

Automatic fusion of clinical risk factors and inertial sensor data for accurate fall risk assessment during balance assessment

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Abstract— Falls in the elderly are a serious problem worldwide, with enormous associated societal costs. Deficits in balance and postural control have long been associated with falls risk in elderly adults. The gold standard for quantitative assessment of balance in a clinical setting is the force plate which is very expensive, non-portable and requires specialized personnel to operate. The present study aims to evaluate the accuracy of a combination of (1) self-reported clinical falls risk factors and (2) an inertial sensor based quantification of standing balance for assessment of falls risk in community dwelling older adults. 277 participants (99 male, 178 female) each received a comprehensive geriatric assessment and were administered standing balance tests (eyes open and eight eyes closed) while wearing a lumbar mounted IMU. Results obtained through classifier fusion, validated using nested cross-validation, suggest that quantification of standing balance from inertial sensor data combined with clinical risk factors are significantly more accurate (67.9%) than a model based only on clinical risk factors (58.1%) or a model based only on the Berg balance scale (59.2%). The present method may be suitable for deployment on a smartphone device for assessment of balance and fall risk in the home environment.

I. INTRODUCTION

The world's population is ageing and this trend is set to increase dramatically over the next century. This demographic shift will be felt most acutely in Europe, North America and Japan, placing an enormous burden on healthcare systems. Modern technological approaches may facilitate more efficient delivery of healthcare. A move towards low-cost wearable technologies to deliver healthcare more efficiently is proposed as a means of reducing the strain on traditional hospital based healthcare delivery systems. This will increase the quality of life and independence of all patients, especially elders and those with chronic illnesses, and also serve to reduce the costs inherent in the current hospital-centric system. This will reduce the number of preventable visits to health-care professionals, provide accurate, reliable and useful clinical information and efficiently synchronise to electronic health records complementing current health-care provision.

Falls in the older adult population are a significant problem worldwide, and can lead to serious injury, hospitalisation, restricted mobility, and institutionalisation [1]. The cost of falls each year, among elderly people in the U.S. alone, has been estimated to be in the region of U.S. \$30

billion [2]. Deficits in postural stability and balance have long been associated with falls in older adults. An impaired stability when standing and slow voluntary stepping, have also been shown to be associated with falls [4]. Common methods of falls risk assessment, including the Berg Balance Scale [1] and the Timed Up and Go (TUG) test [2], are clinic-based, variable in administration and require supervision by clinical staff. Inertial Measurement Unit (IMU) based systems have emerged as a viable alternative for quantitative assessment of balance and falls risk, suitable for use in hospital and community clinics as well as in the home [5,6]. Such advances need to be objective, repeatable and easily used by a non-expert. In a review, Melzer et al. [7] describes five studies which associates falls with various force platform measures, primarily metrics derived from variations in the centre of pressure. However, the costs associated with force platforms, difficulties with installation and the lack of portability make them unsuitable for home and community assessment of falls risk. An objective system to allow an older adult to assess their falls risk in the home environment could be of significant clinical benefit.

The present study aims to examine the accuracy of a new falls risk assessment in older adults, which combines IMU data from standing balance tests with self-reported clinical risk factors, using a classifier fusion approach.

II. DATA

A. Data collection

Two hundred and seventy-seven (178 female, age 74.7 ± 6.6 years) participants were assessed between 2007 and 2012 as part of a wider study on ageing. All participants had their balance assessed during a standing balance test. Each participant wore an inertial sensor mounted on their lower back, near the L3 vertebrae, using adhesive tape. Data were sampled at 102.4 Hz using a body-worn inertial sensor acquisition system (Kinesis Health Technologies, Dublin, Ireland) and calibrated using a standard method [3].

Testing was carried out in St James's Hospital (SJH), Dublin, Ireland. Data were obtained in three separate waves. Inclusion criteria were subjects 60 years and older, with no history of stroke, able to walk without assistance. Ethical approval was received from the local research ethics committee in each instance as well as informed consent from each subject.

History of falls for each subject was obtained by means of a questionnaire. A fall was defined as using a standard definition [4]. Fall outcome data were verified using available hospital records as well as information provided by relatives.

Each participant completed a balance test by standing still for a short period of time. Tests were completed with both eyes open and closed. 100 participants reported a history of falls, and were designated fallers. 138 participants were

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deemed to have polypharmacy, while 78 had orthostatic hypotension.

B. Clinical assessment

Clinical fall risk factors were captured for each subject by means of a comprehensive geriatric assessment [5]. Eyesight was assessed using the Pelli-Robson contrast sensitivity scale and the binocular logMAR scale. Each subject was checked for orthostatic hypotension (defined as orthostatic systolic blood pressure drop > 20mmHg), using a Finometer (Finapres Medical Systems, Amsterdam, Netherlands). Each subject’s prescription medications were reviewed to determine if they had a polypharmacy issue, where polypharmacy is defined as the use of four or more prescription medications. Table 1 below details the clinical data for the cohort.

Variable	Faller (N=100)	Non-faller (N=177)
N=277	Mean ± Std	Mean ±Std
Gender (M/F)	29/71	70/107
Height (cm)*	163.10±9.23	166.44±9.36
Weight (kg)*	71.94±12.50	76.13±13.98
Age (yrs)*	74.53±6.97	72.57±7.05
Polypharmacy (N)	56	82
Impaired Vision (N)	15	9
Orthostatic Hypotension (N)	32	46
BBS*	52.06±4.85	53.64±3.63

Table 1: Summary of clinical data. Items marked with * are significantly ($p < 0.05$) different for fallers compared to non-fallers.

III. METHODS

A. Experimental protocol

Participants completed six standing balance trials, three trials with eyes open (EO) and three trials with eyes closed (EC). Each EO trial was 40 seconds long, while each EC trial was 30 seconds. Participants were asked to remove their shoes and to stand in a semi-tandem stance for EO trials (front of one foot placed beside the heel of the other foot). During the EC trials, participants were asked to stand with a narrow stance (left and right feet touching). The order in which EO and EC trials were completed was randomized. Each participant was also evaluated using the Berg balance scale (BBS) [1] to provide a standard measure of balance and falls risk for each participant (for comparison with the sensor-based method presented here).

B. Clinical risk factor based fall risk assessment

Each participant underwent a comprehensive geriatric assessment in order to capture the main clinical risk factors linked to falls in older adults [6]. A logistic regression model was created using a number of the self-reported factors as previously reported [7]. All available data were used and the following features were included in the model:

- Gender (M/F)
- Height (cm)

- Weight (Kg)
- Age (years)
- Polypharmacy (yes/no)
- Vision impairment (yes/no)
- Orthostatic hypotension (yes/no)

C. Inertial sensor signal processing

All inertial sensor measures were derived from the inertial sensor using a previous reported method [8]. Accelerometer and gyroscope data were band-pass filtered between 0.1–5 Hz. To allow for settling at the start of each test, the first and last five seconds were removed. The RMS amplitude of the X-axis and Y-axis acceleration were used to quantify postural sway in each direction. The frequency domain variability of the signals obtained by the inertial sensor was also examined for both acceleration and angular velocity signals using the spectral edge frequency (SEF), defined as the frequency below which 95% of the power spectrum of the signal is contained, and the median frequency, defined as the frequency below which 50% of the power spectrum is contained [8]. The spectral entropy (H), a measure of signal complexity [9] of the accelerometer and angular velocity signals, was also calculated. The mean of each feature across iterations for each participant was included in the analysis. A sample of the inertial sensor data for two participants is shown in Fig. 1.

The ratio of each feature under EO and EC (EO/EC) conditions, known as the Romberg ratio (R) was also calculated. The mean value taken across all trials for each condition is used. The EO feature set contains only features from balance tasks taken under EO conditions, EC feature set contain features from only EC tasks while R feature set contains features EO, EC and R conditions.

Inertial sensor-based fall risk assessment

Previously, we reported an inertial sensor-based method to assess balance and falls risk using a combination of sensors assessments (including an inertial sensor) and a support vector machine [10]. In this study we employ a logistic regression classifier model to obtain a statistical fall risk estimate (FRE_{sensor}), validated using 10 repetitions of five-fold cross validation [11], to estimate the generalized classifier performance. Using only the training data for each iteration of the cross-validation routine, a potential feature set was evaluated using a second inner cross-validation loop. Once a feature set is identified using the training data, it is tested using the withheld data for this iteration of the outer cross-validation loop [12], a process known as ‘nested’ cross-validation. Training and testing sets were randomly selected for each repetition.

Combined clinical and inertial sensor fall risk assessment

A combined fall risk estimate (FRE_{combined}) is obtained by applying classifier combination theory [13], also known as classifier fusion. Averaging the posterior probabilities produced for a given subject by the sensor-based FRE (FRE_{sensor}) and the clinical FRE (FRE_{clinical}) produces a combined FRE (FRE_{combined}):

$$FRE_{\text{combined}} = (FRE_{\text{sensor}} + FRE_{\text{clinical}}) / 2$$

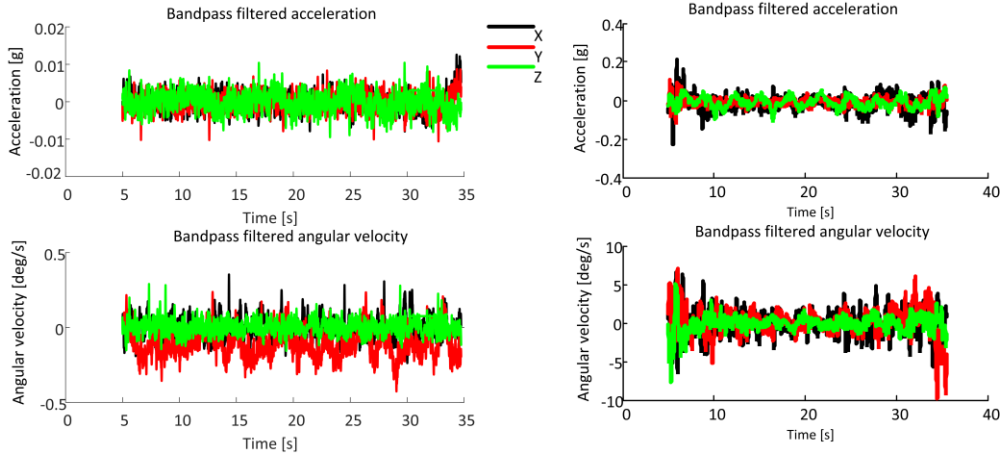


Figure 1 Sample tri-axial accelerometer (with gravity removed for ease of interpretation) and gyroscope signals for two participants.

The performance of $FRE_{combined}$ relative to FRE_{sensor} and $FRE_{clinical}$, is detailed in Table 3 below. The classifier performance for each model was estimated using Leave-One-Out (LOO) cross-validation, where $N-1$ samples were used to train the classifier model and the remaining sample used to test the performance, with this process repeated for each sample. The FRE_{sensor} feature and model selection was conducted using the nested cross-validation as discussed above, where model selection is conducted using 10 repetitions of five-fold cross-validation using only the training data, within the LOO procedure.

Statistical Analysis

Each classifier’s performance was assessed using standard performance measures; classification accuracy (Acc), is defined as the percentage of participants correctly classified by the algorithm as being a faller or non-faller. The sensitivity (Sens) is defined as the percentage of the fallers classified correctly. Similarly, specificity (Spec) is defined as the percentage of the non-fallers correctly identified as such by the system. Positive and negative predictive values were also calculated to provide a measure of the predictive power of positive and negative classifications. The positive predictive value (PPV) is defined as the proportion of the fallers classified correctly by the algorithm. Similarly, the negative predictive value (NPV) is the proportion of the non-fallers classified correctly. The values reported for each classifier performance metric were averaged across all cross-validation folds and repetitions. A Wilcoxon rank-sum test was used to determine if there were any statistical differences in any of the clinical data between the faller and non-faller groups.

IV. RESULTS

Results for the IMU based fall risk assessment algorithm (see Table 2) suggest that the EO features were more accurate than EC features in classifying falls while the combined EO, EC and R features improved the performance.

FRE_{sensor}	EO	EC	R
Acc (%)	65.83	65.47	65.47
Sens (%)	90.59	89.47	88.76
Spec (%)	29.29	29.00	32.32
PPV (%)	68.75	68.30	69.12
NPV (%)	64.44	61.70	62.75

Table 2: Fall risk classification results for IMU balance fall risk assessment method under eyes open (EO), eyes closed (EC) and ratio of Romberg (R) ratio conditions.

Results for the classifier fusion approach (see Table 3) suggest that the combination of clinical risk factors with IMU data (R condition) yields improved classification accuracy than either method taken alone. In addition, both IMU and combined clinical risk factors with IMU data outperformed the BBS in assessing falls risk.

	Combined ($FRE_{combined}$)	IMU (FRE_{sensor})	Clinical ($FRE_{clinical}$)	BBS
Acc (%)	67.87	65.34	58.12	59.21
Sens (%)	77.12	81.05	67.97	86.27
Spec (%)	56.45	45.97	45.97	25.81
PPV (%)	68.60	64.92	60.82	58.93
NPV (%)	66.67	66.28	53.77	60.38

Table 3: Nested cross-validation results for fall classification for $FRE_{combined}$ and FRE_{sensor} , $FRE_{clinical}$ and BBS.

Figure 2 below shows the Receiver Operating Characteristic (ROC) curves for the classifiers detailed in Tables 2 and 3.

V. DISCUSSION

This study suggests that classification of falls risk is improved by combining an instrumented balance assessment with clinical fall risk factors. Based on sensor data obtained from an IMU placed on the lower back, combined with self-reported questionnaire data and logistic regression classifier models, we have shown that classification of participants with a history of falls using a classifier fusion approach on both data sets yields more accurate results than those obtained from either classifier taken alone. Furthermore, we

have shown that the present method is more accurate than the BBS in classifying fallers.

It is worth noting that the classification presented here for a combination of IMU quantified balance and clinical factors is considerably lower than other combined approaches, based on quantification of the Timed Up and Go Test (ref). Nonetheless, these findings are encouraging as the balance test is one that could potentially be self administered in the home whereas the TUG requires supervision during data collection.

When interpreting the results presented here caution needs to be exercised, as we relied on self-reported falls history and self-report can be unreliable as a source of medical outcome data. The present study classified participants based on their history of falling, which is an established risk factor for future falls [14] and may be more useful than prospective data for evaluation of sensor based fall risk assessment algorithms [15]. A large proportion of the participants in this

[3] F. Ferraris, U. Grimaldi, and M. Parvis, "Procedure for effortless in-field calibration of three-axis rate gyros and accelerometers," *Sens. Mater.*, vol. 7, pp. 311-330, 1995.

[4] M. E. Tinetti, M. Speechley, and S. F. Ginter, "Risk factors for falls among elderly persons living in the community," *The New England journal of medicine*, vol. 319, pp. 1701-7, Dec 29 1988.

[5] B. R. Greene, E. P. Doheny, C. Walsh, C. Cunningham, L. Crosby, and R. A. Kenny, "Evaluation of falls risk in community-dwelling older adults using body-worn sensors " *Gerontology*, vol. 58 pp. 472-80, 2012.

[6] A. G. S. Panel on Prevention of Falls in Older Persons, British Geriatrics Society, "Summary of the Updated American Geriatrics Society/British Geriatrics Society Clinical Practice Guideline for Prevention of Falls in Older Persons," *Journal of the American Geriatrics Society*, vol. 59, pp. 148-157, 2011.

[7] B. R. Greene, S. J. Redmond, and B. Caulfield, "Fall risk assessment through automatic combination of clinical fall risk factors and body-worn sensor data," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, pp. 1-1, 2016.

[8] E. Doheny, P. , B. Greene, R. , T. Foran, C. Cunningham, C. W. Fan, and R. A. Kenny, "Diurnal variations in the outcomes of instrumented gait and quiet standing balance assessments and

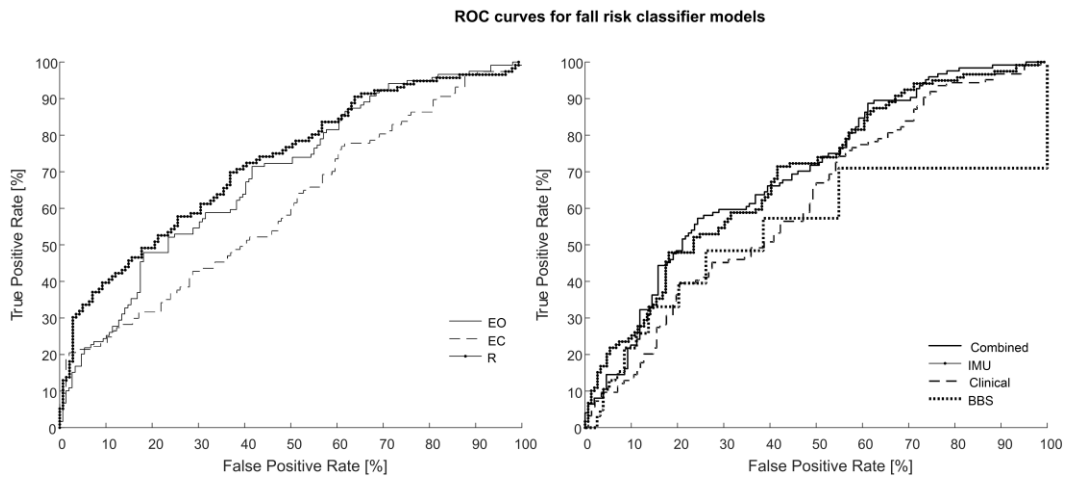


Figure 2 ROC curves for classifier performance under (a) Eyes Open (EO), Eyes Closed (EC) and ratio of EO/EC conditions and (b) Classifier performance for $FRE_{combined}$ compared to $FRE_{clinical}$, FRE_{sensor} and BBS.

study were self-referred which could indicate differences when compared hospital in-patients or nursing home residents. The use of nested cross-validation aims to ensure the statistical models used were generalized across the study population, however given the heterogeneous nature of this sort of data [7], differences may exist when compared to the general population.

The present algorithm may be suitable for deployment as a smartphone application that an older adult could use unsupervised in the home environment.

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REFERENCES

[1] K. Berg, "Measuring balance in the elderly: preliminary development of an instrument," *Physiotherapy Canada*, vol. 41, pp. 304-311, 1989.

[2] D. Podsiadlo and S. Richardson, "The timed "Up & Go": a test of basic functional mobility for frail elderly persons," *J Am Geriatr Soc*, vol. 39, pp. 142-148, 1991.

their association with falls history," *Physiological Measurement*, vol. 33, p. 361, 2012.

[9] H. Viertio-Oja, V. Maja, M. Särkelä, P. Talja, N. Tenkanen, H. Tolvanen-Laakso, *et al.*, "Description of the Entropy™ algorithm as applied in the Daxex-Ohmeda S/5™ Entropy Module," *Acta Anaesthesiologica Scandinavica*, vol. 48, pp. 154-161, 2004.

[10] B. R. Greene, D. McGrath, L. Walsh, E. P. Doheny, D. McKeown, C. Garattini, *et al.*, "Quantitative falls risk estimation through multi-sensor assessment of standing balance," *Phys Meas*, vol. 33, pp. 2049-2063, 2012.

[11] T. Hastie, R. Tibshirani, and J. H. Friedman, *The Elements of Statistical Learning*, 2nd ed.: Springer, 2009.

[12] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artificial Intelligence*, vol. 97, pp. 273-324, 1997.

[13] L. I. Kuncheva, *Combining Pattern Classifiers; Methods and Algorithms.*: Wiley, 2004.

[14] P. A. Stalenhoef, J. P. M. Diederiks, J. A. Knottnerus, A. D. M. Kester, and H. F. J. M. Crebolder, "A risk model for the prediction of recurrent falls in community-dwelling elderly: A prospective cohort study," *Journal of clinical epidemiology*, vol. 55, pp. 1088-1094, 2002.

[15] B. R. Greene, D. McGrath, and B. Caulfield, "A comparison of cross-sectional and prospective algorithms for falls risk assessment," *IEEE Engineering in Medicine & Biology Conference*, pp. 4527-4530, 26-30 Aug. 2014.