Fall-Risk Classification of the Timed Up-And-Go Test with Principle Component Analysis

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Abstract

This study aimed to show that important fall risk measures among the elderly can be classified using multiple parameters obtained from wearable inertial sensors. The timed up-and-go (TUG) test, a well-known standard assessment test, was used to evaluate the risk of falling among elderly individuals. The use of wearable inertial sensors enables extraction of triaxial acceleration and angular velocity signals for offline analysis. Thirty-eight elderly patients from Fujimoto Hayasuzu Hospital participated in this study. Specific results were provided from the signals obtained from acceleration and angular velocity, and analysis was carried out in each phase of various activities, such as sit-to-stand, walking, etc. Seventy-eight parameters were obtained from the extracted acceleration and angular velocity signals in all phases to classify the risk of falling among the elderly. Using principle component analysis, the most important measures were selected from the gathered parameters. The most influential measure in differentiating subjects with high and low fall risks was the turning angular velocity signal.

Keywords: Fall; Wearable inertial sensor; TUG; Acceleration; Angular velocity; PCA

Introduction

As the elderly population continues to increase, the welfare and health care systems are also expected to expand significantly to ensure continued improvement of the elderly population’s quality of life (QOL). Falls among the elderly have become a major concern; almost 30% of individuals aged 65 years and above fall each year [1-4], and most cases are unwitnessed. Falls lead to deterioration in health and physical activities; physiological distress; pain caused by injuries, impairment, or imbalanced gait; fear of repeated falling; and deterioration of QOL. Various physical assessment tools have been developed to reduce the risk of falling among the elderly [5]. One established standard assessment used by therapists worldwide to measure basic mobility function and evaluate the risk of falling among the elderly is the timed up-and-go (TUG) test. However, in classifying the risk of falling using this method, age-related ability was identified to have limited clinical value. The literature recognizes a myriad of risk factors for falls, including demographic factors, historical factors, physical deficits, environment factors, and others [6,7]. Diverse factors associated with physical deficits contribute to falling. The likelihood of falling increases with the number of risk factors. Classification of the fall risk using several important measures selected from various gathered parameters is essential to enhance interest in this topic.

In current practice, many therapists use time parameters as measured with a stopwatch to classify the risk of falling among the elderly. New sensor technology implemented by previous researchers enables extraction of acceleration and angular velocity signals for fall risk assessment. Sway and standing balance have been estimated using accelerometry and gyro-sensors. Several other gait performance measures, including the TUG test, have also been evaluated [8-21]. Various parameters have been measured and collected to classify the risk of falling among the elderly. These parameters include position and angle, angular velocity, linear acceleration step and stride, cadence, speed, energy, and frequency. The root mean square of the vertical linear acceleration has been used to measure gait smoothness, with larger values linked to an increased risk of falling. However, it is difficult to identify the parameters that most strongly influence the risk of falling. Generally, an increase in spatial and temporal variability is associated with an increased risk of falls [2]. In addition to the TUG test, several phases are available for measurement (e.g., sit-to-stand, walking turn), and knowledge of which phases and parameters are the most significant with respect to the risk of falls would be clinically beneficial.

The risk of falls is currently predicted using derived models as opposed to correlating variables with the risk or occurrence of falls. The decision tree, neural network, linear discriminate function, cluster analysis, and support vector machine have all been candidates for fall risk prediction. The stability and variability of walking can be identified by a simple control theory such as the Lyapunov exponent [22]. A review by Howcroft et al. [8] suggested that intelligent computing methods such as neural networks and Bayesian classifiers might be more appropriate for fall risk classification than regression techniques [8]. However, no studies have identified the parameters that play the most important roles in the risk of falls.

Several parameters (usually highly correlated) can be computed from the signals recorded during the test. To avoid redundancy and identify the features that are most sensitive to locomotor performance, a dimensionality reduction was performed through principal component analysis (PCA).

In this study, we performed a quantitative analysis using the dataset obtained from wireless inertial sensors during the TUG test and classified the risk of falling among elderly subjects using multivariate analysis to identify the most effective parameter. Furthermore, the result will interpret and discuss with the clinical point of view.

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Methods

Subjects

Thirty-eight elderly subjects (male, 20; female, 18) with an average age of 65.18 ± 8.90 years from Fujimoto Hayasuzu Hospital, Japan participated in the TUG test. The low-fall-risk (LFR) group comprised 27 subjects, and the high-fall-risk (HFR) group comprised 11 subjects.

Ethical approval was obtained from the Fujimoto Hayasuzu Hospital Ethics Committee. A previous study by Shumway-Cook et al. reported that the use of 13.5 s as a threshold achieved 87% sensitivity for multiple fallers and 87% specificity for nonfallers [20]. Accordingly, the subjects were categorized as LFR upon completing the test within 13.5 s, while subjects who could not complete the test within that time were classified as HFR.
Experimental set-up

This experiment was based on the TUG test, which was introduced by Podsiadlo and Richardson in 1991. Figure 1(a) shows the main principle of the TUG test.

For the sake of simplicity, the subjects wore only one inertial sensor dorsally on the waist while performing the test. The sensor was tightly attached to the waist to minimize motion artifacts. For this purpose, the sensor was slotted in a belt that was attached to the waist, as shown in Figure 1(b). Throughout the experiment, a therapist was present for safety reasons. The experiment was conducted as follows:

1. The subject sat on an armless chair with a back (approximate seat height of 46 cm).
2. The subject rose from the chair.
3. The subject began to walk toward a marked post 3 m away.
4. The subject turned after reaching the marked post.
5. The subject walked another 3 m to return to the seat.
6. The subject turned to face forward before sitting.

Signal analysis

a) Parameters selected during the TUG test

The parameters obtained from the wearable inertial sensor during the TUG test are shown in Table 1. Each phase was divided by 12 and comprised time, accelerometer, and angular velocity parameters, as well as spatial and temporal parameters, such as step and stride [23].

The first analysis involved comparison of each feature between the two groups via a t-test. The threshold was 13.5 s based on a previous study [20]. Significant parameters were then chosen, but in accordance with our aim, the time data were eliminated.

At the beginning of the study, we divided all subjects into HFR and LFR groups using the total time parameters. Due to their important influence, we removed all time parameters to determine whether other parameters could be used to correctly classify the elderly subjects into their respective groups.

b) PCA

The most important objective of PCA is to represent multivariate data as low-dimensional data. By combining the data that account for the most variation among the original multivariate data, the data are summarized with minimal loss of information. By projecting all observations onto this low-dimensional subspace and plotting the results, it is possible to visualize the structure of the dataset. From the new low-dimensional constructed principal component, the variables that contribute most to the patterns among the observations could be determined. Therefore, PCA may also frequently indicate which parameters of which variables account for the patterns among the observations. The variables that influence the pattern and the correlations among the variables in a dataset are important—some of these low-performance variables might therefore be removed from consideration to simplify the overall analyses.

c) Preprocessing of the data

In this study, 78 parameters were collected from the signals shown in Tables 1 and 2. In total, 44 parameters were found to have significant value in differentiating the HFR and LFR groups. Of 44 significant parameters, 35 were selected (9 time parameters had been removed

<table>
<thead>
<tr>
<th>Parameter</th>
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<tr>
<td>P1</td>
<td>Time-sit-bend</td>
<td>P27</td>
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<tr>
<td>P2</td>
<td>Time-sit-stand</td>
<td>P28</td>
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<tr>
<td>P3</td>
<td>Time-walk 1</td>
<td>P29</td>
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<tr>
<td>P4</td>
<td>Time-turn 1</td>
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<tr>
<td>P5</td>
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<td>P6</td>
<td>Time-walk 2</td>
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<tr>
<td>P7</td>
<td>Time-turn 2</td>
<td>P33</td>
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<tr>
<td>P8</td>
<td>Time-sit-stand</td>
<td>P34</td>
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<tr>
<td>P9</td>
<td>Time-bend-sit</td>
<td>P35</td>
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<td>P10</td>
<td>Time-sit-stand</td>
<td>P36</td>
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<td>P11</td>
<td>Time-total</td>
<td>P37</td>
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<tr>
<td>P12</td>
<td>AMP.angvel-sit-stand</td>
<td>P38</td>
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<tr>
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<td>AMP.angvel-bend-stand</td>
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<td>AMP.angvel-sit-stand</td>
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<td>P15</td>
<td>AMP.angvel-Y Turn 2</td>
<td>P41</td>
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<td>P16</td>
<td>AMP.angvel-Y Turn 2</td>
<td>P42</td>
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<tr>
<td>P17</td>
<td>AMP.angvel-sit-stand</td>
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<td>AMP.angvel-Y-sit-stand</td>
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<td>P45</td>
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<tr>
<td>P20</td>
<td>RMS.acc.ML-bend-bend</td>
<td>P46</td>
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<td>P22</td>
<td>RMS.acc.AP-stand-stand</td>
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<td>P24</td>
<td>RMS.acc.ML-stand-stand</td>
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<td>P26</td>
<td>RMS.acc.ML-stand-stand</td>
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Where AMP is amplitude, RMS is root mean square. "angvel" is angular velocity signal. Y, P and R are yaw, pitch and roll directions, respectively. "acc" is acceleration signal. ML, AP and V are medio-lateral, antero-posterior, vertical directions, respectively.

Table 2: Selected parameters Yellow cells indicate parameters statistically significant between the HFR and LFR groups.
from the dataset). These 35 significant parameters underwent PCA, and the parameters that influenced the data most strongly were ranked.

**Results**

Based on PCA of the 35 principal components, the most important parameter in PC1 was P16 (amplitude of angular velocity signal during the turn 2 phase in the yaw direction). Meanwhile, the most important parameter in PC2 was P75 (cadence parameter in the turn 1 phase). The first component contributed 49.46% of the variance to the whole dataset. PC1 is insufficient to model the systematic variation of a dataset; thus, the second component was considered. PC2 contributed 20.16% of the variance. The bar graph of each component's variance in Figure 2 shows how the first two components influenced the data. PC1 and PC2 were adequate for classification, allowing for discovery of ~70% of the variance in the dataset. In general, it was assumed that these two components explained a sufficient amount of the variance, providing a meaningful visual representation of the subjects and parameters.

Figure 3(a) and (b) use bar graphs to rank the important parameters PC1 and PC2, respectively. For PC1, the most important positive parameters were P16, P75, P15, P14, P73, P74, P51, P38, P37, P52, P54, P53, P33, P49, and P50, while the most important negative parameters were P59, P64, P55, P56, and P60. For PC2, the most important positive parameter was P75, while the most important negative parameters were P74, P73, P38, P16, P15, P41, P37, P52, P54, P51, and P53.

By projecting all observation onto the lower-dimensional subspace and plotting the results, it was possible to visualize the pattern of the 38 subjects using all 35 parameters, as illustrated in Figure 4. Using the first principal component, the subjects were distributed into two groups. The HFR subjects were plotted on the left side of the graph, and the LFR subjects were scattered throughout the right side of the graph. The subjects were classified into their respective groups relatively accurately by PC1. For PC1, the negative values influenced the classification of subjects in the HFR group, while the positive values influenced the classification of subjects in the LFR group. As seen in the figure, the HFR and LFR subjects could be classified into their respective groups with almost 100% accuracy. Therefore, the parameters listed for PC1 were used to classify the subjects.

**Discussion**

For fall-risk assessment, an instrumented TUG test that uses portable inertial sensors (iTUG test) has been proposed to improve the TUG test in several ways; namely, by allowing for automatic detection and separation of each performance, facilitating a detailed analysis of each and enabling a higher sensitivity than the TUG test [21,24-26]. Sensitive and reliable measures for fall-risk assessment have been provided by measurement of wearable inertial sensors [27]. These measures might be of primary interest for clinical applications [25,26]. Gait measures can be divided into three subcategories: temporal gait, range of motion, and spatial gait.

Temporal gait measures are calculated based on the time of gait events, which are often measured with a stopwatch. Wearable motion sensors calculate the cadence, stance, etc. The range of motion of the trunk segment is estimated by integrating the signals from the angular velocity sensor. Furthermore, spatial gait measures, including stride length and velocity, are estimated using a biomechanical model [27]. In our study, these measures were easily obtained from the wearable inertial sensor.

The TUG test is classified into 6 phases: sit-to-bend, bend-to-stand, walking, turning, walking, turn-to-sit, and bend-to-sit and two combined phases of sit-to-stand and stand-to-sit. The selected parameters related to movement are shown in Table 1. The parameters we skipped were not strongly involved in movement. Turning speed is important, but it is difficult to estimate the turning distance; thus, the speed could not be obtained. Nevertheless, we selected 78 parameters and then 44 significant parameters; 35 parameters were ultimately selected (9 time parameters were removed). These 35 significant parameters...
Figure 3: (a): Ranking of important parameters in PC1 using significant parameters (excluding time parameters).
(b) Ranking of important parameters in PC2 using significant measures (excluding time parameters).
parameters were calculated by PCA and were found the influence for the fall risk.

The principle parameter score was the turning amplitude of the angular velocity signal during the turn phase in the yaw direction. The turn-to-sit movement is a combination of the turning and stand-to-sit transition, and is the most important and difficult task for elderly individuals whose physical activity has declined. PCA clearly showed the distribution of the HFR and LFR subjects. The peak angular velocity of the trunk during the turn-to-sit transition was important [24-28].

The TUG test includes performance of several movements and provides objective measures related to the four major components of the test: gait, turning, sit-to-stand, walking, turning, and turn-to-sit, we determined the principle component was angular velocity in the yaw direction. Furthermore, in each phase; i.e., sit-to-stand, walking, turning, and turn-to-sit, we determined the principle component scores, which are significant measures of the risk of falling.

We attempted a simple PCA analysis and the results were in agreement with previous quantitative research. Thus we found that PCA could easily estimate a simple measure for fall risk in TUG.

Acknowledgement

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References


