Predicting Fall Probability Based on a Validated Balance Scale

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Abstract

Accidental falls are the most frequent injury of old age and have dramatic implications on the individual, family, and the society as a whole. To date, fall prediction estimation is clinical, relying on the expertise of the physiotherapist for performing the diagnosis based on standard scales, such as the highly common and validated Berg Balance Scale (BBS). Unfortunately, the BBS is a time consuming subjective score, prone to variability and inconsistency between examiners. In this study, we developed an objective, computational tool, which automates the BBS fall assessment process and allows easy, efficient and accessible assessment of fall risk. The tool is based on a novel multi depth-camera human motion tracking system integrated with Machine Learning algorithms. The system enables large scale screening of the general public at very little cost while significantly reducing physiotherapist resources. The system was pilot tested in the physiotherapy unit at a major hospital and showed high rates of fall risk predictions as well as correlation with physiotherapists BBS scores on individual BBS motion tasks.

1. Introduction

Accidental falls are the leading cause of injury-related death and hospitalization in old age [34, 4], with over one-third of the older adults experiencing at least one fall or more each year. Considering that the elderly population is dramatically increasing in number, with expected elderly population (age 60 and older) reaching 22% worldwide by year 2050, with 35% in Europe, and 28% in North America [37, 38], the necessity for fall risk assessment is imminent.

To date, fall prediction estimation is clinical, relying on the expertise of the physiotherapist for performing the diagnosis. The extent and severity of fall risk is quantified using standard scales. One of the most common, is the comprehensive Berg Balance Scale (BBS). This is a time consuming subjective score, prone to variability and inconsistency between examiners. Currently, the BBS diagnosis relies on expensive and limited medical professional resources, strongly restricting the number of patients diagnosed and monitored. New and more efficient methods for fall prediction are necessary to identify and monitor older people at high risk of falling who would benefit from participating in fall prevention programs [20, 47].

In response to these calls we developed a study to automate the fall assessment process and allow easy, efficient and accessible assessment to be performed, thus reducing wait times for patients and exploiting medical professional resources more efficiently.

In this paper, we present an objective, computational tool, which automates the BBS fall assessment process and allows easy, efficient and accessible assessment of fall risk. The tool is based on a novel multi depth-camera human motion tracking system developed by the authors integrated with Machine Learning algorithms. The system was pilot tested in the Physiotherapy Unit at the Galilee Medical Center, a major hospital in Israel, and showed high rates of fall risk predictions as well as correlation with physiotherapists BBS scores on individual BBS motion tasks.

The high rate of successful automatic BBS scoring, and the ease of use of the system, will allow the system to be deployed in local medical centers, community centers and even at homes. This will increase accessibility to the elderly, allow greater number of individuals to undergo testing and thus detect greater number of elderly individuals that are at high fall risk and require intervention.

2. Background

2.1. Assessing Balance and Fall Risk

Estimation of balance and risk of fall is traditionally performed by physiotherapists and medical professionals using standardized and validated measures. These are typically motor functioning evaluations where a subject performs an action or task which is graded by the medical professional. The evaluations range from single task tests to a systematic battery of tests (see review in [46]).

Several single task tests focus on evaluating gait such as the 2-meter walk [7], 10-meter walk [17], and the 6 minute walk [40] where the score is the time to cover the distance or the distance within the specified time. These tests are very fast to implement and have been studied in the context of gait deterioration in diseases. A more extended comprehensive gait test is the Dynamic Gait Index [44] developed to evaluate gait, balance and fall risk. It encompasses a battery of gait related tasks at different levels of difficulty.

Another family of tests incorporate rising from a chair, as this is also an important aspect of daily life. The 30 second chair stand [29], 5X-Sit-to-Stand [6] and 10X-Sit-to-Stand require subjects to rise and sit in a chair as fast as they can measuring the number of repetitions in a specific time or the time to perform a number of repetitions. These tests asses functionality and strength of lower body extremes [29]. and can serve to predict falls [10].

A very popular test that combines chair and gait tests is the Timed Up and Go test [33, 41] that measures the time to rise from a chair, walk speedily for 3 meters, turn and return to sit in the chair. A subject is considered at high fall risk of fall if the task took longer than 14 seconds [45]. This is a quick test and is easy to perform, though several repetitions are recommended [5].

Other approaches to balance evaluation test for static pose, e.g. the Single-Legged / Unipedal Stance test [18], Unilateral Forefoot Balance Test [11], and Romberg test [42]. These require subjects to stand on both feet, aligned, in tandem or toe to heel, with eyes opened or closed. The 4-Stage Balance Test [43] is an assessment combining the above, with four different and increasingly challenging standing positions which must be maintained for 10 seconds.

Finally, other tests for balance induce various localized stepping such as the Step Test [24] where subject must raise foot on and off a step in succession as quickly as possible, the Four Square Step Test [14, 36] where subjects perform a sequence of steps over low objects in a square path, and the Y Balance Test [39] where subjects take lunging steps in 3 directions from a central pivot point.

The collection of single tasks balance evaluations described above are quick and easy to perform, usually requiring few and readily available equipment. However for medical assessment and intervention programs, medical professionals often prefer a more comprehensive balance test, that provides scores on a battery of tasks thus allowing a more detailed diagnosis and a personalized treatment. These tests are, of course, time consuming. Popular tests include the Berg Balance Scale (BBS) [2], the Tinetti Assessment Tool (TAT) [49], the Short Physical Performance Battery [21], each consisting of tasks relating to pose, gait and chair stand-sit. the Balance Evaluation Systems Test [26] is especially long. It is used for determining the source balance system that causes instability of an individual.

Advances in cameras and sensing technologies as well as in machine learning tools, has promoted the study of automatically evaluating balance and risk of fall. For example wearable sensors [48], inertial sensors [27] and visual sensors [32, 52] have been used to test for balance and fall risk. Camera sensors are ideal for hospitals, or old age homes, and home care systems [1], where they have significant advantages over other sensors since they are non-intrusive and can analyze multiple events simultaneously [50]. However, RGB cameras used in balance assessment lack depth information, which increases the number of false alarms [31]. Using multiple cameras to obtain depth information, requires calibration, and synchronization [52]. In our proposed study we use depth sensors in a novel multi-depth camera tracking system which does not require calibration sessions. Using 3D sensors has been shown to be successful on the single test Get-Up-and-Go [30], on the 10-meter walk test [19], Single-Legged Stance test [16] and on gait assessment [12].

2.2. The Berg Balance Scale BBS

The Berg Balance Scale (BBS) [2, 3] was developed to evaluate balance in older people by assessing their performance of specific functional tasks. The BBS is a standard measure used in the medical community at large. It is comprehensive and validated with relatively small inter-raters variation. The advantage of this scale is its high sensitivity and specificity. The test includes 14 simple balance tasks, ranging from unsupported sitting and standing to reaching forward while standing and standing on one leg (Figure 1). The level of success in achieving a task is credited a score of zero (unable) to four (independent), and the final mea-

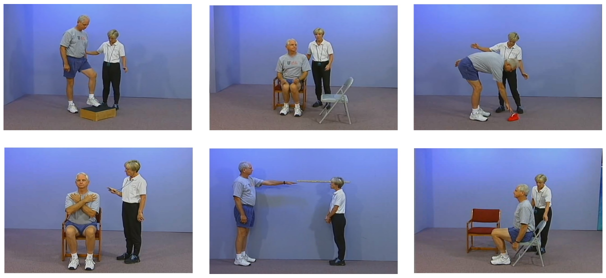

Figure 1. The BBS is a physical test, used to evaluate stability and fall risk. It includes 14 motor tasks that are evaluated by a medical professional. (Source: The Fall Prevention Center of Excellence (StopFalls.org)).

sure is the sum of all individual scores [3]. The BBS has been validated and it has been shown that a score of 36 or less, indicates a near 100% chance of fall within 6 months [44]. In practice a score of 0-20 is considered high fall risk, 21-40 medium fall risk and 41-56 low fall risk.

3. Automated BBS Assessment

The automated BBS assessment system requires tracking and recording patients motion while performing the BBS motor tasks. Following acquisition, the data is analyzed and a BBS score is predicted. Considering its usage and target population, the system must be non-intrusive, portable, and easy to use (even by a patient in a home setting). Score predictions must be reliable and consistent.

The proposed system, consists of two major components:

1. Motion tracking technology, including sensors and cameras.
2. Data analysis and score prediction algorithms that rely on training machine learning algorithms.

3.1. Motion Capture and Tracking

To achieve a non-intrusive, portable and inexpensive motion capture system, we used Kinect 3D cameras [23, 51] that provide, depth information of the scene. Using Time of Flight technology, the depth sensors provide a distance from camera for every point in the scene at each video frame. From this data, a body pose representation is extracted in the form of a skeleton, where body joints are positioned in a 3D coordinate system relative to the camera (Figure 2).

The BBS motion tasks, require patients to move in various directions including a full 360° turn (task #11). Thus to capture the full range of body motion we use a 2-camera setup (Figure 3), where 2 depth sensing cameras are positioned 2 meters apart and directed approximately 45° inward. Additionally, this setup allows integration of data from the two camera sources consequently reducing noise and skeleton errors. With any multi-camera system there is a need for synchronization and calibration, however this

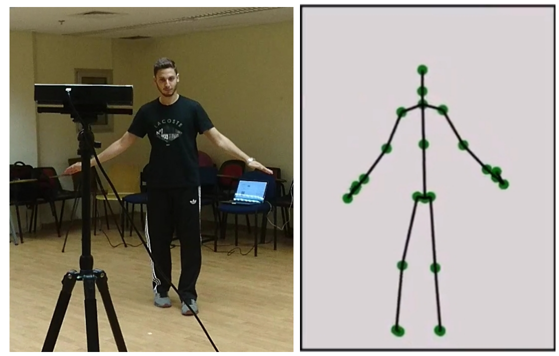

Figure 2. The 3D sensor measures distances of points in the scene from which (left) from which a skeleton representation of the body pose is produced (right).

process typically requires a designated calibration session with special calibration tools. We implemented the approach in [15] where synchronization and calibration is performed on the fly using patient motion. Thus, eliminating the need for calibration sessions, and creating an easy to use system. The automated calibration, allows integration of the skeletal data as well as the additional data required for analysis such as the ground position and object location.

During filming, the system outputs per video frame: the skeletal 3D joint position, the floor position and orientation per frame, the 3D point cloud data in the patient's immediate surrounding, and objects in the scene relevant to the BBS task.

3.2. Data analysis and BBS Score Prediction

The goal of the system is to predict the BBS score of patients as correlated with the scores given by physiotherapists: the 14 individual BBS scores and the final fall risk assessment deduced from the 14 BBS scores. We adopted a machine learning algorithm and trained it using labeled patient data (Figure 4).

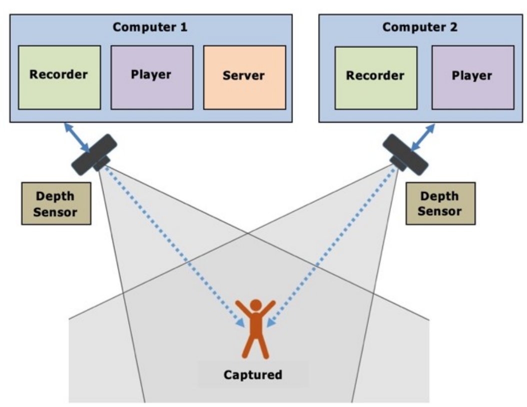

Figure 3. The 3D camera setup includes two depth sensors to allow capture of full range of patient motion, and to allow data merging to reduce noise and skeleton errors.

3.2.1 Data Collection

To train and evaluate the ML algorithm, we recorded 129 subjects at the physiotherapy unit at the Galilee Medical Center. 100 of the subjects were in-patients and 29 were visitors that were recruited as subjects for the lower risk category. All subjects were aged 65 or older. All The patients were recorded using the multi camera tracking system (Section 3.1), while preforming the 14 BBS tasks. Concurrently, two physiotherapists assessed the patient using the BBS scoring system. The physiotherapists scores served as labels for the training samples. When an inconsistency in the physiotherapists' scores occurred, the more conservative score was used. Fortunately this occurred in relatively few cases.

3.2.2 Feature Extraction

For every subject and for each of the 14 tasks, features were extracted to serve as ML training for a Random Forest classifier [25]. For each video frame, spatio-temporal features were extracted from the skeletal and 3D cloud point data including: relative position of skeleton joints, distance between body parts, angle at body joints, height of joints from ground and more (Figure 5). All features were relative (to start position, to other body parts to ground plane, etc) and thus invariant to the position of camera with respect to the subject. All features were measured in metric units. From these, global spatio-temporal features associated with the task's complete motion sequence were computed: average speed and acceleration of joints, motion-paths, maximal/minimal/mean values of the spatio-temporal features and more. These global features served as the representation of each sample video for the machine learning training.

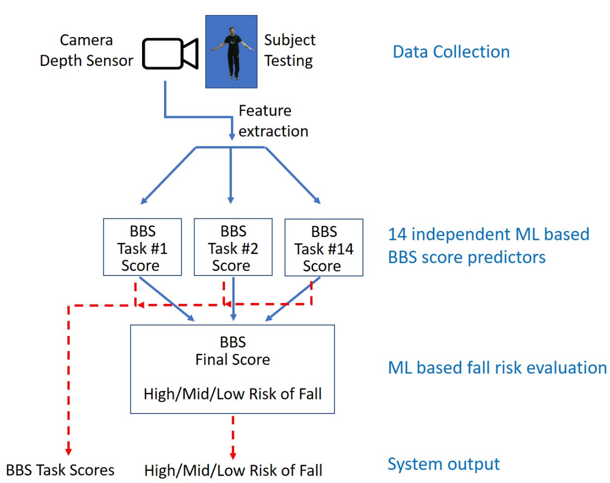

Figure 4. Schematic diagram of the BBS score and fall risk prediction system.

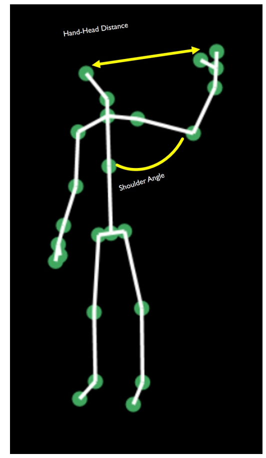

Figure 5. Spatio-temporal features were computed from the skeleton data in each recorded video frame.

To optimize training of the system, feature selection was performed, by considering the most informative features as deduced by the trained ML system, as well as directly recommended by the physiotherapists.Thus, the relevant features used in training and testing ranged between 100-200 dependent on the specific BBS task. The BBS score assigned by the physiotherapist to each subject in each video sequence, served as the label of each such video sample and its associated feature vector.

The predicted labels of the 14 classifiers were supplied as input features to an additional SVM [13] classifier to predict the final BBS fall risk category (low fall risk / medium fall risk / high fall risk) (see Figure 4).

3.2.3 Training

A separate Random Forest classifier [25] was trained for each of the 14 tasks. The parameters for the classifiers were chosen using a grid search algorithm, which exhaustively searched through a manually specified subset of hyperparameters [28]. An additional SVM classifier was trained for the ternary fall-risk classification (low fall risk / medium fall risk / high fall risk), whose parameters were also chosen using a grid search algorithm. The chosen kernel for the SVM classifier was a Radial Basis Function(RBF) [9], with a gamma coefficient of $1/nf$, where nf is the number of features, and a regularization parameter $C = 3$. Since our dataset is not large enough to split into training, validation and test sets, we used the leave-one-out-cross-validation method (LOOV) [35], leaving one subject out on each iteration, to evaluate the accuracy of the classifiers. This method also represents the classifiers' performance when given a single new subject to classify, rather than a batch of new subjects.

4. Results

To evaluate the performance of the automated BBS score prediction system, we evaluated the classification performance into the five score classes (0-4) for each task. Additionally we evaluated the final risk assessment into the three classes of High, Medium and Low risk of fall, given by the threshold levels defined on the final BBS score of the physiotherapist: a score of 0-20 is considered high fall risk, 21-40 medium fall risk and 41-56 low fall risk.

Table 1 shows the accuracy in predicting the score of every BBS task. N is the number of samples tested in each task (differences between tasks are due to patients not completing some of the BBS tasks, or technical failures in some of the recordings) and the number of samples for each of the five classes. The table also shows the chance level since the distribution of samples was not evenly spread across the classes (some BBS tasks are very easy and are never scored low, e.g. Task #3 Sitting with Back Unsupported). The Table also shows the Mean Square Error for the misclassifications. The low MSE values indicate that when erred, the classification error was at most one score unit.

More importantly, is the accuracy in determining the level of fall risk. Figure 6a shows the performance of the system by displaying the confusion matrix between the predicted risk level and the true level determined by the sum of BBS task scores assessed by the physiotherapist. Success rate is at 75%, with Mean Square Error (MSE) of 0.25, however, when assessing risk of fall, false negatives (FN) should be minimized. The matrix shows that 9 high risk samples were categorized as medium risk. We can control the level of FN by optimizing for different thresholds while still maintaining a good level of success. Figure 6b shows the resulting confusion matrix when this approach was adopted. It can be seen that FN was reduced to 4 samples, however, at the expense of increased number of false positives and a small increase in MSE to 0.29. The intent is to allow the physicians to select the level of accuracy, and achieve a satisfying false negative percentage as well as a satisfying overall accuracy.

Finally, we performed feature ranking to determine the tasks most influencing the final risk of fall. We found that the following five BBS tasks contributed the most to the classifier output (in decreasing order):

- Turn 360° (Task #11)
- Alternate Feet on Step (Task #12)
- Transfers (Task #5)
- Reaching forward with outstretched arm (Task #8)
- Standing with Feet Together (Task #7)

The importance of the tasks was determined using an Analysis of Variance (ANOVA) F-test algorithm [22], that scores the features by calculating their F-statistic (ratio of the between-group variability to the within-group variability). Our physiotherapists (co-authors) indeed confirmed that they consider the first two as the major contributors to the BBS evaluation.

5. Conclusion

We developed an automated system for evaluating the BBS fall assessment scores. The system is based on a novel multi depth-camera human motion tracking system integrated with Machine Learning algorithms. The system is non-invasive, portable and easy to use. The system enables

Task	Task Description	N	Samples per Class <0,1,2,3,4>	Chance Level	Accuracy	MSE
1	**Sitting to Standing**	102	0,0,0,66,36	65%	82%	0.18
2	**Standing Unsupported**	111	0,0,15,24,72	66%	72%	0.36
3	**Sitting with Back Unsupported**	112	0,0,0,0,112	100%	100%	0.0
4	**Standing to Sitting**	105	0,0,0,53,52	50%	85%	0.15
5	**Transfers**	96	0,0,22,39,35	41%	73%	0.36
6	**Standing Unsupported, Eyes Closed**	101	0,0,0,49,52	51%	68%	0.32
7	**Standing Unsupported, Feet Together**	106	13,13,0,33,47	44%	72%	0.37
8	**Reaching Forward**	75	0,17,0,24,34	45%	69%	0.51
9	**Pickup Object from the Floor**	99	7,0,0,39,53	54%	72%	0.31
10	**Look Behind Shoulders**	102	7,9,8,32,46	45%	52%	1.25
11	**Turn 360°**	100	14,26,20,7,33	33%	66%	0.60
12	**Alternate Feet on Step**	93	39,11,12,0,31	42%	75%	0.34
13	**Standing Unsupported, One Foot in Front**	93	30,14,30,0,19	32%	74%	0.54
14	**Standing on One Leg**	109	39,40,8,0,22	37%	66%	0.80

Table 1. MultiClass classification prediction of BBS score per task.

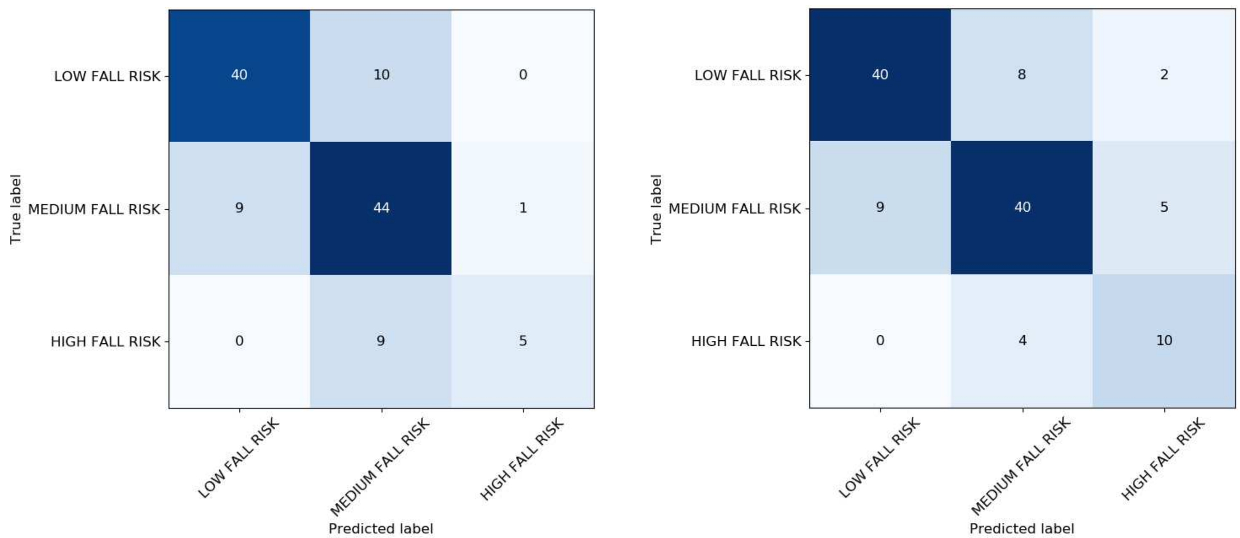

Figure 6. Confusion matrix between the predicted risk level and the true level. a) Using Standard BBS thresholds for risk of fall. b) Using thresholds that reduce false negatives.

large scale screening of the general public at very little cost while significantly reducing physiotherapist resources. The system was pilot tested in a major hospital and showed high rates of fall risk predictions as well as correlation with physiotherapists BBS scores on individual BBS motion tasks.

Further studies will continue to improve performance of the system by collecting additional data, improving on feature detection and selection and incorporating more advanced ML techniques as well as technologies. Our system relies on depth sensors to obtain 3D skeletons of the human subject. Improved performance is obtained using the new version of the Kinect (Kinect Azure). Technology is also expected to improve and allow 3D skeletons from 2D data. Currently, such available systems (e.g [8]) require very strong computational power that is not readily accessible and appropriate for the simple low cost system as we propose in this paper.

Finally, we mention that this study focused on evaluating fall risk via the BBS scoring system. A similar approach can easily be applied to any other motor based fall assessment tasks such as the Tinetti Assessment Tool (TAT) [49] and others.

References

[1] M. Aslan, A. Sengur, Y. Xiao, H. Wang, M. C. Ince, and X. Ma. Shape feature encoding via fisher vector for efficient fall detection in depth-videos. *Applied Soft Computing*, 37:1023–1028, 2015. 2

[2] K. O. Berg, S. Wood-Dauphine, I. J. Williams, and D. Gayton. Measuring balance in the elderly: preliminary development of an instrument. *Physiotherapy Canada*, 41(6):304–311, 1989. 2

[3] K. O. Berg, S. L. Wood-Dauphinee, J. I. Williams, and B. Maki. Measuring balance in the elderly: validation of an instrument. *Canadian journal of public health*, 83:S7–11, 1992. 2, 3

[4] G. Bergen. Falls and fall injuries among adults aged $\geq$ 65 years—united states, 2014. *MMWR. Morbidity and mortality weekly report*, 65, 2016. 1

[5] M. L. Bloch, L. R. Jønsson, and M. T. Kristensen. Introducing a third timed up & go test trial improves performances of hospitalized and community-dwelling older individuals. *Journal of geriatric physical therapy (2001)*, 40(3):121, 2017. 2

[6] S. Buatois, D. Miljkovic, P. Manckoundia, R. Gueguen, P. Miget, G. Vançon, P. Perrin, and A. Benetos. Five times sit to stand test is a predictor of recurrent falls in healthy community-living subjects aged 65 and older. *Journal of the American Geriatrics Society*, 56(8):1575–1577, 2008. 2

[7] R. J. Butland, J. Pang, E. R. Gross, A. A. Woodcock, and D. M. Geddes. Two-, six-, and 12-minute walking tests in respiratory disease. *British medical journal (Clinical research ed.)*, 284(6329):1607, 1982. 2

[8] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2019. 6

[9] Y.-W. Chang, C.-J. Hsieh, K.-W. Chang, M. Ringgaard, and C.-J. Lin. Training and testing low-degree polynomial data mappings via linear svm. *Journal of Machine Learning Research*, 11(Apr):1471–1490, 2010. 4

[10] Y.-Y. Cheng, S.-H. Wei, P.-Y. Chen, M.-W. Tsai, I.-C. Cheng, D.-H. Liu, and C.-L. Kao. Can sit-to-stand lower limb muscle power predict fall status? *Gait & posture*, 40(3):403–407, 2014. 2

[11] M. S. Clark. The unilateral forefoot balance test: Reliability and validity for measuring balance in late midlife women. *New Zealand Journal of Physiotherapy*, 35(3):110, 2007. 2

[12] R. Clark, S. Vernon, B. Mentiplay, K. Miller, J. Mcginley, Y. Pua, K. Paterson, and K. Bower. Instrumenting gait as-

sessment using the kinect in people living with stroke: Reliability and association with balance tests. *Journal of NeuroEngineering and Rehabilitation*, 12, 12 2015. 2

[13] C. Cortes and V. Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995. 4

[14] W. Dite and V. A. Temple. Four square step test (fsst). *Archives of Physical Medicine and Rehabilitation*, 83(11):1566–71, 2002. 2

[15] N. Eichler, H. Hel-Or, I. Shimshoni, D. Itah, B. Gross, and S. Raz. 3d motion capture system for assessing patient motion during fugl-meyer stroke rehabilitation testing. *IET Computer Vision*, 12(7):963–975, 2018. 3

[16] M. Eltoukhy, C. Kuenze, J. Oh, and J. Signorile. Balance assessment using microsoft xbox kinect: 1136 board number 315. *Medicine & Science in Sports & Exercise*, 49:315, 05 2017. 2

[17] U.-B. Flansbjer, A. M. Holmbäck, D. Downham, C. Patten, and J. Lexell. Reliability of gait performance tests in men and women with hemiparesis after stroke. *Journal of rehabilitation medicine*, 37(2):75–82, 2005. 2

[18] A. R. Fregly and A. Graybiel. An ataxia test battery not requiring rails. *Aerospace Medicine*, 39(3):277–282, 1968. 2

[19] D. J. Geerse, B. H. Coolen, and M. Roerdink. Kinematic validation of a multi-kinect v2 instrumented 10-meter walkway for quantitative gait assessments. *PloS one*, 10(10):e0139913, 2015. 2

[20] L. D. Gillespie, M. C. Robertson, W. J. Gillespie, C. Sherrington, S. Gates, L. M. Clemson, and S. E. Lamb. Interventions for preventing falls in older people living in the community. *Cochrane database of systematic reviews*, 9, 2012. 1

[21] J. M. Guralnik, L. Ferrucci, C. F. Pieper, S. G. Leveille, K. S. Markides, G. V. Ostir, S. Studenski, L. F. Berkman, and R. B. Wallace. Lower extremity function and subsequent disability: consistency across studies, predictive models, and value of gait speed alone compared with the short physical performance battery. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 55(4):M221–M231, 2000. 2

[22] D. L. Hahs-Vaughn and R. G. Lomax. *Statistical Concepts-A Second Course: A Second Course*. Routledge, 2013. 5

[23] Han, Shao, Xu, and Shotton. Enhanced computer vision with microsoft kinect sensor: A review. *IEEE Transactions on Cybernetics*, 43(5):1318–1334, 2013. 3

[24] K. D. Hill, J. Bernhardt, A. M. McGann, D. Maltese, and D. Berkovits. A new test of dynamic standing balance for stroke patients: reliability, validity and comparison with healthy elderly. *Physiotherapy Canada*, 48(4):257–262, 1996. 2

[25] T. K. Ho. The random subspace method for constructing decision forests. *IEEE transactions on pattern analysis and machine intelligence*, 20(8):832–844, 1998. 4

[26] F. B. Horak, D. M. Wrisley, and J. Frank. The balance evaluation systems test (BESTest) to differentiate balance deficits. *Physical therapy*, 89(5):484–498, 2009. 2

[27] J. Howcroft, J. Kofman, and E. D. Lemaire. Review of fall risk assessment in geriatric populations using inertial sensors. *Journal of neuroengineering and rehabilitation*, 10(1):91, 2013. 2

[28] C.-W. Hsu, C.-C. Chang, C.-J. Lin, et al. A practical guide to support vector classification, 2003. 4

[29] C. J. Jones, R. E. Rikli, and W. C. Beam. 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):113–119, 1999. 2

[30] A. B. Kargar, A. Mollahosseini, T. Struemph, W. Pace, R. D. Nielsen, and M. H. Mahoor. Automatic measurement of physical mobility in get-up-and-go test using kinect sensor. In *International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 3492–3495, 2014. 2

[31] B. Kwolek and M. Kepski. Human fall detection on embedded platform using depth maps and wireless accelerometer. *Computer methods and programs in biomedicine*, 117(3):489–501, 2014. 2

[32] R. Luque, E. Casilari, M.-J. Morón, and G. Redondo. Comparison and characterization of android-based fall detection systems. *Sensors*, 14(10):18543–18574, 2014. 2

[33] S. Mathias, U. Nayak, and B. Isaacs. Balance in elderly patients: the "get-up and go" test. *Archives of physical medicine and rehabilitation*, 67(6):387–389, 1986. 2

[34] M. McCarthy. Falls are leading cause of injury deaths among older people, US study finds, 2016. 1

[35] A. M. Molinaro, R. Simon, and R. M. Pfeiffer. Prediction error estimation: a comparison of resampling methods. *Bioinformatics*, 21(15):3301–3307, 2005. 4

[36] M. Moore and K. Barker. The validity and reliability of the four square step test in different adult populations: a systematic review. *Systematic reviews*, 6(1):187, 2017. 2

[37] U. Nations. World population prospects: 2017 revision. 1

[38] U. Nations. World population prospects 2019. 1

[39] L. Neves. The Y balance test – how and why to do it? *International Physical Medicine & Rehabilitation Journal*, 2, 12 2017. 2

[40] A. C. on Proficiency Standards for Clinical Pulmonary Function Laboratories et al. Ats statement: guidelines for the six-minute walk test. *Am J Respir Crit Care Med*, 166:111–117, 2002. 2

[41] D. Podsiadlo and S. Richardson. The timed "up & go": a test of basic functional mobility for frail elderly persons. *Journal of the American geriatrics Society*, 39(2):142–148, 1991. 2

[42] J. Rogers. Romberg and his test. *The Journal of Laryngology & Otology*, 94(12):1401–1404, 1980. 2

[43] J. E. Rossiter-Fornoff, S. L. Wolf, L. I. Wolfson, D. M. Buchner, and F. Group. A cross-sectional validation study of the ficsit common data base static balance measures. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 50(6):M291–M297, 1995. 2

[44] A. Shumway-Cook, M. Baldwin, N. L. Polissar, and W. Gruber. Predicting the probability for falls in community-dwelling older adults. *Physical therapy*, 77(8):812–819, 1997. 2, 3

[45] A. Shumway-Cook, S. Brauer, and M. Woollacott. Predicting the probability for falls in community-dwelling older adults using the timed up & go test. *Physical therapy*, 80(9):896–903, 2000. 2

[46] R. Soubra, A. Chkeir, and J.-L. Novella. A systematic review of thirty-one assessment tests to evaluate mobility in older adults. *BioMed Research International*, 2019, 2019. 2

[47] J. A. Stevens and R. Lee. The potential to reduce falls and avert costs by clinically managing fall risk. *American journal of preventive medicine*, 55(3):290–297, 2018. 1

[48] R. Sun and J. J. Sosnoff. Novel sensing technology in fall risk assessment in older adults: a systematic review. *BMC geriatrics*, 18(1):14, 2018. 2

[49] M. E. Tinetti, T. F. Williams, and R. Mayewski. Fall risk index for elderly patients based on number of chronic disabilities. *The American journal of medicine*, 80(3):429–434, 1986. 2, 6

[50] P. Vallabh and R. Malekian. Fall detection monitoring systems: a comprehensive review. *Journal of Ambient Intelligence and Humanized Computing*, 9(6):1809–1833, 2018. 2

[51] Wang, Kurillo, Ofli, and Bajcsy. Evaluation of pose tracking accuracy in the first and second generations of microsoft kinect. In *International Conference on Healthcare Informatics (ICHI)*, pages 380–389. IEEE, 2015. 3

[52] L. Yang, Y. Ren, H. Hu, and B. Tian. New fast fall detection method based on spatio-temporal context tracking of head by using depth images. *Sensors*, 15(9):23004–23019, 2015. 2