Fall Risk Analysis for Elderly with Wearable Accelerometers Measurements

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Abstract — **Emerging with aging populations in developed countries, continuously rising incidences of fall has consistently raised the concern in elderly and long-term care. In this research paper, the relationship between Berg Balance Scale (BBS) and elderly movement data captured by wearable accelerometers are determined. In situations where it is not known if the elderly is prone to falls, a clustering model is established to segment different groups of distinguished gait pattern and evaluate the feasibility to stratify the risk of falling variates with the harmonic ratio of measurements in three perpendicular directions during gait pattern assessment. It purely relies on the measurements of body movement without any judgement subjected to individual medical professional which opinions even can be variated among each other. Robustness of this model are further verified by appropriate tests of statistical significance. The present study, as an authentic complement, evaluates the effectiveness of using wearable accelerometers to assess the fall risk for elderly. It is also an alternative reference for IoT or wearable device manufacturers to further research and develop a system to estimate fall risk individually, predict any fall activity and thus prevent from its occurrence.**

Index Terms — IoT, Wearable Devices, Unsupervised Learning, Elderly Care, Tracking

I. Introduction

FALLS and its related injuries profoundly impact on an individual especially for the elderly, for instance, suffering from injuries like head trauma and broken bones [5]. Even worse, that can diminish their psychological, social and physical well-being, and even take away one's life [4,6,13,22]. Wrist fractures, hip fractures and vertebral fractures are some of the injuries that can be resulted from fall. According to the WHO global report, the fall cases of people aged 65 and above has increased from 28 - 35% to 32 - 42% when they aged over 70 [28]. Age-related biological change is likely to result in exponential growth of falls and related injuries. During the last three decades, the number of fall-related injuries has increased by 131%. It is expected that there will be a 100% increase in the numbers of related injuries in 2030 [12].

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Additionally, that casts heavy burdens on the economy and the society. The direct medical costs in 2012 are $616.5 million and $30.3 billion for fatal and non-fatal injuries respectively in the USA [21]. The financial toll will even further soar up to $67.7 billion by 2020 [21]. As the population ages [27], the impacts mentioned above would further dampen the society.

Traditionally, fall risk assessment relies on both identification of fall risk factors and clinical tests, such as 3-meter Timed Up and Go (3M TUG) Test and Berg Balance Scale (BBS) score, etc. Still, with the aid of rapid development of sensor technology, the emergence of the possible effective fall risk assessment tool – wearable sensors, can be a more sensitive and specific method that can provide timely quantitative assessment.

II. Literature Review

The causes of fall could be separated into distinct risk factors, including biomedical, behavioral and environmental. While some factors like aging and gender are unalterable, most of these risk factors can be avoided by adjusting one's lifestyle, number and type of medications, and physical environment [28].

Nevertheless, those commonly used motor performance tests such as Berg scale, Timed Up and Go, POMA etc. are generally not capable to provide quantitative predictive assessment of gait stability and fall risk [9]. Fall prediction rate of 50% sensitivity and 43% specificity are low even in test batteries specifically designed for fall risk assessment due to the error in step detection leading to inconsistent results during identifying gait cycles [14,25].

That could be resolved by nonlinear analysis techniques, for example, Harmonic ratio (HR), the Index of harmonicity (IH), Multiscale entropy (MSE), and Recurrence quantification analysis (RQA) of trunk accelerations during gait [26]. Furthermore, wearable sensor became an agreed potential useful technology for fall risk assessment [18].

In general, three main types of methodologies are available to evaluate the fall risk that are functional, system or physiological and quantitative assessments. In regards of functional assessments, fall risk assessment in an intuitive and cost-effective approach to evaluate the balance status and variation in intervention such as 3-meter Timed Up and Go (TUG) Test and Berg Balance Scale. Balance [2,8,9,10,16,19]. Still, the limitations are heavy reliance of expertise input and low responsiveness to minor change in the balance ability while the performance reaches only acceptable level [3,7].

Secondly, system disorders can differentiate distinct types

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of balance disorder. The sensorimotor mechanisms can be identified via physiological assessments that cause balance deficit. Two advanced scoring system are the Balance Evaluation Systems Test (BESTest) and the Physiological Profile Approach (PPA). Former has similar inter-rater reliability as functional balance tests, but it is more time consuming [16]. Later has high sensitivity and specificity, however, therapists cannot make direct treatment decision. Moreover, variability exists when conducted by different examiners for both scoring systems [16].

Quantitative assessment is to measure subjects with computerized systems and wearable sensors, which is competent to overcome the shortage of above two approaches with non-subjective measurements. The outcome is thus more specific, sensitive, and responsive [16]. Accelerometer as a type of inertial sensor to record the human motions is one of the quantitative measuring tools for fall risk assessment. Most of the detection systems adopt threshold-based algorithms for fall detection with performance indicators of precision and specificity [24]. The sensor can be placed at the mid or lower lumbar spine (L2 or L5) [16,20,24] but the positioning at anterior superior iliac spine should be avoided.

III. METHODOLOGYB

A. Hypothesis

1) Harmonic ratio of at least one direction is correlated to the Berge Balance Scale which the level of fall risk is quantified.
2) Gait pattern of elderly can be segmented as multiple groups which are also distinguished among each other.
3) Risk of fall can be stratified by movement data of the elderly which is collected by accelerometer during gait pattern assessment.
4) There is the relationship between stratified groups of fall risk by clustering and that by Berge Balance Scale.

B. Data collection and processing

A wearable accelerometer, X16-4 USB Accelerometer Data Logger, was adopted for 3-axis data collection and mounted at the lower lumbar spine (L4-L5) during 10-meter corridor walking test and 3M timed up and go test. 31 elderly residents from one of elderly care center in Hong Kong participated in the study.

The acceleration data is transformed into individual 3-axis harmonics ratio as gait stability indicator with Discrete Fourier Transform (DFT) for further analysis. The trunk acceleration of the directions of vertical (V), mediolateral (ML) and antero-posterior (AP) will be represented by ***X***, ***Y*** and ***Z*** respectively [1,11,25].

C. Analysis and Modeling

To examine the relationship between movement data and fall risk level, Pearson correlation coefficient is derived from the pair of BBS and harmonic ratio at one direction. Hence, three pairs of that in total could be taken to be computed since there are three directions of harmonic ratio.

Without any supervision on the individual fall risk, K-means clustering as non-hierarchical clustering techniques is proposed to stratify the risk group. Four candidates of cluster models are trained in line with all possible combination of multiple directions of motions, i.e., ***XYZ***, ***XY***, ***XZ*** and ***YZ***. In order to ensure the model stability, the constraint is added that the minimum size of a cluster is set to be ten percent of the total sample size which means at least 3 samples.

For each candidate, the trial value of k, i.e., number of clusters is set from 2 to 5. The optimal k is determined by the greatest value of Calinski-Harabasz criterion (CH) to better distinguish the clusters by minimizing within-group variation and maximizing variation among group [15].

$$CH = \frac{n-k}{k-1}\frac{tr(SSB)}{tr(SSW)}$$

, where n is number of data instances, SSB is sum of square error between groups and SSW is sum of square error within a group. The final model which has the greatest value of CH criterion among the four candidates. Moreover, t-test and one-way ANOVA are also conducted to compare the clusters if there are statistically significant differences between or among the centroid of clusters under 95% confidence level.

After that, the model performance should be further validated with Berg Balance Scale (BBS) by dividing two groups of higher and lower risk of falling with cut-off score of 45 in terms of F1 score, harmonic mean of precision and recall [17] under the circumstance that there is no specific preference to minimize either Type I or Type II error. Meanwhile, Chi-square test is applied to determine any relationship between stratified group of fall risk by clustering and that by BBS cut-off score.

IV. RESULTS

Pearson correlation coefficient between BBS and Harmonic ratio (HR) with ***X***, ***Y*** and ***Z*** directions are 0.3655, -0.1426 and 0.4998 respectively. Only the pair of BBS and HR in ***Z*** direction is found to be positive correlated that it is significant at $p < .05$. Apparently, the first hypothesis in section IIIA is accepted.

Regarding clustering analysis, resultant four trained clustering model are established under the given optimization objective and constraints with corresponding cluster sizes and CH criterion (Refer to Table I). Apparently, the cluster model of ***XZ*** combination with 2 cluster performs the best. The results of t-test and one-way ANOVA shows a consistent result that the two groups are distinguished under the level of statistical significance, 0.05. As a result, the second hypothesis is accepted.

TABLE I
COMPARISON OF RESULTANT CLUSTER MODEL CANDIDATES

Combinations of HRs	No. of cluster (Cluster sizes)	CH Criterion
XYZ	2 (12, 19)	25.20
XY	3 (6, 18, 7)	29.91
YZ	3 (14, 11, 6)	33.50
XZ	2 (21, 10)	34.34

However, the difference of mean value of BBS score between two clusters generated by XZ clustering model does not show a significant difference with .169 p-value by conducted independent t-test. The third hypothesis is rejected accordingly.

Besides, the confusion matrix is constructed in the Table II to compare with risk group classification by BBS scores. Accuracy, precision, sensitivity and F1 score are 67.7%, 71.4%, 78.95 and 0.75 respectively which the stratification of risk of fall seems to be associated between the clustering method and BBS cut-off scores. Nonetheless, the fourth hypothesis mentioned in section IIIA is rejected under significant level 0.05 since Chi-square statistics is 2.82 and p-value is 0.09 under one degree of freedom.

TABLE II
CONFUSION MATRIX OF CLUSTER GROUPS AND RISK GROUP DIVIDED BY BBS SCORE

Cut-off score of BBS = 45	***XZ*** Cluster 1 (Higher BBS)	***XZ*** Cluster 2 (Lower BBS)
BBS - High fall risk	15	4
BBS - Low fall risk	6	6

V. DISCUSSION

Aforementioned in the previous section, the positive correlation between BBS and ***Z***-direction HR ratio has been observed. It indicates that the elderly with higher gait stability along the direction of antero-posterior tends to obtain higher BBS score and thus less risk of falling. As a result, readings in this direction and corresponding stability indicator can be closely monitored to prevent from any fall. The result is consistent with the finding that AP (Z) and V (X) directions are useful for differentiating fall risk groups [11,29].

The chosen clustering model has proved that the gait pattern of elderly can be segmented as two distinguishable groups. Despite the groups showing different the level of gait stability in both vertical (***X***) and antero-posterior (***Z***) directions, that does not therefore imply significant differences on the risk of fall. In the meantime, there is no significant relationship between cluster groups and groups divided by BBS cut-off score, which implies that the harmonic ratio and thus gait stability in both antero-posterior and vertical direction are not competent enough to distinguish risk level of fall. Asides from the gait pattern, other factors impacting the risk should be considered to enhance the model accuracy and robustness. In spite of that, this model still possesses acceptable model performance in terms of F1 score, precision and sensitivity. As a consequence, it could be applied to roughly estimate the fall risk for the elderly that is never evaluated by BBS or other assessments.

VI. CONCLUSION

To sum up, total two of four hypotheses are accepted with detail explanations in the previous section. The relationship between gait stability and fall risk quantified by BBS is identified. Moreover, the clustering model could differentiate the gait stability of elderly along vertical and antero-posterior directions but not risk level of fall. The proposed model, which still sufficiently could be a classifier to preliminarily estimate whether the elderly is high risk of fall with wearable device data, could be adopted before conducted more detail and reliable but time-consuming assessments.

REFERENCES

[1] Bellanca, J. L., Lowry, K. A., VanSwearingen, J. M., Brach, J. S., & Redferna, M. S. (2013). Harmonic ratios: A quantification of step to step symmetry. Journal of Biomechanics, 46, 828- 831
[2] Berg, K., & Norman, K.E. (1996). Functional assessment of balance and gait. Clin.Geriatr.Med, 12, 705–723.
[3] Blum, L., & Korner-Bitensky, N. (2008). Usefulness of the Berg Balance Scale in stroke rehabilitation: a systematic review. Phys.Ther, 88, 559–566.
[4] Boyce, R. D., Hanlon, J. T., Karp, J. F., Kloke, J., Saleh, A., & Handler, S.M. (2012). A Review of the Effectiveness of Antidepressant Medications for Depressed Nursing Home Residents. Journal of The American Medical Directors Association, 13(4), 326-331.
[5] Centre for Health Protection. (2013). Falls in the Elderly [PDF]. Non-Communicable Diseases Watch. Retrieved from http://www.chp.gov.hk/files/pdf/ncd_watch_nov2013.pdf
[6] Currie, L. (2008). Fall and injury prevention. In: R. G. Hughes, Ed., Patient Safety and Quality: An Evidence-Based Handbook for Nurses, Agency for Healthcare Research and Quality, US Department of Health and Human Services, Rockville, 195-250.
[7] Downs, S. (2015). The Berg Balance Scale. Journal of Physiotherapy, 61(46).
[8] Giorgetti, M. M., Harris, B. A., & Jette, A. (1998). Reliability of clinical balance outcome measures in the elderly. Physiother.Res.Int, 3, 274–283.
[9] Hamacher, D., Singh, N. B., Van Dieën, J. H., Heller, M .O., & Taylor, W. R. (2011). Kinematic measures for assessing gait stability in elderly individuals: a systematic review. The Royal Society. doi:10.1098/rsif.2011.0416. Retrieved from http://rsif.royalsocietypublishing.org/content/8/65/1682
[10] Horak, F. B. (1997). Clinical assessment of balance disorders. Gait & Posture, 6, 76–84.
[11] Hylton, B. M., Stephen, R. L., & Richard, C. F. (2003). Acceleration Patterns of the Head and Pelvis When Walking are Associated with Risk of Falling in Community-Dwelling Older People. Journal of Gerontology: MEDICAL SCIENCES, 58A(5), 446- 452
[12] Kannus, P., Palvanen, M., Niemi, S., Parkkari, J. (2007). Alarming rise in the number and incidence of fall-induced cervical spine injuries among older adults. Journal of Gerontology: Biological Sciences and Medical Sciences, 62(2), 180-183.
[13] Khanuja, K., Joki, J., Bachmann, G., & Cuccurullo, S. (2018, April). Gait and balance in the aging population: Fall prevention using innovation and technology. Maturitas, 110, 51- 56.
[14] Laessoe U., Hoeck H. C., Simonsen O., Sinkjaer T., Voigt M. (2007). Fall risk in an active elderly population—can it be assessed? J. Negat. Results Biomed, 6, 2. doi:10.1186/1477-5751-6-2
[15] Liu, Y., Li, Z. M., Xiong, H., Gao, X. D., & Wu, J. J. (2010). Understanding of Internal Clustering Validation Measures. IEEE International Conference on Data Mining.
[16] Mancini, M., & Horak, F. B. (2010). The relevance of clinical balance assessment tools to differentiate balance deficits. European Journal of Physical and Rehabilitation Medicine, 46(2), 239–248.
[17] Markham, K. (2014). Simple guide to confusion matrix terminology. Retrieved from http://www.dataschool.io/simple-guide-to-confusion-matrix-terminology/
[18] Marschollek, M., Schulze, M., Gietzelt, M. & Lovel, N. & Redmond, S. J. (2013). Fall prediction with wearable sensors- an empirical study on expert opinions. Studies in health technology and informatics, 190, 138-140. doi:10.3233/978-1-61499-276-9-138.
[19] McMichael, K. A., Vander Bilt, J., Lavery, L., Rodriguez, E., & Ganguli, M. (2008). Simple Balance and Mobility Tests Can Assess Falls Risk When Cognition Is Impaired. Geriatric Nursing (New York, N.Y.), 29(5), 311–323.
[20] Montesinos, L., Castaldo, R., & Pecchia, L. (2018). Wearable Inertial Sensors for Fall Risk Assessment and Prediction in Older Adults: A Systematic Review and Meta-Analysis. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(3), 573- 582.
[21] NCOA (2017). Falls Prevention Facts. Retrieved from https://www.ncoa.org/news/resources-for-reporters/get-the-facts/falls-prevention-facts/
[22] Pin, S., & Spini, D. (2016). Impact of falling on social participation and social support trajectories in a middle-aged and elderly European sample. SSM- Population Health, 2, 382- 389.
[23] Rajagopalan, R., Litvan, I., & Jung, T.-P. (2017). Fall Prediction and Prevention Systems: Recent Trends, Challenges, and Future Research Directions. Sensors (Basel, Switzerland), 17(11), 2509. http://doi.org/10.3390/s17112509

[24] Rispens, S. M., Pijnappels, M., van Schooten, K. S., Beek, P. J., Daffertshofer, A., & van Dieën, J. H. (2014). Consistency of gait characteristics as determined from acceleration data collected at different trunk locations. Gait Posture. 40(1), 187-92. doi: 10.1016/j.gaitpost.2014.03.182. Epub 2014 Apr 3.

[25] Riva, F., Diee ´n, J.H. van., Pijnappels, M., Stagni, R., & Toebes, M. J. P. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. SciVerse Science Direct, 38, 170- 174.

[26] Stevens, J. A., Ballesteros, M. F., Mack, K. A., Rudd, R. A., DeCaro, E., Adler, G. (2012). Gender differences in seeking care for falls in the aged Medicare Population. Am J Prev Med, 43, 59- 62.

[27] United Nations, Department of Economic and Social Affairs, Population Division (2015). World Population Ageing 2015 (ST/ESA/SER.A/390).

[28] World Health Organization (2007). WHO Global Report on Falls Prevention in Older Age [PDF]. Retrieved from http://www.who.int/ageing/publications/Falls_prevention7March.pdf?ua=1

[29] Yack, H. J., & Berger, R. C. (1993). Dynamic stability in the elderly: identifying a possible measure. J Gerontol Med Sci. 48. M225–M230.

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