Fall Risk Analysis for Elderly with Wearable Accelerometers Measurements

Hon Keung Yau, Yuen Sze Lee, Ho Yi Tang

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. Even worse, that can diminish their psychological, social and physical well-being, and even take away one’s life [2,8,9,10,16,19]. Fractures are some of the injuries that can be resulted from fall-related injuries [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].

Additional costs 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 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
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. METHODOLOGY

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].

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

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>
<thead>
<tr>
<th>TABLE I</th>
<th>COMPARISON OF RESULTANT CLUSTER MODEL CANDIDATES</th>
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<tbody>
<tr>
<td>Combinations of HRs</td>
<td>No. of cluster (Cluster sizes)</td>
</tr>
<tr>
<td>XYZ</td>
<td>2 (12, 19)</td>
</tr>
<tr>
<td>XY</td>
<td>3 (6, 18, 7)</td>
</tr>
<tr>
<td>YZ</td>
<td>3 (14, 11, 6)</td>
</tr>
<tr>
<td>XZ</td>
<td>2 (21, 10)</td>
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</table>

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.
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


TABLE II

<table>
<thead>
<tr>
<th>Cut-off score of BBS</th>
<th>XZ Cluster 1 (Higher BBS)</th>
<th>XZ Cluster 2 (Lower BBS)</th>
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<tbody>
<tr>
<td>BBS - High fall risk</td>
<td>15</td>
<td>4</td>
</tr>
<tr>
<td>BBS - Low fall risk</td>
<td>6</td>
<td>6</td>
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