



Body postural sway analysis in older people with different fall histories

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Received: 2 March 2017 / Accepted: 16 September 2018 / Published online: 26 September 2018

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Abstract

A cross-sectional study of postural sway analysis in older non-fallers, once-fallers and multiple-fallers using five common standing tests was conducted. Eighty-six older subjects with an average age of 80.4 years ($SD \pm 7.9$) participated in the study. The angular rotation and velocity of the trunk of the participants in the roll (lateral) and pitch (sagittal) planes were recorded using an inertial sensor mounted on their lower backs. The Gaussian Mixture Models (GMM), Expectation-Maximisation (EM) and the Minimum Message Length (MML) algorithms were applied to the acquired data to obtain an index indicative of the body sway. The standing with feet together and standing with one foot in front, sway index distinguished older fallers from non-fallers with specificity of 75.7% and 77.7%, respectively, and sensitivity of 78.6% and 82.1%, respectively. This compares favourably with the Berg Balance Scales (BBS) with specificity of 70.5% and sensitivity of 75.3%. The results suggest that the proposed method has potential as a protocol to diagnose balance disorder in older people.

Keywords Older people · Postural sway analysis · Balance assessment · Inertial sensor

1 Introduction

Under conditions of quiet standing, the human body naturally sways. However, sway can increase as the result of age or disease [1, 2]. The postural body sway in older people has been examined in many studies. For example, in a study conducted by Fernie et al. [3], significantly greater average speed of sway in older fallers compared with that in non-fallers is

reported. In a study by Melzer et al. [4], no significant difference in body sway whilst standing with feet wide apart was observed. However, an increase in mediolateral sway was identified for a narrow stance among the older subjects with fall histories. Laughton et al. [5] report a significantly higher degree of sway in the anteroposterior direction in older subjects with fall histories whilst standing still. This is supported by an earlier study by Maki et al. [6].

Many studies express sway as the displacements of the coordinates of the Centre of Pressure (CoP), usually determined by the utilisation of force platforms [7–9]. In a study by Ladislao and Fioretti [10], anteroposterior displacements of the CoP were recorded by force platforms and the nature of obtained data is later analysed with a nonlinear determinism test. In another study, by Rocchi et al. [11], the most sensitive features of the COP trajectory to postural performance were identified using force platforms.

In recent studies, inertial measurement units (IMU) have been widely utilised in biomechanics and bioengineering fields. The IMUs can be used for movement analysis of the daily-living tasks performed in the real-world environments whilst the force platforms provide information on the simulated activities in a clinical environment [12]. Inertial sensors are used for balance assessment among older people and there are several review papers summarising advances made in this field [13, 14].

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Gill et al. [15] analysed trunk sway by measuring trunk angular velocity and position in the anteroposterior and mediolateral directions using an inertial sensor. Compared to both young and middle-aged subjects, the older subjects recorded greater angular sway of the trunk and greater angular velocity in both anteroposterior and mediolateral directions whilst standing.

The present study is aimed at developing a method to score the body sway in different standing conditions in older people with different fall histories. An inertial sensor was utilised for postural sway analysis. The protocol used included all of the static tests of the Berg Balance Scale (BBS) [16]. The tasks consisted of standing with eyes open, standing with eyes closed, standing with feet together, standing with one foot in front of the other and where possible, standing on one foot. Using the data produced by the sensor, the angular displacement and velocity of the trunk for a range of subjects in different tests were measured and analysed. Based on the analysis, a single value for each subject in each test was defined as the sway index. The BBS provided by a clinician was used as a comparative balance measurement.

The remainder of this paper is structured as follows. The experimental design and data acquisition process are presented in Section 2. The data analysis algorithms, methods and the proposed method of body sway assessment are presented in Section 3. The results of the experimental work are provided in Section 4. Some conclusions are drawn in Section 5 and potential future work is discussed.

2 Methods

2.1 Participants

In total, 101 older subjects aged 61–95 were recruited for this study. The subjects were older adults who were referred to two local hospitals (Bulli Hospital, Wollongong Hospital) for either annual health check-up or senility issues. Ten participants were excluded because of their frailty and poor balance, and the data recorded for five participants were excluded because of technical problems. In total, 86 participants who met the following recruitment criteria were included in the final analysis: (a) able to stand for at least 2 min independently, (b) able to hear and understand instructions.

Based on the fall histories of the participants, they were categorised into three groups: non-fallers, once-fallers and multiple fallers.

2.2 Experimental tests and protocol

The primary aim of the study was to measure the spontaneous body sway. In this case, the standing tests from Berg balance protocol were used. The following five standing tests were conducted:

- Standing with eyes open test: In this test, subjects were required to stand without any extra movements for 2 min, look straight ahead and keep their hands at their sides.
- Standing with eyes closed: The participants stood quietly with eyes closed for 30 s.
- Standing on one foot: Subjects were asked to stand on one foot (whichever at their convenience) for 10 s without holding. Although the initial target was 30 s, none of the participants could stand on one foot for more than 10 s.
- Standing with feet together for 1 min.
- Standing with one foot in front of the other: Subjects placed one foot in front of the other with one heel touching the toes of the other foot for 1 min.

All of the subjects were given appropriate rest periods of up to 10 min after each test so that the subsequent test was not affected by fatigue. During the tests, the subjects were asked to try to maintain their balance without any extra movements, look straight ahead and keep their hands at their sides. An attending physiotherapist supervised all the tests to prevent any possible accident. The physiotherapist also assessed each subject's balance using the BBS protocol.

2.3 Motion capture

In this study, we utilised an inertial 3D motion sensor (MTw from Xsens technology) mounted directly above the pelvis in the back lumbar region (Fig. 1).

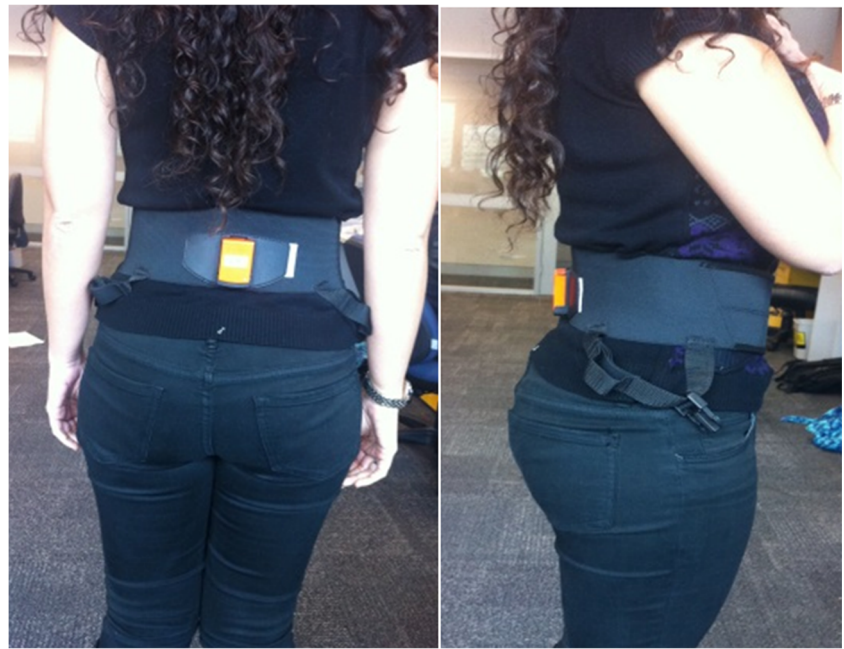
The sampling rate was 50 Hz. The data was transmitted wirelessly to a computer and the recorded data for each test was subsequently analysed with Matlab. To minimise the influence of any idiosyncratic body movement at the start and termination of each task, the first and the last seconds of the recorded data were not included in the data analysis.

2.4 Analysis

The angular displacement and velocity in two planes of roll and pitch (mediolateral and anteroposterior) were recorded as illustrated in Fig. 2.

In Figs. 3 and 4, representative examples of orientation angle of the trunk and its angular velocity are shown, respectively. According to Fig. 3, the multiple-faller has higher mediolateral trunk sway compared to the non-faller whilst standing with feet together. In Fig. 4, an increase in the sway velocity of the roll and pitch directions for the feet together

Fig. 1 The MTw motion sensor was worn at the pelvis level in the lumbar region of the back



and one foot in front standing tasks in the older multiple-faller can be observed.

The data obtained from the sensor was arranged in a matrix of four columns of the angular displacement in the roll plane (AD_r), the angular displacement in the pitch plane (AD_p), the angular velocity in the roll plane (AV_r) and the angular velocity in the pitch plane (AV_p) (Eq. 1).

$$[AD_r, AD_p, AV_r, AV_p] \tag{1}$$

Clustering was subsequently applied to the recorded data, as a form of unsupervised learning and data reduction protocol, in order to identify meaningful patterns and associated structures within the data. Clustering is useful in interpreting

data with high dimensionality [17]. The combined multivariate data recorded for all subjects across all the standing tests was employed to develop a global machine-learned Gaussian Mixture Model (GMM). The process of clustering the data and the establishment of the best set of clusters in terms of how well they fit or represent the data (the suitable number of clusters) was conducted at the same time. This process was determined based on an EM-MML algorithm utilising the Expectation-Maximisation (EM) and the Minimum Message Length (MML) algorithms [18]. Expectation-Maximisation is an iterative algorithm, which alternates between two steps; the expectation step (E-step) and the maximisation step (M-step). It assigns each datum to a Gaussian probability density with a maximum probability.

A GMM can be defined as a parametric probability density function, represented as a weighted sum of Gaussian component densities. The probability distribution can be described by:

$$p(x) = \sum_{i=1}^K \pi_i N(x|\mu_i, \Sigma_i) \tag{2}$$

Where $N(x|\mu_i, \Sigma_i)$ is the multivariate Gaussian Probability Density Function (PDF) with mean $\mu_i \in R^d$ and a covariance $\Sigma_i \in R^{d \times d}$ for a model of K clusters evaluated at data vector x_n [19].

Here, the number of clusters (K) is identified using MML, which is based on the minimal coding length of combined model and data representations [20]. From information theory, the minimum coding length of any message is given by Eq. 3:

$$L(E) = -\log(P(E)) \tag{3}$$

where E is the data, and H is a probable hypothesis.

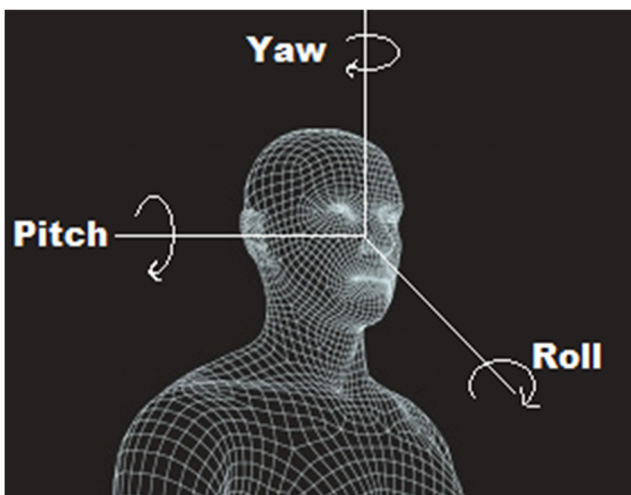


Fig. 2 Yaw, roll and pitch rotations of the human body. Roll and pitch angles are indicative of sway respectively in left-right and forward-backward planes

Fig. 3 Representative examples of the trunk angle orientation of a multiple-faller and a non-faller whilst standing with eyes open and standing with feet together

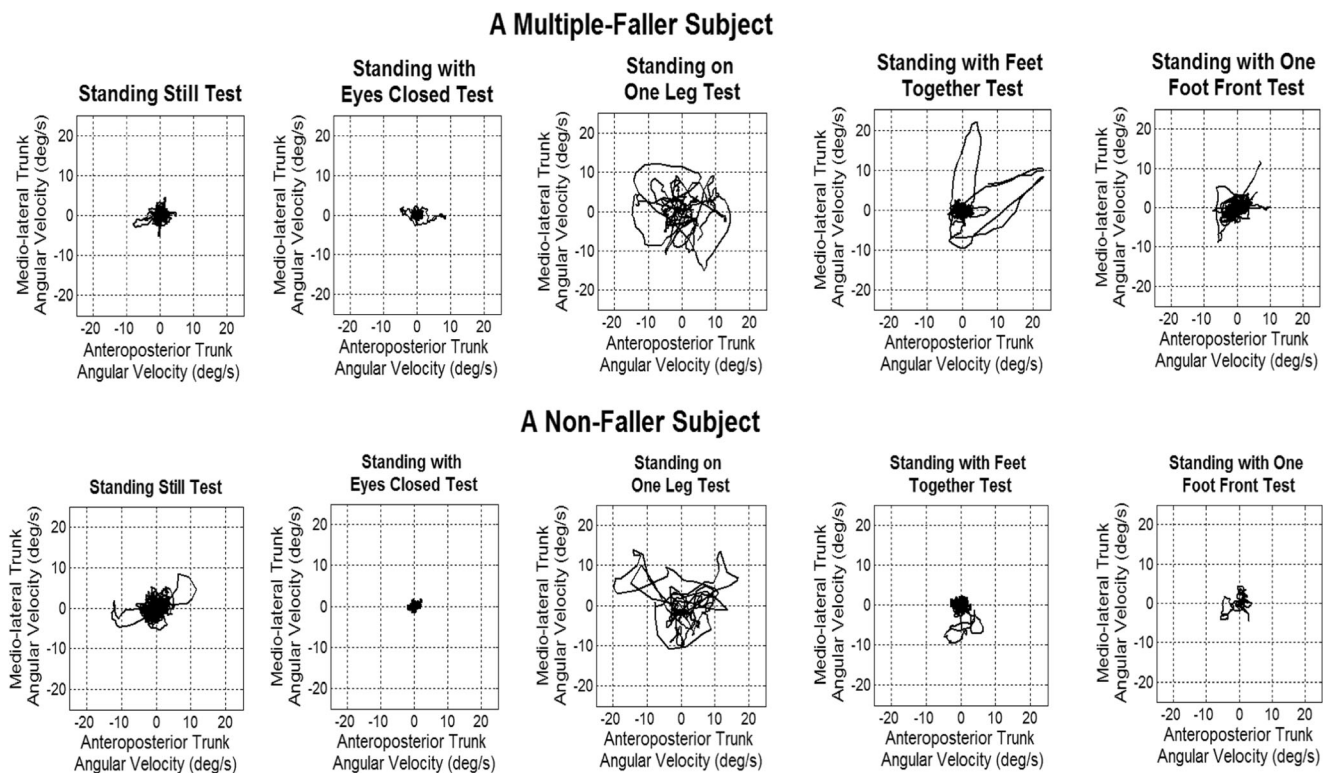
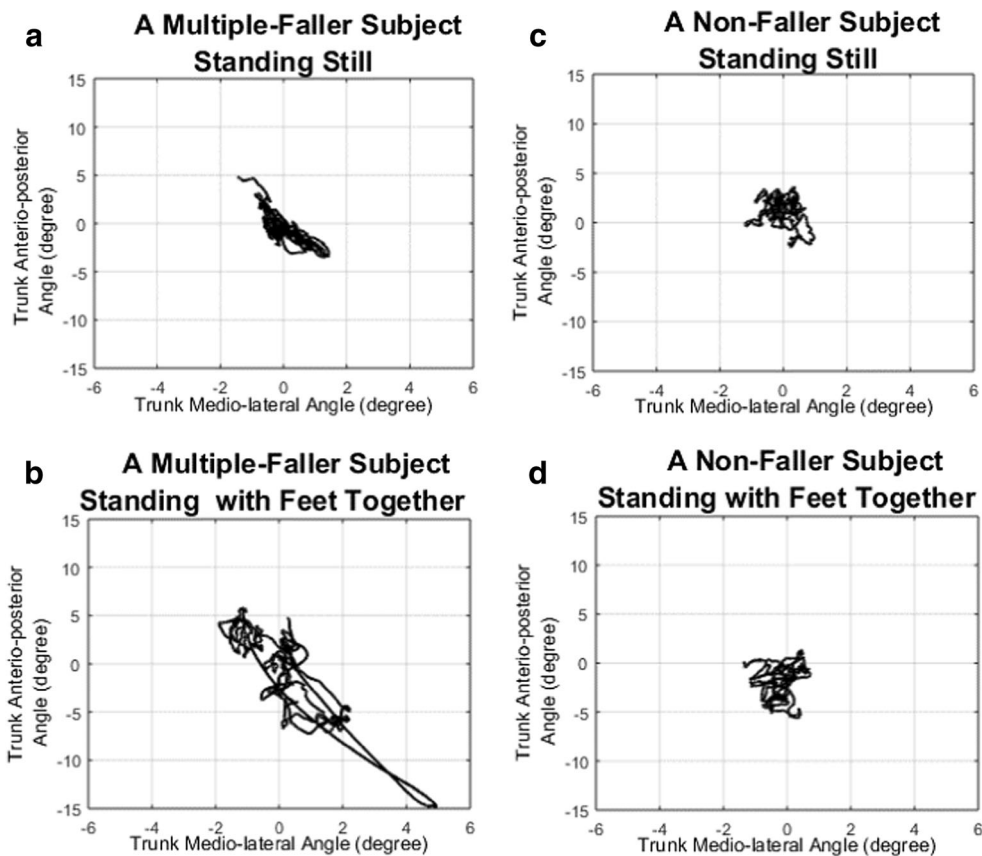


Fig. 4 Typical examples of angular velocity of the trunk of a multiple-faller and a non-faller in all the standing tests. An increase in the sway velocity in the roll and pitch directions for the feet together and one foot in front standing tasks in the older multiple-faller can be observed

$$P(E|H) \cdot P(H) = P(H \cap E) \tag{4}$$

Maximising the probability that the evidence supports the hypothesis is equivalent to minimising the message length.

$$\operatorname{argmax} P(H \cap E) = \operatorname{argmin} \left(-\log(P(E|H)) - \log(P(H)) \right) \tag{5}$$

Equations (4) and (5) model some of the probabilistic segmentation processes that are facilitated within the EM-MML algorithm [20]. Indeed, as E in Eqs. (3–5) represents the motion data, H is the hypothesised cluster to that E most likely belongs. The MML algorithm continues the segmentation process seeking the best cluster set which yields the shortest message length. A reasonable balance point is found, i.e. a minimal sufficiency between the number of clusters and the message length [21]. The parameter K is increased until there is a negligible improvement in message length reduction as indicated in Fig. 5.

The algorithm was controlled and run in Matlab. Using this approach, the multivariate time series data was progressively segmented into a series of gradually improving GMMs, each composed of a specific set of elements or clusters. This process continued until the rate of improvement or the reduction in the MML message length plateaued. Using this process, the near-optimum GMM was identified as a set of some six postural states (or clusters).

The temporal sequence of these postural states corresponds to a subject’s sway motion. Some examples are provided in Fig. 6 for three subjects undertaking the standing tests.

As shown in the various subplots of Fig. 6, most of the postural states are aligned with cluster 6. This cluster (postural state) is the most abundant, or the most common, to all subjects, as it represents the bulk of the multivariable data. In the context of sway, this cluster also indicates that the pelvis is at a stationary position at the origin of the coordinate frame. Any data outside this cluster can be viewed as resulting from involuntary movements at the pelvis or, in other words, postural

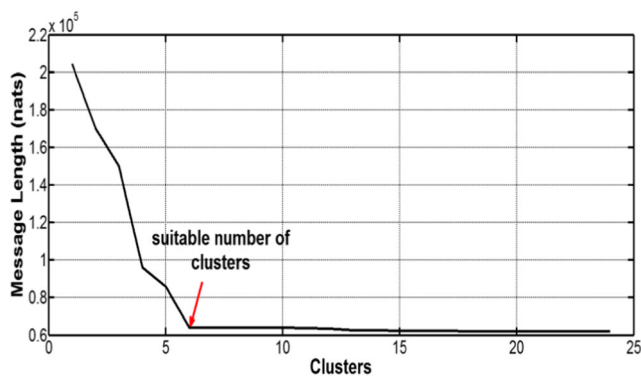


Fig. 5 Selection of number of clusters using MML. The near-optimum GMM was identified as a set of some six postural states (or clusters)

sway. The body motion primitive pose can be observed using the mean of the Gaussian mixtures (Fig. 7).

In order to compare each participant’s sway based on these postural states or data clustering, we propose a sway index, as defined by Eq. 6.

$$\text{Sway Index} = \frac{(N_d - N_c)}{N_d} \tag{6}$$

Where N_d is the number of all data samples, and N_c is the number of data in the common cluster (in the example above, cluster number 6). The sway index is presented as a percentage.

3 Results

3.1 Non-fallers versus fallers

We were not able to analyse body sway in the one-legged stance test, as 47 out of the 86 participants could not undergo the task for 10 s. The other standing sway indices and the BBS for the three groups are shown in Table 1.

There are statistically significant differences between participant groups as determined by one-way analysis of variance (ANOVA) in the standing with feet together sway index ($F(2, 83) = 42.45, p < 0.001$), the standing with one foot front sway index ($F(2, 83) = 36.03, p < 0.001$) and the BBS ($F(2, 83) = 42.45, p < 0.001$). No statistically significant differences are found between the standing with eyes open and the standing with eyes closed sway index of the different groups.

A Tukey post hoc test shows that the standing with one foot in front sway index is significantly smaller in older non-fallers ($M = 37.09\%$, $SD = 7.07\%$) compared to older once-fallers ($M = 47.70\%$, $SD = 560\%$, $p < 0.001$) and older multiple-fallers ($M = 51.78\%$, $SD = 9.04\%$, $p < 0.001$). No statistically significant difference is found between the standing with one foot in front sway index of older non-fallers and older once-fallers.

Older non-fallers have a statistically smaller standing with feet together sway index ($M = 39.34\%$, $SD = 14.56\%$) compared to older once-fallers ($M = 51.13\%$, $SD = 20.40\%$, $p = 0.02$) and older multiple-fallers ($M = 58.99\%$, $SD = 10.5\%$, $p < 0.001$). No statistically significant difference is found between the older once-fallers and older multiple-fallers standing with one foot in front sway index.

3.2 Correlation with BBS

The BBS was inversely correlated with the sway index when standing with feet together ($r = -0.609, p < 0.001$) and when standing with one foot in front ($r = -0.667, p < 0.001$). Small negative correlations were found between the BBS and the

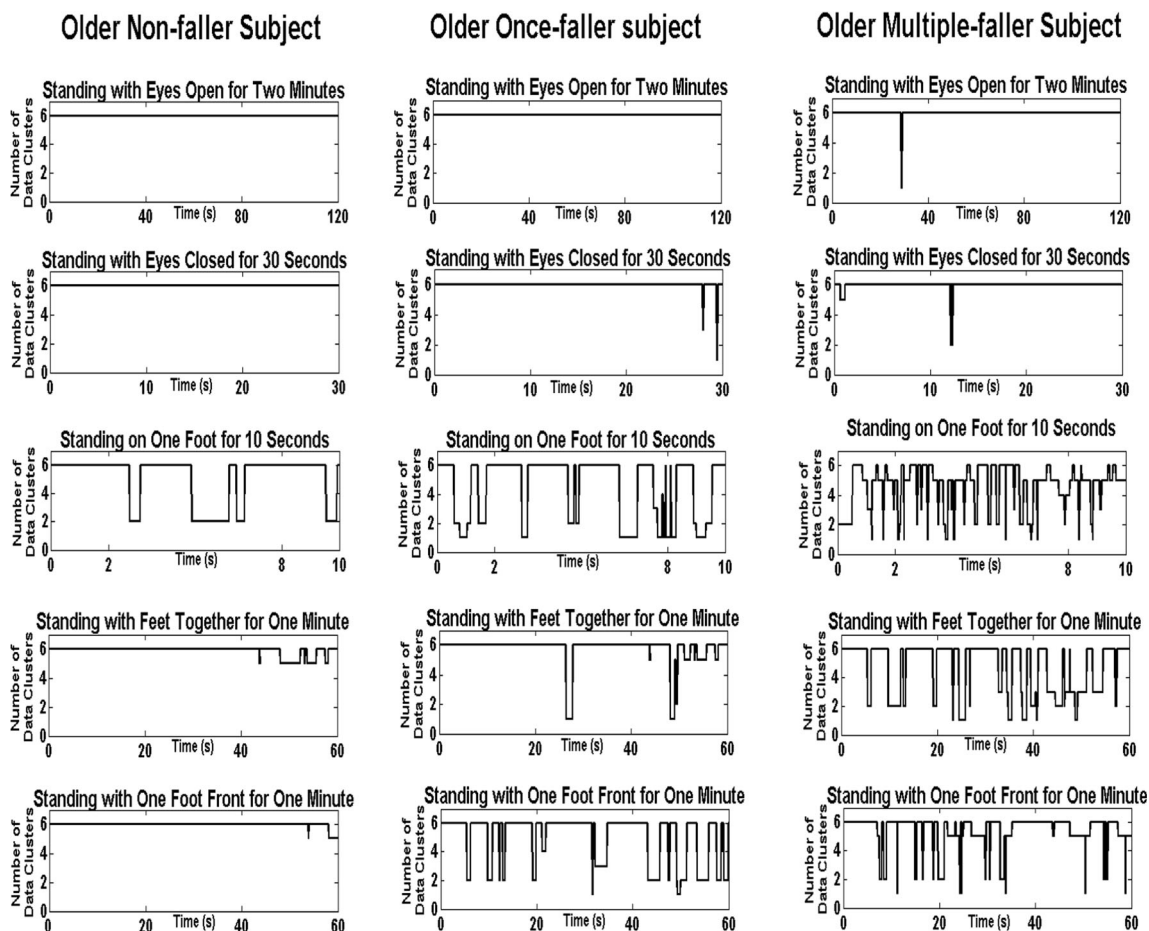


Fig. 6 Data clustering of the multivariate data of the trunk of an older non-faller, an older once-faller and an older multiple-faller participant whilst undergoing the different standing tests. The data is classified into six different clusters

sway index when standing with eyes open ($r = -0.255$, $p = 0.001$), and standing with eyes closed ($r = -0.231$, $p = 0.002$).

4 Discussion

The present study illustrates how postural sway can be analysed using an inertial sensor. The sensor proved to be lightweight, did not hinder the subject's natural freedom of movement and was easy and fast to set up. In addition, the inertial-based sway analysis technique was highly portable, as it utilised wireless communications to transfer the acquired data. Most of the other techniques employed to analyse body sway use force platforms to investigate the movements of the CoP [22]. Using a force platform, the body motion is often assumed as an inverted pendulum, although this assumption is rejected by some studies [15] [23]. Force platforms generally require a significant amount of space and associated infrastructure, and are not usually portable. This makes their deployment rather limited in a clinical environment [24].

In this study, a multivariable matrix of angular displacement and angular velocity data was recorded and subsequently transformed with an EM-MML algorithm into a GMM containing a univariate set of clusters. The EM-MML algorithm integrated estimation and model selection in a single algorithm that computationally outperformed other well-known criteria such as the Bayesian Information Criterion (BIC) [19]. Using data segmentation, a single index was proposed as the sway metric in each standing test for all participants.

The experimental tests consisted of standing with eyes open, standing with eyes closed, standing on one leg, standing with one foot in front of the other and standing with feet together.

For every standing test, statistical methods were used to compare the results for different groups of subjects (non-fallers, once-fallers and multiple-fallers). In two tests of standing with feet together and standing with one foot in front, multiple-fallers and once-fallers had a significantly larger sway index compared to non-fallers.

In the normal standing with eyes open test, we could not identify any significant difference between non-fallers, once-fallers and multiple-fallers. In the work by Melzer et al. [4], no

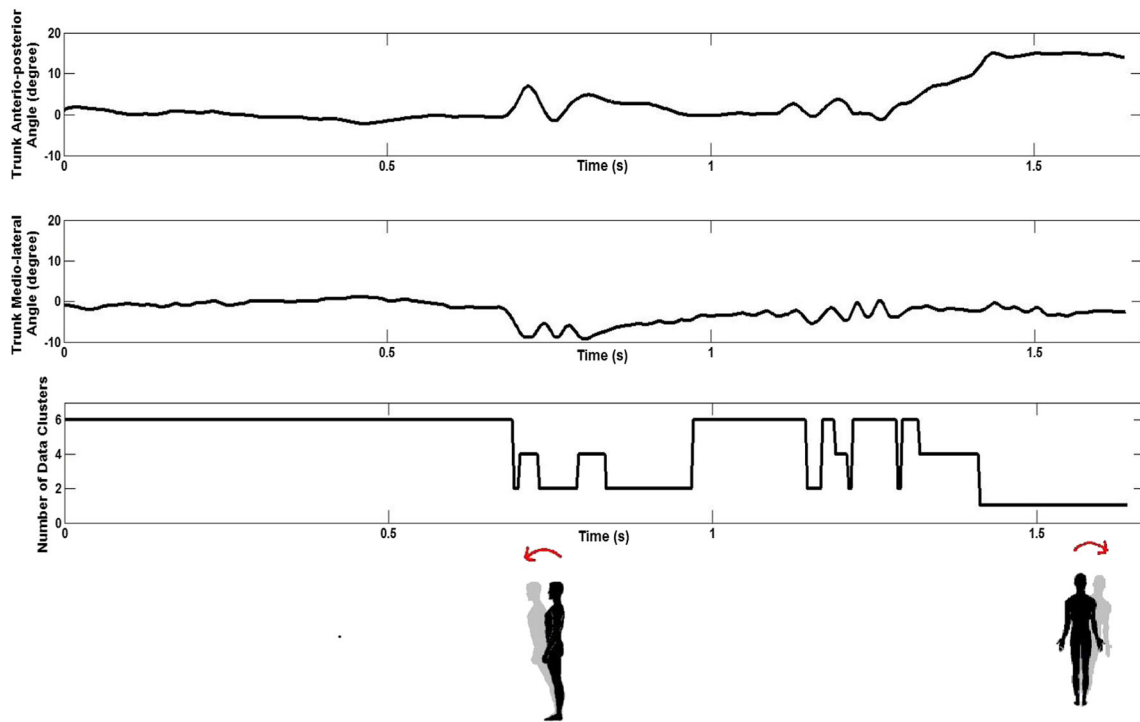


Fig. 7 A typical example of identified motion states or data clusters and the corresponding mediolateral and anteroposterior angular displacement. In the context of sway, cluster 6 indicates that the pelvis is at a stationary position at the origin of the coordinate frame

significant difference was identified in the postural stability of the different groups of young, middle-aged and older subjects. Some other studies, however, found contrary results [5].

In the standing with feet together and standing with one-foot front tests, the sway index of older non-fallers was significantly smaller than the sway index of once-fallers and multiple-fallers. Whilst standing with one foot in front, subjects tended to sway more in the mediolateral direction. A narrow stance was also reported to be a good test for postural balance deficiency analysis [4, 22]. No significant difference was found between the sway index of older once-fallers and older multiple-fallers in these tests. This could be because of the repetitive nature of falls in older people. Those who have fallen once are at the risk of further falls and 52% of such individuals fall again in the following 12 months [25].

In this study, the standing with eyes closed test was not found to effectively distinguish between older fallers and older non-fallers. Similarly, Brocklehurst et al. [26] did not find such correlation between vision and postural sway.

In our experimental work, the standing on one foot test proved impractical, as many participants were not confident enough to attempt it for fear of losing their balance. As the body support base significantly reduces when standing on one foot, maintaining one’s centre of gravity with a single supporting leg is difficult. In a study by Potvin et al. [27], the one-legged stance test was found to be the most sensitive standing test concerning age. However, we were not able to analyse body sway in the one-legged stance test as 47 out of the 86 participants either could not undertake the test or declined for fear of falling. Fear of falling is the main psychological factor among older people and leads to increased risks of falling [28]. In a study by Era and Heikkinen [29], only 41% of the aged group could perform the one-legged stance test.

The BBS was negatively correlated with the sway index for the standing with feet together and the standing with one foot in front tests.

Table 1 The means and the standard deviation of BBS and the standing tests sway indices of three groups of non-fallers, once-fallers and multiple-fallers

	Number	Standing with eyes open sway index	Standing with eyes closed sway index	Standing with feet together sway index	Standing with one foot front sway index	BBS
Non-fallers	30	1.82% (SD = 1.38%)	1.51% (SD = 1.04%)	39.34% (SD = 14.56%)	37.09% (SD = 7.70%)	52.23 (SD = 2.21)
Once-fallers	18	2.23% (SD = 1.06%)	1.91% (SD = 0.88%)	51.13% (SD = 20.40%)	47.70% (SD = 5.60%)	51.06 (SD = 2.11)
Multiple-fallers	38	2.43% (SD = 1.21%)	2.31% (SD = 2.04%)	58.99% (SD = 10.5%)	51.78% (SD = 9.04%)	49.92 (SD = 4.01)

The receiver operating characteristic (ROC) curves for all the standing sway indices and BBS were generated (Fig. 8). In order to quantify the sway indices and BBS performance, the area under the curve (AUC), the sensitivity and the specificity were measured. The results are shown in Table 2.

The results show that the standing with feet together yields a sensitivity of 78.6% and a specificity of 75.7%, the standing with feet together sway index yields a sensitivity of 82.1% and a specificity of 77.7% and the BBS yields a sensitivity and specificity of 75.3% and 70.5% respectively. The AUC for the standing with feet together sway index and the standing with one foot in front sway index is respectively 0.84 and 0.9, while the AUC for the BBS is 0.79.

To the best of our knowledge, the present study is the first to propose a single index for balance assessment. Our studies show that standing with feet together and standing with one foot in front are effective methods to assess balance in older people.

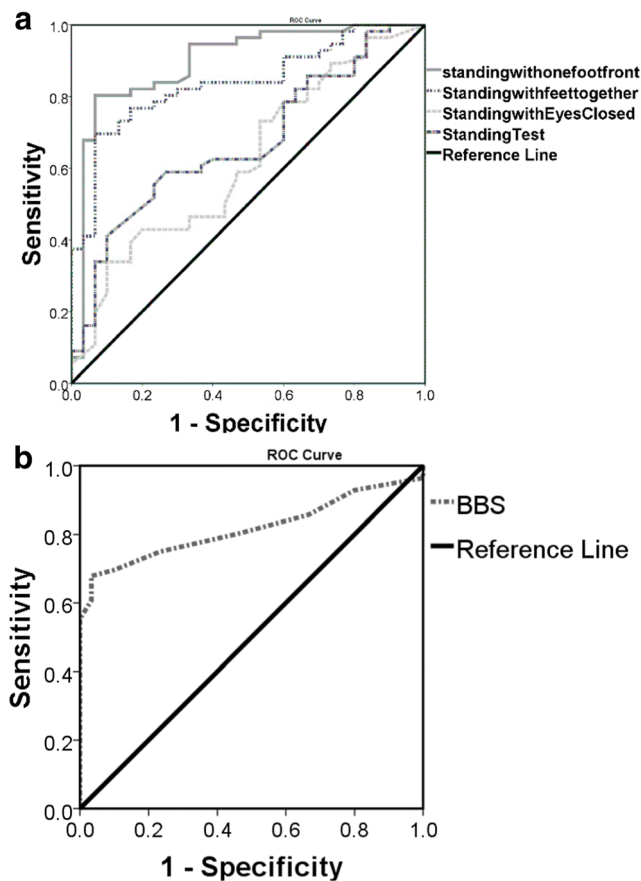


Fig. 8 **a** Receiver-operator characteristic (ROC) curve of standing tests' sway indices for the prediction of fallers (once-fallers and multiple-fallers). Area under the curve (AUC) is 0.84 (95% CI, 0.75–0.92) for the standing with feet together sway index, 0.9 (95% CI, 0.82–0.97) for the standing with one foot in front sway index, 0.66 (95% CI, 0.55–0.79) for the standing with eyes open sway index and 0.62 (95% CI, 0.50–0.74) for the standing with eyes closed sway index. **b** ROC curve of BBS for the prediction of fallers (once-fallers and multiple-fallers). AUC is 0.79 (95% CI, 0.71–0.89)

Table 2 Comparison of the performance of the standing tests sway indices and BBS

	Standing with eyes open sway index	Standing with eyes closed sway index	Standing with feet together sway index	Standing with one foot in front sway index	BBS
Sensitivity%	55%	58.9%	78.6%	82.1%	75.3%
Specificity%	76.7%	53.7%	75.7%	77.7%	70.5%
AUC	0.657	0.621	0.838	0.897	0.788

There are several studies using a single inertial sensor for postural balance assessment among faller and non-faller older subjects. O'Sullivan et al. [30] showed that the acceleration data recorded from a waist-mounted tri-axial accelerometer was significantly different between fallers and non-fallers in the standing with eyes open on a mat test. Although the correlation of the results with the two standard clinical fall risk assessment tools (BBS, timed get up and go (TUG)) was measured, the sensitivity and specificity of the results were not reported.

Greene et al. [31] used support vector machine (SVM) classifier models on data acquired from a body-worn inertial sensor and a pressure sensitive platform sensor, yielding a sensitivity of 65.38% and a specificity of 68.36%.

Giansanti et al. [32] reported a neural network-based method for balance and falls risk assessment using a body-worn accelerometer and gyroscope. The authors reported high specificity (≥ 0.88) and sensitivity (≥ 0.87) of the model in distinguishing patients classified as levels 1 to 3 on the Tinetti balance scale. Similarly, in another study, a body-worn inertial sensor was used along with Mahalanobis distance-based statistical clustering to distinguish patients with different Tinetti balance scales. A specificity of 93.0% and a sensitivity of 93.9% were reported [33]. In contrast to our study where subjects were classified based on their history of falling, in those studies, the subjects were classified based on their risk. This could be the reason for higher specificity and slightly higher sensitivity values reported in those works compared to those in the present study.

5 Conclusion

A study conducted to assess body sway using an inertial sensor was reported in this paper. The analysis of the orientation angles and angular velocities obtained from the sensor mounted on the pelvis provided strong indication of postural body sway. We were able to analyse the body sway for different subjects in different standing tests and evaluate their performance using a quantitative and objective method.

Significant differences between older non-fallers and fallers were observed in the body sway indices for standing with feet together and standing with one foot in front. These two standing tests can be used to identify older subjects with disturbed balance. The retrospectivity of this study is one of its major limitations, which will be addressed in the future work. In addition, the approach will be applied to a larger cohort of subjects in different age groups including younger, middle-aged and older people. An extended analysis of the data to develop an effective balance assessment tool will also be undertaken.

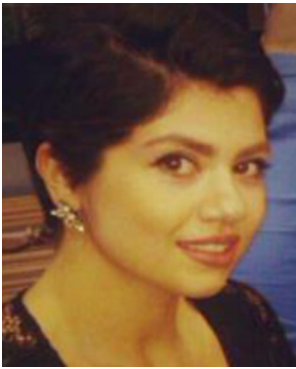
Acknowledgements The authors thank Melissa Roach, the clinical physiotherapist, for her supervision during the experimental tests. Miss Maryam Ghahramani, the chief investigator, did this study as a part of her PhD. thesis. Her PhD scholarship was funded by Illawarra Shoalhaven Local Health District (ISLHD). The authors wish to acknowledge that Bulli Hospital, Bulli, Australia, and Wollongong Hospital, Wollongong, Australia, provided this study with older participants.

Compliance with ethical standards

The participants were asked to read and sign an informed consent statement. The ethics committee of the University of Wollongong, Wollongong, Australia (HE13/125), approved this study.

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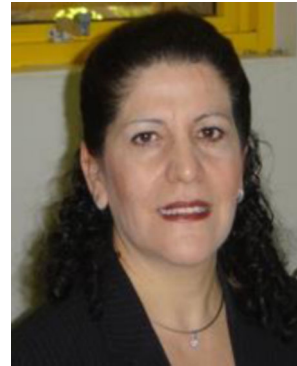
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