55,59,60].

$$\alpha = \frac{k}{k-1} \cdot (1 - \frac{\sum_{i=1}^{k} var(x_i)}{var_T}) \tag{6}$$

where $x \in RR, DET, ENT, L$, i refers to items in x, and $var(x_i)$ refers to the inter-item variance of the i^{th} items in both randomly split halves. var_T is the total variance or the variance of the sum of two half-split population distributions, and k is the number of items in the half set, i.e., for each test sample with n items, $k = n/2$.

To assess the absolute reliability, we used the standard error of measurement (SEM) with α as the reliability coefficient; this was calculated as SEM = std(x_i) $\cdot \sqrt{1-\alpha}$, where std(x_i) represents the standard deviation of the test scores, as given in [61,62]. The minimal metrically detectable change (MMDC) or change that could be considered clinically different between two measurements is defined as the 95% CI of the SEM of the RQA measure, i.e, MMDC = $\pm$ 1.96 $\cdot$ SEM [62,63]. In addition, the coefficient of variation (CV) was determined for the comparison of the absolute reliability between RQA measures and was calculated as CV = (std(x_i)/mean(x_i)) $\cdot$ 100, where mean(x_i) and std(x_i) are the mean and standard deviation of x_i, respectively.

3. Results

Tables 1 and 2 demonstrate α with the respective 95% CIs, SEM, MMDC, and CV for different RQA variables for the relative and absolute internal consistency reliability of the Si2St and St2Si activities in *RoomSet1* and *RoomSet2*, respectively. There was no significant difference, i.e., all of the t-tests yielded p-values between 0.5 and 0.7 between the mean scores over two randomly split halves of data records for the %DET and ENT measures in all cases, which indicates the absence of any systematic bias due to the measuring device or method applied. According to Munro's criterion, %RR and ENT showed high reliability and %DET showed borderline values between moderate and high correlation with respect to α for the Si2St activity in *RoomSet1*. %DET, ENT, and L showed high reliability for the Si2St activity in *RoomSet2*. In the case of the St2Si activity, %DET and ENT showed a moderate to high correlation in most cases for the data collected in both *RoomSet1* and *RoomSet2*. SEM values as low as 0.5, 0.04, and 0.39 were observed for the measurements of %RR, %DET, and ENT, respectively, which shows that there was a small spread of measurement error across repeated measurements. L showed a very high standard deviation and, accordingly, upper bound for the SEM and CV in both Si2St (SEM = 10.32, CV = 82.74) and St2Si (SEM = 7.08, CV = 94.11) cases, and is thus reported to be unreliable.

Table 1. Reliability analysis of the RQA measures in the activities of Si2St (n = 34) and St2Si (n = 54) for *RoomSet1*.

	Si2St				St2Si			
	α (95% CI)	**SEM**	**MMDC**	**CV(%)**	**α (95% CI)**	**SEM**	**MMDC**	**CV(%)**
RR	**0.58** (0.12 0.72)	0.05	0.10	22.00	0.35 (0.07 0.52)	0.06	0.12	22.57
DET	**0.54** (0.23 0.74)	0.11	0.21	0.04	**0.51** (0.44 0.59)	0.04	0.08	0.00
ENT	**0.72** (0.48 0.86)	0.39	0.76	13.91	**0.64** (0.37 0.81)	0.56	1.10	17.18
L	0.21 (0.08 0.78)	8.32	16.30	82.74	0.45 (0.26 0.69)	6.88	13.50	94.11

Moderate to high correlations with $0.5 < \alpha < 0.89$ is shown in bold. RQA: recurrence quantification analysis, α: Cronbach's alpha, SEM: standard error of measurement, MMDC: minimal metrically detectable change, CV: coefficient of variation.

Table 2. Reliability analysis of the RQA measures in the activities of Si2St (n = 10) and St2Si (n = 18) for *RoomSet2*.

	Si2St				St2Si			
	α (95% CI)	**SEM**	**MMDC**	**CV(%)**	**α (95% CI)**	**SEM**	**MMDC**	**CV(%)**
RR	0.16 (0.08 0.32)	2.04	3.99	25.64	0.25 (-0.1 0.32)	1.40	2.74	19.07
DET	**0.68** (0.33 0.86)	0.45	0.88	0.64	0.29 (0.01 0.35)	0.16	0.31	0.50
ENT	**0.71** (0.48 0.86)	2.23	4.37	5.81	**0.69** (0.37 0.81)	2.56	5.01	6.41
L	**0.55** (0.43 0.88)	10.32	20.22	39.74	0.18 (0.06 0.38)	7.08	13.87	44.31

Moderate to high correlations with $0.5 < \alpha < 0.89$ are shown in bold. RQA: recurrence quantification analysis, α: Cronbach's alpha, SEM: standard error of measurement, MMDC: minimal metrically detectable change, CV: coefficient of variation.

4. Discussion

The relative reliability in terms of the correlation coefficient α indicates a prediction of the correlation between two samples that are drawn randomly from a population. It shows how consistent the components are with the entire measurement.

The higher and significant correlations reported for %DET and ENT suggest that the consistent feature values obtained for %DET and ENT reflect similar repeated body movements for Si2St and St2Si across almost all trials and subjects for the signals recorded in both *RoomSet1* and *RoomSet2*. Hence, the %DET and ENT are the most reliable RQA features for use in the quantification and characterization of Si2St and St2Si body movements in healthy older adults. The %RR proved to be reliable in some cases, and L showed a large spread in values in almost all cases. Hence, both %RR and L are suggested to be unreliable features in the current study. Although the number of experimental trials and subjects can affect changes in the numerical values of the parameters, a larger population might provide a better insight into the reliability of these parameters.

The absolute reliability was found to be higher for the %RR, %DET, and ENT, which was consistent with the relative reliability. The smaller the SEM is, the more precise the measurement capacity of the instrument will be. Overall, the low values for the SEM showed the precision of the RQA measures for the repeated records of the Si2St and St2Si acceleration signals that were acquired using wearable sensing equipment. Consequently, smaller standard errors translated into more sensitive measurements of a state change. The MMDC determined by the SEM in this case represented the minimal changes in the values of %RR, %DET, ENT, and L that corresponded to the lower bound of a clinically significant change in body movement. Consistently low MMDC values were shown for %RR, %DET, and ENT, which means that they represented changes in movement more sensitively. L showed a very high CV, and could hence not be used further, as similarly reported in [45]. These findings suggest that while the sensor used and RQA measures based on the recorded acceleration signals showed acceptable reliability in a clinical or residential room setting, the %DET and ENT were the most reliable nonlinear recurrence features, and they are suggested to be used further for activity and intent recognition algorithms for the early detection of falls according to Si2St and St2Si body movements in healthy older adults.

Different types of features—namely time-domain, [30,31], frequency-domain [25,28,52,64–66], autoregressive [28,29], and biomechanical features, such as the vertical displacement and tilt angle [67], correlation, spectral energy, and maximum and approximate entropy [31]—have been used in the literature, and their authenticity has been proven in terms of their good classification performance in activity and intent recognition. A similar future study on the reliable RQA features reported here can be performed to assess their discrimination capabilities in intent recognition algorithms for different phases of body movements while performing Si2St and St2Si. Since different subjects recorded the test ADL activities in *RoomSet1* (subject ID 1–9) and *RoomSet2* (subject ID 10–14), the test–retest and parallel-form reliability could not be assessed due to the lack of standardization of the test. Furthermore, the number of samples used to compute the statistics was enough for *RoomSet1*, but was not enough for *RoomSet2*. A more comprehensive and standardized test could be performed with larger numbers of repeated measurements, i.e., with a greater sampling size and in different sessions with respect to time or location. In addition, the subjects performing the body movements for this particular study belonged to a healthy older group. In the future, we would like to explore other datasets with subjects that belong to a different age group or that have neurological or physical disorders.

5. Conclusions

The current research presented a relative and absolute reliability analysis of recurrence measures for the characterization of sit-to-stand and stand-to-sit activities in healthy older adults. The reliability statistics indicated a reliable representation in terms of determinism and entropy for acceleration signals that were acquired through wearable sensors with a minimum error of measurement for both the Si2St and St2Si activities; hence, they can be used further for fall risk analysis in older adults while standing or sitting.

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Abbreviations

The following abbreviations are used in this manuscript:

RFID	Radio frequency identification
RQA	Recurrence quantification analysis
Si2St	Sit-to-stand
St2Si	Stand-to-sit
RR	Recurrence rate
DET	Determinism
ENT	Entropy
L	Average diagonal length
FNN	False nearest neighbors

References

1. Kralj, A.; Jaeger, R.J.; Munih, M. Analysis of standing up and sitting down in humans: Definitions and normative data presentation. *J. Biomech.* **1990**, *23*, 1123–1138. [CrossRef]
2. Martinez-Hernandez, U.; Dehghani-Sanij, A.A. Probabilistic identification of sit-to-stand and stand-to-sit with a wearable sensor. *Pattern Recognit. Lett.* **2019**, *118*, 32–41. [CrossRef]
3. Massé, F.; Bourke, A.K.; Chardonnens, J.; Paraschiv-Ionescu, A.; Aminian, K. Suitability of commercial barometric pressure sensors to distinguish sitting and standing activities for wearable monitoring. *Med. Eng. Phys.* **2014**, *36*, 739–744. [CrossRef] [PubMed]
4. Schenkman, M.; Berger, R.A.; Riley, P.O.; Mann, R.W.; Hodge, W.A. Whole-body movements during rising to standing from sitting. *Phys. Ther.* **1990**, *70*, 638–648. [CrossRef]
5. Aggarwal, J.K.; Ryoo, M.S. Human activity analysis: A review. *ACM Comput. Surv.* **2011**, *43*, 1–43. [CrossRef]
6. Mourey, F.; Grishin, A.; d'Athis, P.; Pozzo, T.; Stapley, P. Standing up from a chair as a dynamic equilibrium task: A comparison between young and elderly subjects. *J. Gerontol. Ser. A Biol. Sci. Med. Sci.* **2000**, *55*, B425–B431. [CrossRef] [PubMed]
7. de Morais Faria, C.D.C.; Saliba, V.A.; Teixeira-Salmela, L.F. Musculoskeletal biomechanics in sit-to-stand and stand-to-sit activities with stroke subjects: A systematic review. *Fisioter. Em Mov.* **2010**, *23*, 35–52. [CrossRef]
8. Nuzik, S.; Lamb, R.; VanSant, A.; Hirt, S. Sit-to-stand movement pattern: A kinematic study. *Phys. Ther.* **1986**, *66*, 1708–1713. [CrossRef]
9. Cadore, E.L.; Izquierdo, M. New strategies for the concurrent strength-, power-, and endurance-training prescription in elderly individuals. *J. Am. Med. Dir. Assoc.* **2013**, *14*, 623–624. [CrossRef]
10. Cadore, E.L.; Rodríguez-Mañas, L.; Sinclair, A.; Izquierdo, M. Effects of different exercise interventions on risk of falls, gait ability, and balance in physically frail older adults: A systematic review. *Rejuvenation Res.* **2013**, *16*, 105–114. [CrossRef]
11. Cadore, E.L.; Casas-Herrero, A.; Zambom-Ferraresi, F.; Idoate, F.; Millor, N.; Gómez, M.; Rodriguez-Mañas, L.; Izquierdo, M. Multicomponent exercises including muscle power training enhance muscle mass, power output, and functional outcomes in institutionalized frail nonagenarians. *Age* **2014**, *36*, 773–785. [CrossRef] [PubMed]
12. Aissaoui, R.; Dansereau, J. Biomechanical analysis and modelling of sit to stand task: A literature review. In Proceedings of the IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 99CH37028), Tokyo, Japan, 12–15 October 1999; Volume 1, pp. 141–146.
13. Deandrea, S.; Lucenteforte, E.; Bravi, F.; Foschi, R.; La Vecchia, C.; Negri, E. Risk factors for falls in community-dwelling older people: A systematic review and meta-analysis. *Epidemiology* **2010**, *21*, 658–668. [CrossRef] [PubMed]
14. Tinetti, M.E. Preventing falls in elderly persons. *N. Engl. J. Med.* **2003**, *348*, 42–49. [CrossRef]

15. Tinetti, M.E.; Williams, C.S. Falls, injuries due to falls, and the risk of admission to a nursing home. *N. Engl. J. Med.* **1997**, *337*, 1279–1284. [CrossRef] [PubMed]
16. Schultz, A.B.; Alexander, N.B.; Ashton-Miller, J.A. Biomechanical analyses of rising from a chair. *J. Biomech.* **1992**, *25*, 1383–1391. [CrossRef]
17. Bernardi, M.; Rosponi, A.; Castellano, V.; Rodio, A.; Traballesi, M.; Delussu, A.; Marchetti, M. Determinants of sit-to-stand capability in the motor impaired elderly. *J. Electromyogr. Kinesiol.* **2004**, *14*, 401–410. [CrossRef] [PubMed]
18. Doulah, A.; Shen, X.; Sazonov, E. A method for early detection of the initiation of sit-to-stand posture transitions. *Physiol. Meas.* **2016**, *37*, 515. [CrossRef]
19. Wolf, K.H.; Hetzer, K.; Zu Schwabedissen, H.; Wiese, B.; Marschollek, M. Development and pilot study of a bed-exit alarm based on a body-worn accelerometer. *Z. Gerontol. Geriatr.* **2013**, *46*, 727–733. [CrossRef]
20. Ganea, R.; Paraschiv-Ionescu, A.; Büla, C.; Rochat, S.; Aminian, K. Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people. *Med. Eng. Phys.* **2011**, *33*, 1086–1093. [CrossRef]
21. Janssen, W.G.; Kulcu, D.G.; Horemans, H.L.; Stam, H.J.; Bussmann, J.B. Sensitivity of accelerometry to assess balance control during sit-to-stand movement. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2008**, *16*, 479–484. [CrossRef]
22. Janssen, W.G.; Bussmann, J.B.; Horemans, H.L.; Stam, H.J. Validity of accelerometry in assessing the duration of the sit-to-stand movement. *Med. Biol. Eng. Comput.* **2008**, *46*, 879–887. [CrossRef] [PubMed]
23. Pozaic, T.; Lindemann, U.; Grebe, A.K.; Stork, W. Sit-to-Stand Transition Reveals Acute Fall Risk in Activities of Daily Living. *IEEE J. Transl. Eng. Health Med.* **2016**, *4*. [CrossRef]
24. Ejupi, A.; Brodie, M.; Lord, S.R.; Annegarn, J.; Redmond, S.J.; Delbaere, K. Wavelet-Based Sit-To-Stand Detection and Assessment of Fall Risk in Older People Using a Wearable Pendant Device. *IEEE Trans. Biomed. Eng.* **2017**, *64*, 1602–1607. [CrossRef] [PubMed]
25. Torres, R.L.S.; Ranasinghe, D.C.; Shi, Q. Evaluation of wearable sensor tag data segmentation approaches for real time activity classification in elderly. In Proceedings of the International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services, Tokyo, Japan, 2–4 December 2013; Springer: Cham, Switzerland, 2013; pp. 384–395.
26. Penatti, O.A.; Santos, M.F. Human activity recognition from mobile inertial sensors using recurrence plots. *arXiv* **2017**, arXiv:1712.01429.
27. Capela, N.A.; Lemaire, E.D.; Baddour, N. Improving classification of sit, stand, and lie in a smartphone human activity recognition system. In Proceedings of the 2015 IEEE International Symposium on Medical Measurements and Applications (MeMeA) Proceedings, Turin, Italy, 7–9 May 2015; pp. 473–478.
28. Wickramasinghe, A.; Ranasinghe, D.C. Recognising activities in real time using body worn passive sensors with sparse data streams: To interpolate or not to interpolate? In Proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, Coimbra, Portugal, 22–24 July 2016; pp. 21–30. [CrossRef]
29. Khan, A.M.; Lee, Y.K.; Lee, S.Y.; Kim, T.S. A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. *IEEE Trans. Inf. Technol. Biomed.* **2010**, *14*, 1166–1172. [CrossRef] [PubMed]
30. Bao, L.; Intille, S.S. Activity recognition from user-annotated acceleration data. In Proceedings of the International Conference on Pervasive Computing, Vienna, Austria, 21–23 April 2004; Springer: Berlin/Heidelberg, Germany, 2004; pp. 1–17.
31. Ravi, N.; Dandekar, N.; Mysore, P.; Littman, M.L. Activity recognition from accelerometer data. In Proceedings of the Twentieth National Conference on Artificial Intelligence and the Seventeenth Innovative Applications of Artificial Intelligence Conference, Pittsburgh, PA, USA, 9–13 July 2005; Volume 5, pp. 1541–1546.
32. Parlitz, U. Nonlinear time-series analysis. In *Nonlinear Modeling*; Springer: Berlin/Heidelberg, Germany, 1998; pp. 209–239.
33. Riley, M.; Balasubramaniam, R.; Turvey, M. Recurrence quantification analysis of postural fluctuations. *Gait Posture* **1999**, *9*, 65–78. [CrossRef]
34. Marwan, N.; Romano, M.C.; Thiel, M.; Kurths, J. Recurrence plots for the analysis of complex systems. *Phys. Rep.* **2007**, *438*, 237–329. [CrossRef]
35. Webber, C.; Marwan, N. Recurrence quantification analysis. In *Theory and Best Practices*; Springer: Cham, Switzerland, 2015.
36. Ramdani, S.; Tallon, G.; Bernard, P.L.; Blain, H. Recurrence quantification analysis of human postural fluctuations in older fallers and non-fallers. *Ann. Biomed. Eng.* **2013**, *41*, 1713–1725. [CrossRef]
37. Anderson, N.C.; Bischof, W.F.; Laidlaw, K.E.; Risko, E.F.; Kingstone, A. Recurrence quantification analysis of eye movements. *Behav. Res. Methods* **2013**, *45*, 842–856. [CrossRef]
38. Gurtner, L.M.; Bischof, W.F.; Mast, F.W. Recurrence quantification analysis of eye movements during mental imagery. *J. Vis.* **2019**, *19*, 1–17. [CrossRef]
39. Fragkou, A.D.; Karakasidis, T.E.; Nathanail, E. Detection of traffic incidents using nonlinear time series analysis. *Chaos* **2018**, *28*, 063108. [CrossRef]
40. Santos, B.R.; Delisle, A.; Larivière, C.; Plamondon, A.; Imbeau, D. Reliability of centre of pressure summary measures of postural steadiness in healthy young adults. *Gait Posture* **2008**, *27*, 408–415. [CrossRef]
41. Green, S.B.; Yang, Y.; Alt, M.; Brinkley, S.; Gray, S.; Hogan, T.; Cowan, N. Use of internal consistency coefficients for estimating reliability of experimental task scores. *Psychon. Bull. Rev.* **2016**, *23*, 750–763. [CrossRef]
42. Varghese, R.; Hui-Chan, C.W.; Wang, E.; Bhatt, T. Internal consistency and test-retest reliability of an instrumented functional reaching task using wireless electromyographic sensors. *J. Electromyogr. Kinesiol.* **2014**, *24*, 593–600. [CrossRef] [PubMed]
43. Cronbach, L.J. Coefficient alpha and the internal structure of tests. *Psychometrika* **1951**, *16*, 297–334. [CrossRef]

44. Cronbach, L.J.; Shavelson, R.J. My current thoughts on coefficient alpha and successor procedures. *Educ. Psychol. Meas.* **2004**, *64*, 391–418. [CrossRef]
45. Mazaheri, M.; Negahban, H.; Salavati, M.; Sanjari, M.A.; Parnianpour, M. Reliability of recurrence quantification analysis measures of the center of pressure during standing in individuals with musculoskeletal disorders. *Med. Eng. Phys.* **2010**, *32*, 808–812. [CrossRef] [PubMed]
46. van Lummel, R.C.; Walgaard, S.; Maier, A.B.; Ainsworth, E.; Beek, P.J.; van Dieën, J.H. The Instrumented Sit-to-Stand Test (iSTS) has greater clinical relevance than the manually recorded sit-to-stand test in older adults. *PLoS ONE* **2016**, *11*, e0157968. [CrossRef] [PubMed]
47. Torres, R.L.S.; Ranasinghe, D.C.; Shi, Q.; Sample, A.P. Sensor enabled wearable RFID technology for mitigating the risk of falls near beds. In Proceedings of the 2013 IEEE International Conference on RFID (RFID), Orlando, FL, USA, 30 April–2 May 2013; pp. 191–198.
48. Roberto, L.S.T.; Damith, R. Activity Recognition with Healthy Older People Using a Batteryless Wearable Sensor. 2016. Available online: https://archive.ics.uci.edu/ml/datasets/Activity+recognition+with+healthy+older+people+using+a+batteryless+wearable+sensor (accessed on 23 June 2021).
49. Dua, D.; Graff, C. Irvine, CA: University of California, School of Information and Computer Science *UCI Machine Learning Repository*. 2017. Available online: https://archive.ics.uci.edu/ml/citation_policy.html (accessed on 30 September 2021).
50. Kaufmann, T.; Ranasinghe, D.C.; Zhou, M.; Fumeaux, C. Wearable quarter-wave folded microstrip antenna for passive UHF RFID applications. *Int. J. Antennas Propag.* **2013**, *2013*, 129839. [CrossRef]
51. Janssen, W.G.; Bussmann, J.B.; Horemans, H.L.; Stam, H.J. Analysis and decomposition of accelerometric signals of trunk and thigh obtained during the sit-to-stand movement. *Med. Biol. Eng. Comput.* **2005**, *43*, 265–272. [CrossRef]
52. Doheny, E.P.; Walsh, C.; Foran, T.; Greene, B.R.; Fan, C.W.; Cunningham, C.; Kenny, R.A. Falls classification using tri-axial accelerometers during the five-times-sit-to-stand test. *Gait Posture* **2013**, *38*, 1021–1025. [CrossRef] [PubMed]
53. Millor, N.; Lecumberri, P.; Gomez, M.; Martinez-Ramirez, A.; Izquierdo, M. Kinematic parameters to evaluate functional performance of sit-to-stand and stand-to-sit transitions using motion sensor devices: A systematic review. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2014**, *22*, 926–936. [CrossRef] [PubMed]
54. Taslim Reza, S.M.; Ahmad, N.; Choudhury, I.A.; Ghazilla, R.A.R. A fuzzy controller for lower limb exoskeletons during sit-to-stand and stand-to-sit movement using wearable sensors. *Sensors* **2014**, *14*, 4342–4363. [CrossRef] [PubMed]
55. Carter, R.; Lubinsky, J. *Rehabilitation Research: Principles and Applications*; Elsevier: Amsterdam, The Netherlands, 2015.
56. Cao, L. Practical method for determining the minimum embedding dimension of a scalar time series. *Phys. D Nonlinear Phenom.* **1997**, *110*, 43–50. [CrossRef]
57. Rosenstein, M.T.; Collins, J.J.; De Luca, C.J. Reconstruction expansion as a geometry-based framework for choosing proper delay times. *Phys. D Nonlinear Phenom.* **1994**, *73*, 82–98. [CrossRef]
58. Tavakol, M.; Dennick, R. Making sense of Cronbach's alpha. *Int. J. Med. Educ.* **2011**, *2*, 53. [CrossRef]
59. Kellar, S.P.; Kelvin, E.A. *Munro's Statistical Methods for Health Care Research*; Wolters Kluwer Health/Lippincott Williams & Wilkins: Philadelphia, PA, USA, 2013.
60. Munro, C.A. The development of a pressure ulcer risk-assessment scale for perioperative patients. *Aorn J.* **2010**, *92*, 272–287. [CrossRef]
61. Atkinson, G.; Nevill, A.M. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Med.* **1998**, *26*, 217–238. [CrossRef]
62. Donoghue, O.A.; Savva, G.M.; Börsch-Supan, A.; Kenny, R.A. Reliability, measurement error and minimum detectable change in mobility measures: A cohort study of community-dwelling adults aged 50 years and over in Ireland. *BMJ Open* **2019**, *9*, e030475. [CrossRef] [PubMed]
63. Corriveau, H.; Hébert, R.; Prince, F.; Raîche, M. Intrasession reliability of the "center of pressure minus center of mass" variable of postural control in the healthy elderly. *Arch. Phys. Med. Rehabil.* **2000**, *81*, 45–48. [PubMed]
64. He, Z.; Jin, L. Activity recognition from acceleration data based on discrete cosine transform and SVM. In Proceedings of the 2009 IEEE International Conference on Systems, Man and Cybernetics, San Antonio, TX, USA, 11–14 October 2009; pp. 5041–5044.
65. Muhammad, S.A.; Klein, B.N.; Van Laerhoven, K.; David, K. A feature set evaluation for activity recognition with body-worn inertial sensors. In Proceedings of the International Joint Conference on Ambient Intelligence, Amsterdam, The Netherlands, 16–18 November 2011; Springer: Berlin/Heidelberg, Germany, 2011; pp. 101–109.
66. Shinmoto Torres, R.L.; Visvanathan, R.; Hoskins, S.; Van den Hengel, A.; Ranasinghe, D.C. Effectiveness of a batteryless and wireless wearable sensor system for identifying bed and chair exits in healthy older people. *Sensors* **2016**, *16*, 546. [CrossRef]
67. Najafi, B.; Aminian, K.; Paraschiv-Ionescu, A.; Loew, F.; Bula, C.J.; 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*, 711–723. [CrossRef] [PubMed]