Comparing Machine Learning Approaches for Fall Risk Assessment

Joana Silva[1], João Madureira[1], Cláudia Tonelo[2], Daniela Baltazar[3], Catarina Silva[3], Anabela Martins[3]
Carlos Alcobia[2] and Inês Sousa[1]
[1]*Fraunhofer Portugal AICOS, Porto, Portugal*
[2]*Sensing Future Technologies, Coimbra, Portugal*
[3]*ESTeSC Coimbra Health School, Physiotherapy Department, Coimbra, Portugal*

Keywords: Fall Risk Assessment, Inertial Sensors, Pressure Platform, Timed-up and Go Test, Sit-to-Stand, 4-Stage Test, Machine Learning, Classification, Regression.

Abstract: Traditional fall risk assessment tests are based on timing certain physical tasks, such as the timed up and go test, counting the number of repetitions in a certain time-frame, as the 30-second sit-to-stand or observation such as the 4-stage balance test. A systematic comparison of multifactorial assessment tools and their instrumentation for fall risk classification based on machine learning approaches were studied for a population of 296 community-dwelling older persons aged above 50 years old. Using features from inertial sensors and a pressure platform by opposition to using solely the tests scores and personal metrics increased the F-Score of Naïve Bayes classifier from 72.85% to 92.61%. Functional abilities revealed higher association with fall level than personal conditions such as gender, age and health conditions.

1 INTRODUCTION

Fall risk assessment methods have been studied aiming to estimate the risk of falling in order to identify those at higher risk and timely apply the appropriate actions to prevent falls. This kind of assessment can take the form of questionnaires, simple screenings or more comprehensive multidimensional fall risk assessments.

Falls are described as a complex phenomenon caused by the interaction of multiple risk factors. To assess the risk of falling, it is necessary to identify the factors that increase an older person's risk of falling. Intensive research has been conducted in order to identify specific risk factors (Ambrose, Paul, and Hausdorff 2013; Rubenstein 2006; Oliver et al. 2004), which can increase the likelihood of a fall occurrence. The idea behind these studies is to develop preventive strategies based on the identified risk factors.

According to Rubenstein et al. (Rubenstein and Josephson 2002) the most common underlying causes and risk factors for falls include muscle weakness, gait and balance problems, visual impairment, cognitive impairment, depression, functional decline, and particular medications, especially in the presence of environmental hazards.

Similarly to Physiological Profile Assessment (PPA) (Lord, Menz, and Tiedemann 2003), we intend to evaluate the functional ability of subjects and potential impairments that may be related with an increased risk of falling, irrespective of the existence of an underlying disease causing them.

Traditional functional assessment tests are based on timing certain physical tasks, such as the timed up and go (TUG) test (Beauchet et al. 2011), counting the number of repetitions in a certain time-frame, as the 30-second sit-to-stand (STS) (Jones, Rikli, and Beam 1999) or observation, such as balance tests (Agrawa et al. 2011), in particular the 4-stage balance test (4-Stage) (Rossiter-Fornoff et al. 1995; Thomas et al. 2014), or the Tinetti Performance Oriented Mobility Assessment (POMA) (Tinetti 1986). A systematic review of multifactorial and functional mobility assessment tools for fall risk (Scott et al. 2007) compares several studies for community settings.

In this paper, the three fall risk assessment functional tests, TUG, STS and 4-Stage, that have been also used in the follow-up of the participants of the Otago Falls Prevention Program, were instrumented with wearable inertial sensors and a

Silva J., Madureira J., Tonelo C., Baltazar D., Silva C., Martins A., Alcobia C. and Sousa I.
Comparing Machine Learning Approaches for Fall Risk Assessment.
DOI: 10.5220/0006227802230230
In *Proceedings of the 10th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2017)*, pages 223-230
ISBN: 978-989-758-212-7

pressure platform for the extraction of several metrics to perform a comparison with the functional tests' scores for the differentiation of fall risk groups. Machine learning approaches were studied using a fall level as the classification output.

2 METHODS

2.1 Subjects

A total of 296 subjects voluntarily participated in the study. Informed consents were obtained from all participants who responded to personal information, health, previous falls inquiries and completed the three instrumented assessment tests: TUG, STS and 4-stage. The data collection took place in different environments, mostly at community (76.0%), at day-care centres (15.9%), and at nursing homes (8.1%).

Demographic and anthropometric information was annotated for all the subjects along with health related information from two questionnaires: health conditions and medication intake. Fall related information was inquired using a history of falls questionnaire.

The mean age of the sample was 70.2 years (93 persons with age below 65 years), the majority of the subjects were women (68.2%), 25.0% lived alone, 51.0% only have primary education and 11.5% use an assistive device. Diabetes was the most prevalent health condition (15.5%), followed by osteoarthritis (14.2%) and osteoporosis (10.8%).

Urinary incontinence was reported by 22.3% (answering the question: do you leak urine when you cough, laugh, sneeze or lift an object?); fear of falling was reported by 47.0% (answering the question: are you afraid of falling?); 57.4% of the persons referred to intake 4 or more different medicines per day (mean was 4.52 medicines).

During the previous year 30.7% of the persons have fallen (18.9% outdoors) and 8.1% underwent to the emergency service (hospital). The wrist/hand fracture was the most common injury (2.4%) among these persons.

2.2 Screening Protocol

This section describes the fall risk assessment tests applied in this study:

Timed Up and Go Test (TUG) fast pace: the person is asked to start seated on a chair and when test starts, the person should stand up, walk straight for 3 meters, as fast as the person can, turn around, walk back to the chair and sit down (Beauchet et al. 2011). Test score corresponds to the time needed to perform TUG test (*TUG duration*). A threshold of 10s has been found to be associated with falls occurrence in a 12 months follow up period for community-dwelling older adults (Rose, Debra J, Jones, Jessie C, and Lucchese, Nicole 2002).

30 Seconds Sit-to-stand Test (STS): the person is instructed to sit on a chair and repeatedly stand up and sit down as many times as possible over 30 seconds (Jones, Rikli, and Beam 1999). The person must be seated in the middle of the chair, feet should approximately width apart and placed on the floor, and arms crossed by the wrists placed against the chest. Final score of this test is the number of times the person completes a cycle of sit-to-stand and stand-to-sit (*number of STS cycles*). While normative levels are dependent on age and sex (Rikli and Jones 2010), a score of less than 15 transitions in the 30 seconds test duration has been used to identify "fallers" in a group of elderlies (Cho et al. 2012).

4 Stage Balance Test "modified": the person is instructed to progressively maintain four foot positions for 10 seconds each, without moving his/her feet or needing support. The positions are: side by side stance, semi-tandem stance, tandem stance and unipedal stance (Rossiter-Fornoff et al. 1995; Thomas et al. 2014). For each position the subjects were instructed to stand quietly without shoes on the pressure platform, with their arms along the body. In this study, except for the one leg stand position, all positions must be performed with eyes open and then closed. The final score of this test is the number of positions a person can hold for 10 seconds without losing balance (*number of 4-stage exercises*). The inability to complete the tandem stance position has been associated with higher risk of falling (Murphy et al. 2003).

The tests were applied by trained health professionals. Prior to the execution of tests, the test procedure was explained to each person and it was demonstrated how the test should be performed. Auditory cues were also used to instruct the person during the execution of the tests. Only persons who performed the three functional tests (TUG, STS and 4-stage) were included in this study.

2.3 Instrumentation

The participants were instrumented with one wearable inertial sensor during the execution of TUG and 30-seconds sit-to-stand tests. The 4-stage balance test was performed on a pressure platform, as can be seen in Figure 1.

The wearable sensor was developed and

assembled at Fraunhofer AICOS and was placed at the lower back. Inertial data was collected using the built-in 3-axial accelerometer and 3-axis gyroscope, both sampled at 50 Hz. Raw data from the inertial sensors were acquired for all the tests in m/s^2.

The pressure distribution data was measured with PhysioSensing platform (Sensing Future Technologies, Lda) running at frequency of 50Hz. It contains 1600 pressure sensors of size 10mm by 10mm with maximum value of 100N/sensor. Voltage data is converted with an 8-bit A/D converter and is transmitted via USB (Universal Serial Bus). In this way it is possible to receive raw data of each pressure sensor as well as the raw center of pressure coordinates (CoP), in cm. In order to obtain more precision in CoP displacements, an algorithm was employed to obtain CoP positions in mm, using the matrix of pressure sensors (Hsi 2016).

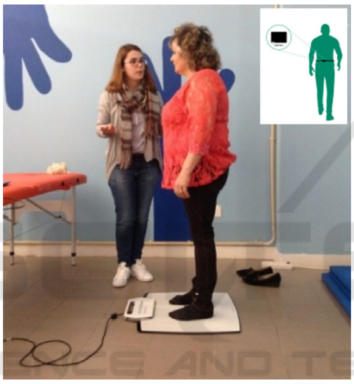

Figure 1: Example of a test set-up, with the pressure platform in the floor and an illustration of the inertial sensor placement of at the lower back, since it is covered by the clothes.

2.4 Inertial Sensors Data Analysis

The accelerometer and gyroscope signals were synchronized and used to segment the TUG test into its several components (stand up, walk forward, turn around, walk back to the chair and sit down) as previously described in (Silva and Sousa 2016) and to identify the stand and sit phases of the STS test. Identification of the STS transition points was made analysing the y-axis of the gyroscope signal. After filtering the signal with a moving average filter of 20 samples window size, zero crossings were identified (Guimaraes, Ribeiro, and Rosado 2013). In order to remove outliers, a minimum of 20 samples were used as difference between consecutive transition points. Since the score is given by the total number of complete cycles, it was considered one cycle between two transitions points, one sit-to-stand and one stand-to-sit. The number of cycles is therefore half the number of transitions points identified, as illustrated in Figure 2.

For each one of the TUG segments and for the whole STS test, statistical and frequency domain features were extracted from the magnitude of the accelerometer signal. The list of features has been reported in (Silva and Sousa 2016) and corresponds to: *mean, median, maximum, minimum, signal height, standard deviation, median deviation, root mean square, inter quartile range, number of times the magnitude signal crosses the mean value, energy, entropy, skewness, kurtosis, average of minima, average of maxima, average signal height, fundamental harmonic of Fast Fourier Transform (FFT) spectrum and fundamental amplitude.*

Additional metrics for each test were calculated from the inertial data: for the TUG test, the *duration of the stand* segment (duration of the first segment) and the *number of steps* (calculated with a step counter algorithm reported by (Aguiar et al. 2014)) taken during the test; for the STS test, the *number of STS cycles* and the *STS power* (Zhang et al. 2014).

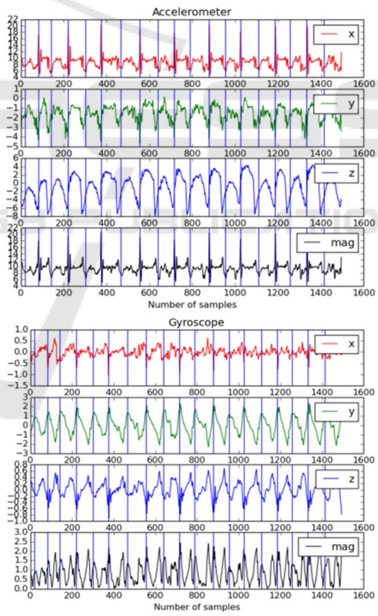

Figure 2: Axis x (red), y (green), z (blue) and magnitude signals (black) of the accelerometer and gyroscope signals for STS test with identification of transition points with blue vertical lines. The interval between two consecutive lines is considered as one STS cycle. Figures are from a low risk person.

2.5 Pressure Platform Data Analysis

For each posture of the 4-stage balance test executed, the pressure values on each sensor of the pressure platform were recorded. The centre of pressure (CoP) coordinates were then obtained and several parameters, which are typically used in postural sway and fall risk assessment (Bigelow and Berme 2011; Guimaraes, Ribeiro, and Rosado 2013; Raymakers, Samson, and Verhaar 2005) were calculated.

For all the medio-lateral (ML) and antero-posterior (AP) CoP position coordinates obtained during each posture execution, the mean (*mean AP CoP positions, ML mean CoP positions*), standard deviation (*std AP CoP positions, std ML CoP positions*), root mean square (*rms AP CoP positions, rms ML CoP positions*), maximum (max *AP CoP positions, max ML CoP positions*) and minimum (min *AP CoP positions, min ML CoP positions*) were calculated.

The displacement of CoP in each direction per time unit gave rise to the mean velocity of CoP displacement (*vm CoP position AP, vm CoP position ML*) metrics.

Another metric extracted was the area of a confidence ellipse containing 95% of the CoP coordinates projected in a 2D plan (*Ellipse area*). Figure 3 shows a comparison of CoP displacements in ML and AP directions for two persons with different fall risk levels during the semi-tandem stance with eyes closed. For a low fall risk person

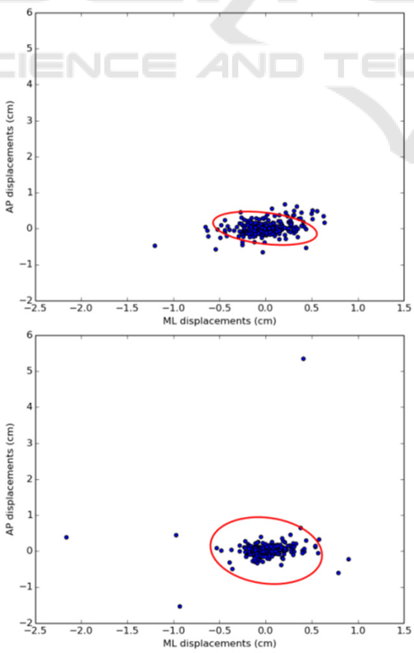

Figure 3: CoP displacements in ML and AP directions and 95% confidence ellipse area (red line) during semi-tandem stance with eyes closed of 4-stage test. Top figure is from a low risk person and botton figure is from a high risk person, showing more outliers in ML and AP directions.

(top figure) the displacement is concentrated around the centre, however for a high fall risk person, more outliers in ML and specially in AP direction are identified, reflecting unbalance situations.

Sway can be defined, in this scope, as the amplitude or absolute distance of CoP oscillations. The sum of all the distances accumulated during the execution of each posture is computed resulting in the CoP path length (*total Sway distance*). The standard deviation of sway distances (*std Sway*) and the maximum and minimum amplitude of CoP oscillations (*maxSway* and *minSway*) were also included as pressure platform metrics.

2.6 Machine Learning Methods

Classification and regression methods were tested to differentiate between high and low fall risk groups using metrics extracted from inertial sensors and pressure platform. Rapid Miner Toolkit was used for the train and test processes. Ten-fold cross validation with random split was used for all the processes. In order to define a metric to divide the groups, a *fall level* was determined based on the history of falls questionnaire and usage of walking aid, as presented in Figure 4, since these two factors have evidence to be more related with risk of falling. The *fall level* is merely an indication if the person shows more or less probability of falling, since the falls occurrence in a 12 months follow up period was not possible to measure. The dimension of the population is 296 subjects. The low risk group represents 83% of the dataset and is composed by 245 subjects (35% within 50-65y.o. and 65% above 65y.o.). The high risk group represents 17% of the dataset and contains the remaining 51 subjects (16% within 50-65y.o. and 84% above 65y.o.). This distribution is in agreement with the falls incidence in the elderly population, which is less than 30% (Bergen, Stevens, and Burns 2016).

Two approaches were compared: first only personal metrics and tests scores were used to construct the feature vector, and then this vector was replaced with features extracted from inertial sensors and pressure platform. The objective was to study the added value of the sensors features to differentiate between fall risk groups.

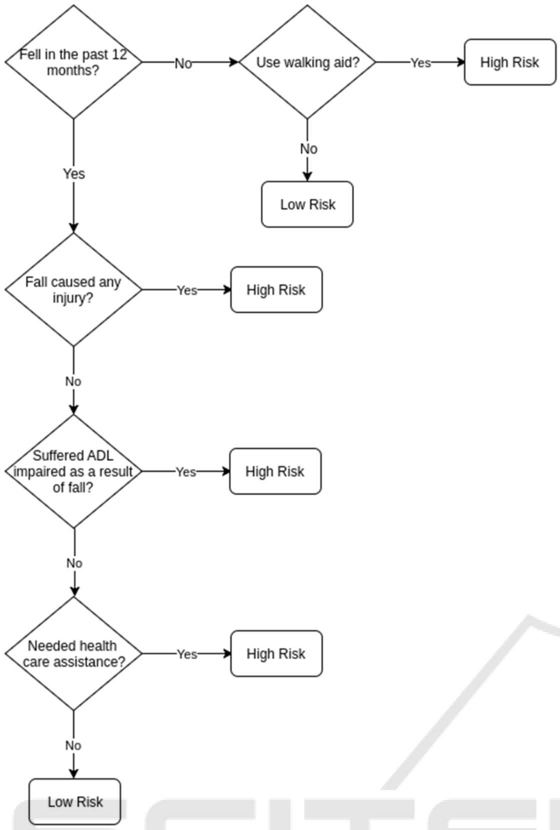

Figure 4: Fall level definition based on history of falls and usage of walking aid.

The performance of several classification and regression methods was compared based on accuracy, precision, recall and F-Score. It was considered low risk as the positive class and high risk as the negative class. TP states for true positive, FP for false positive, TN for true negative and FN for false negative. The performance metrics are calculated as follows:

$$\text{Precision (P)} = TP / (TP+FP) \quad (1)$$

$$\text{Recall (R)} = TP / (TP+FN) \quad (2)$$

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN) \quad (3)$$

$$\text{F-Score} = (2P \times R) / (P+R) \quad (4)$$

3 RESULTS & DISCUSSION

3.1 Statistical Analysis

A statistical analysis has been conducted for the variables: gender, age, body mass index (BMI), number of medicines, number of health conditions, fear of falling, TUG score, STS score and 4-stage score. Cut-off values that have been used in previous studies referred in the introduction section of this paper to distinguish high and low fall risk levels were applied to each of these variables. The Fisher's exact test was applied with the null hypothesis that there are no non-random associations between the two categorical variables: fall level and each of the variables considered. The Fisher's exact test *p*-value and odds ratio (OR) are reported in Table 1 and were calculated with Matlab function *fishertest*.

Table 1: Odds Ratio and Fisher's exact test *p*-value for personal metrics and tests scores with the fall level.

Variable	Odds Ratio	*p*-value
Feminine Gender	1.04	1.00
Age > 65	2.86	0.01
BMI < 13.7 or BMI > 29.7	1.58	0.18
More than 4 Medicines	1.96	0.05
More than 2 Health Conditions	1.56	0.38
Has Fear of Fall	3.35	0.00
TUG Duration > 10 s	6.51	0.00
STS Cycles < 15	11.25	0.00
Not completed 10s Tandem Stance (eyes open)	3.59	0.00

Presence of fear of falling, TUG duration above 10 seconds, number of STS cycles below 15 and not completed the tandem stance with eyes open were the metrics with higher odds ratio with the fall level and *p*-value below 0.05. Thus, the hypothesis of random association between fall level and the variables in shaded lines of Table 1 can be rejected. Age above 65 years old and take more than 4 medicines per day also showed a *p*-value below 0.05 but the OR was lower than for the previously mentioned variables. For the remaining variables, the conclusion is that female individuals, or individuals that have BMI lower than 13.7 or higher than 29.7 or that have more than two health conditions do not have greater odds of having a high fall level than individuals that are male, have a normal BMI and have less than two health conditions. In general, tests scores showed higher association with fall level than personal metrics, reflecting that functional abilities have higher impact on fall level than personal conditions of a person.

3.2 Machine Learning Approaches

Classification and regression methods were studied for the differentiation between low and high fall risk groups using the fall level as label. All algorithms applied were retrieved from the Rapid Miner predictive models.

3.2.1 Functional Tests Scores

As a first analysis, personal metrics (age, gender, BMI, fear of fall, number of health conditions and number of medicines) and test scores (TUG duration, number of STS cycles and number of 4-stage exercises) were used to define the feature vector and fall level as label. The results are summarized in Table 2.

Table 2: Classification and regression results with personal metrics and functional tests scores. Accuracy, precision, recall and F-Score are in percentage (%).

Algorithm	Accuracy	Precision	Recall	F-Score
k-NN, k=4	81.41	69.33	63.00	66.01
Naïve Bayes	84.82	74.58	71.19	72.85
Random Forest	83.13	59.37	53.05	56.03
Decision Tree	81.44	68.28	60.33	64.06
Neural Net	82.45	69.22	64.84	66.96
SVM	82.45	49.08	51.21	50.12
Linear Regression	83.11	69.01	56.05	61.86
Logistic Regression	82.13	67.48	64.88	66.15

Naïve Bayes classifier obtained the higher accuracy, 84.82%. Precision was 74.58% and recall was 71.19%. Random Forest and Linear Regression also obtained acceptable results. In general, all algorithms showed higher precision than recall.

3.2.2 Sensors Features

In order to compare the previous results based on tests scores with the features extracted from inertial sensors and pressure platform, a feature vector containing 224 sensors features was used. For each TUG segment (stand, walk, turn and walk back) 19 statistical and frequency domain features were extracted, yielding 76 features plus 2 metrics, time to stand and the number of steps. For STS test, the same 19 features were extracted plus 2 metrics, the number of STS cycles and the STS power. For the 4-stage test, 17 CoP metrics were extracted for each one of the 7 exercises (when available), yielding 119 features. Additionally, 6 personal metrics were added: age, gender, BMI, fear of fall, number of health conditions and number of medicines. Fall level was used as label. Since the number of features was considerable high, forward feature selection was applied prior to cross validation. Results are presented in Table 3.

Table 3: Classification and regression results for personal metrics and features extracted from sensors. Number of features selected by forward feature selection follows the name of the algorithm. Accuracy, precision, recall and F-Score are in percentage (%).

Algor.	Accuracy	Precision	Recall	F-Score
k-NN, k=4 [5 F.]	85.78	87.79	95.88	91.66
Naïve Bayes [4 F.]	87.16	88.18	97.50	92.61
Neural Net [5 F.]	87.20	88.05	97.94	92.73
SVM [3 F.]	84.82	84.95	99.23	91.54
Random Forest [3 F.]	87.48	87.92	98.43	92.88
Decision Tree [5 F.]	88.17	89.47	97.10	93.13
Linear Reg. [3 F.]	85.89	85.66	99.55	92.08
Logistic Reg. [4 F.]	86.54	86.74	98.78	92.37

Decision tree classifier obtained the higher accuracy, 88.17%. Precision was 89.47% and recall was 97.10%. Comparing the results of Naïve Bayes with the previous analysis, the features obtained from sensors yield higher accuracy than only tests scores. Moreover, features from TUG and 4-stage tests were frequently selected with forward feature selection method. For all algorithms tested, features from sensors provide higher precision and recall values. F-Score obtained with features from sensors were the same across all algorithms tested and considerable higher than F-Score obtained only with tests scores and personal metrics (91-93% against 50-72%).

4 DISCUSSION

Previous studies from (Scott et al. 2007) have compared the accuracy of several functional tests and fall risk tools to differentiate groups with different levels of fall risk. Despite the differences in protocol and population analysed (only for community settings and validated in a prospective study), similar accuracy and sensitivity were reported. Murphy et al. (Murphy et al. 2003) concluded that ‘floor transfer’ and ‘50 ft walk’ tests combined can discriminate fallers from non-fallers with an overall accuracy of 96% (82% sensitivity and 100% specificity).

A similar study from Liu et al. (Liu et al. 2011) has used metrics from instrumented TUG, alternate step test and 5 times STS to classify between fallers and non fallers and the best models have achieved 70% accuracy (68% sensitivity and 73% specificity).

5 CONCLUSIONS

The objective of this study was to compare the performance of functional tests scores and features obtained from inertial sensors and pressure platforms to discriminate between low and high risk of fall. A fall level was defined based on history of falls and usage of walking aid and was used as label in classification and regression algorithms. Only subjects who performed the three functional tests (TUG, STS and 4-stage) were included in this study.

The association between functional tests scores and fear of falling with fall level are not random (Fisher’s exact test *p*-value < 0.05), concluding that individuals with functional disabilities and fear of falling have greater odds of having a higher fall level than individuals without physical disabilities and without fear of falling. Moreover, when comparing personal metrics with fall level, it was concluded for some personal metrics that random association with fall level cannot be excluded.

The differentiation power of personal metrics and tests scores was considerable different when tested with classification and regression methods. Accuracies above 80% were obtained for all algorithms. Naïve Bayes outperforms with an accuracy of 84.82% (74.58% of precision and 71.19% of recall).

However, features from inertial sensors and pressure platform obtained better results for the same algorithms than only tests scores. Naïve Bayes classifier obtained an accuracy of 87.16% (88.18% of precision and 97.50% of recall).

These results support the conclusion that instrumentation of fall risk assessment tests with inertial sensors and pressure platform could better discriminate the individuals at a higher risk of falling.

ACKNOWLEDGEMENTS

Authors would like to thank all participants and centres, clinics and other entities hosting the screenings. Financial support from project *FallSensing: Technological solution for fall risk screening and falls prevention* (POCI-01-0247-FEDER-003464), co-funded by Portugal 2020, framed under the COMPETE 2020 (Operational Programme Competitiveness and Internationalization) and European Regional Development Fund (ERDF) from European Union (EU).

REFERENCES

Agrawa, Yuri, John P. Carey, Howard J. Hoffman, Daniel A. Sklare, and Michael C. Schubert. 2011. ‘The Modified Romberg Balance Test: Normative Data in U.S. Adults’. *Otology & Neurotology* 32 (8): 1309–11. doi:10.1097/MAO.0b013e31822e5bee.

Aguiar, B., J. Silva, T. Rocha, S. Carneiro, and I Sousa. 2014. ‘Monitoring Physical Activity and Energy Expenditure with Smartphones’. In *2014 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)*, 664–67. doi:10.1109/BHI.2014.6864451.

Ambrose, Anne Felicia, Geet Paul, and Jeffrey M Hausdorff. 2013. ‘Risk Factors for Falls among Older Adults: A Review of the Literature’. *Maturitas* 75 (1): 51–61. doi:10.1016/j.maturitas.2013.02.009.

Beauchet, Olivier, B. Fantino, G. Allali, S. W. Muir, M. Montero-Odasso, and C. Annweiler. 2011. ‘Timed up and Go Test and Risk of Falls in Older Adults: A Systematic Review’. *The Journal of Nutrition, Health & Aging* 15 (10): 933–38. doi:10.1007/s12603-011-0062-0.

Bergen, Gwen, Mark R. Stevens, and Elizabeth R. Burns. 2016. ‘Falls and Fall Injuries Among Adults Aged ≥65 Years — United States, 2014’. *MMWR. Morbidity and Mortality Weekly Report* 65 (37): 993–98. doi:10.15585/mmwr.mm6537a2.

Bigelow, Kimberly Edginton, and Necip Berme. 2011. ‘Development of a Protocol for Improving the Clinical Utility of Posturography as a Fall-Risk Screening Tool’. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences* 66 (2): 228–33. doi:10.1093/gerona/glq202.

Cho, Kang Hee, Soo Kyung Bok, Young-Jae Kim, and Seon Lyul Hwang. 2012. ‘Effect of Lower Limb Strength on Falls and Balance of the Elderly’. *Annals of Rehabilitation Medicine* 36 (3): 386–93. doi:10.5535/arm.2012.36.3.386.

Guimaraes, V., D. Ribeiro, and L. Rosado. 2013. ‘A Smartphone-Based Fall Risk Assessment Tool: Measuring One Leg Standing, Sit to Stand and Falls Efficacy Scale’. In *2013 IEEE 15th International*

Conference on E-Health Networking, Applications Services (Healthcom), 529–33. doi:10.1109/HealthCom.2013.6720733.

Hsi, Wei-Li. 2016. 'Analysis of Medial Deviation of Center of Pressure after Initial Heel Contact in Forefoot Varus'. *Journal of the Formosan Medical Association = Taiwan Yi Zhi* 115 (3): 203–9. doi:10.1016/j.jfma.2015.03.004.

Jones, C. Jessie, Roberta E. Rikli, and William C. Beam. 1999. 'A 30-S Chair-Stand Test as a Measure of Lower Body Strength in Community-Residing Older Adults'. *Research Quarterly for Exercise and Sport* 70 (2): 113–19. doi:10.1080/02701367.1999.10608028.

Liu, Ying, S.J. Redmond, Ning Wang, F. Blumenkron, M.R. Narayanan, and N.H. Lovell. 2011. 'Spectral Analysis of Accelerometry Signals From a Directed-Routine for Falls-Risk Estimation'. *IEEE Transactions on Biomedical Engineering* 58 (8): 2308–15. doi:10.1109/TBME.2011.2151193.

Lord, Stephen R., Hylton B. Menz, and Anne Tiedemann. 2003. 'A Physiological Profile Approach to Falls Risk Assessment and Prevention'. *Physical Therapy* 83 (3): 237–52.

Murphy, Mary A, Sharon L Olson, Elizabeth J Protas, and Averell R Overby. 2003. 'Screening for Falls in Community-Dwelling Elderly'. *Journal of Aging and Physical Activity* 11 (1): 66–81.

Oliver, David, Fergus Daly, Finbarr C. Martin, and Marion E. T. McMurdo. 2004. 'Risk Factors and Risk Assessment Tools for Falls in Hospital in-Patients: A Systematic Review'. *Age and Ageing* 33 (2): 122–30. doi:10.1093/ageing/afh017.

Raymakers, J. A., M. M. Samson, and H. J. J. Verhaar. 2005. 'The Assessment of Body Sway and the Choice of the Stability Parameter(s)'. *Gait & Posture* 21 (1): 48–58. doi:10.1016/j.gaitpost.2003.11.006.

Rikli, RE, and JC Jones. 2010. 'Functional Fitness Normative Scores for Community-Residing Older Adults, Ages 60–94'. *Human Kinetics Journals*. April 21. http://journals.humankinetics.com/japa-back-issues/japavolume7issue2april/functional-fitness-normative-scores-for-community-residing-older-adults-ages-60-94.

Rose, Debra J, Jones, Jessie C, and Lucchese, Nicole. 2002. 'Predicting the Probability of Falls in Community-Residing Older Adults Using the 8-Foot Up-and-Go: A New Measure of Functional Mobility'. *Journal of Ageing and Physical Activity* 10 (4): 466–75.

Rossiter-Fornoff, J. E., S. L. Wolf, L. I. Wolfson, and D. M. Buchner. 1995. 'A Cross-Sectional Validation Study of the FICSIT Common Data Base Static Balance Measures. Frailty and Injuries: Cooperative Studies of Intervention Techniques'. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences* 50 (6): M291-297.

Rubenstein, Laurence Z. 2006. 'Falls in Older People: Epidemiology, Risk Factors and Strategies for Prevention'. *Age and Ageing* 35 (suppl 2): ii37-ii41. doi:10.1093/ageing/afl084.

Rubenstein, Laurence Z., and Karen R. Josephson. 2002. 'The Epidemiology of Falls and Syncope'. *Clinics in Geriatric Medicine* 18 (2): 141–58.

Scott, Vicky, Kristine Votova, Andria Scanlan, and Jacqueline Close. 2007. 'Multifactorial and Functional Mobility Assessment Tools for Fall Risk among Older Adults in Community, Home-Support, Long-Term and Acute Care Settings'. *Age and Ageing* 36 (2): 130–39. doi:10.1093/ageing/afl165.

Silva, Joana, and Ines Sousa. 2016. 'Instrumented Timed Up and Go: Fall Risk Assessment Based on Inertial Wearable Sensors'. In *2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA) (MeMeA 2016)*. Benevento, Italy.

Thomas, Julia C., Charles Odonkor, Laura Griffith, Nicole Holt, Sanja Percac-Lima, Suzanne Leveille, Pensheng Ni, Nancy K. Latham, Alan M. Jette, and Jonathan F. Bean. 2014. 'Reconceptualizing Balance: Attributes Associated with Balance Performance'. *Experimental Gerontology* 57 (September): 218–23. doi:10.1016/j.exger.2014.06.012.

Tinetti, Mary E. 1986. 'Performance-Oriented Assessment of Mobility Problems in Elderly Patients'. *Journal of the American Geriatrics Society* 34 (2): 119–26.

Zhang, Wei, G. Ruben H. Regterschot, Hana Schaabova, Heribert Baldus, and Wiebren Zijlstra. 2014. 'Test-Retest Reliability of a Pendant-Worn Sensor Device in Measuring Chair Rise Performance in Older Persons'. *Sensors (Basel, Switzerland)* 14 (5): 8705–17. doi:10.3390/s140508705.