Quantitative Falls Risk Assessment Using the Timed Up and Go Test

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Abstract—Falls are a major problem in older adults worldwide with an estimated 30% of elderly adults over 65 years of age falling each year. The direct and indirect societal costs associated with falls are enormous. A system that could provide an accurate automated assessment of falls risk prior to falling would allow timely intervention and ease the burden on overstretched healthcare systems worldwide. An objective method for assessing falls risk using body-worn kinematic sensors is reported. The gait and balance of 349 community-dwelling elderly adults was assessed using body-worn sensors while each patient performed the “timed up and go” (TUG) test. Patients were also evaluated using the Berg balance scale (BBS). Of the 44 reported parameters derived from body-worn kinematic sensors, 29 provided significant discrimination between patients with a history of falls and those without. Cross-validated estimates of retrospective falls prediction performance using logistic regression models yielded a mean sensitivity of 77.3% and a mean specificity of 75.9%. This compares favorably to the cross-validated performance of logistic regression models based on the combination of high frequency and high susceptibility to injury. Furthermore, the sit-to-stand transition and variabilities in temporal gait parameters have been recommended by the American Geriatrics Society guidelines as a screening tool for identifying older people at increased risk of falls [7]. Previous authors have found that the TUG test has good test/retest reliability and is normally used by a clinician or a physiotherapist in a geriatric clinic. It is not currently known, which specific portions or segments of this test provide its predictive power for falls; however, individual segments of the TUG test have been found to have an association with falls risk. For example, Dite and Temple [9] identified certain turn measures that discriminate between groups of older adults with and without a history of falls and had good sensitivity for identifying multiple fallers. Furthermore, the sit-to-stand transition and variabilities in temporal gait parameters have been associated with falls risk.

I. INTRODUCTION

FALLS in older people are very common and their incidence increases with age. In the community, the proportion of people who sustain at least one fall over a 1-year period varies from 28% to 35% in the over 65 age group to 32% to 42% in the ≥ 75-year age group, with 15% of older people falling at least twice each year [1]. Incidence rates in hospitals are higher, and in long-term care settings approximately 30–50% of people fall each year, with 40% falling recurrently [2]. The cost of falls each year, among elderly people in the U.S. alone, has been estimated to be in the region of U.S. $20 billion [3]. The combination of high frequency and high susceptibility to injury in older people make falls a “geriatric giant” in their own right. Falling has been associated with deteriorating postural stability, muscular strength, and vestibular function. In older people these deteriorations can manifest themselves as problems in walking and turning.

The timed up and go (TUG) test was developed by Mathias et al. [4] as a tool to screen for balance problems in older people. The test was extended and refined by subsequent authors [5], [6], adding time and cognitive loading components. The TUG test consists of the participant getting up from a chair, walking 3 m, turning at a designated spot, returning to the seat and sitting down. The time taken to perform the test is recorded using a stopwatch. Current clinical practice suggests that elders with longer TUG times are more likely to fall than those with shorter times. The performances of elders prone to falling in completing the TUG test and those who do not fall can be dramatically different and so the TUG test is considered one of the most powerful tools for assessing future falls risk in the elderly (i.e., which elders may fall in the future) [6] and has been recommended by the American Geriatrics Society/British Geriatrics Society guidelines as a screening tool for identifying older people at increased risk of falls [7]. Previous authors have found that the TUG test has good test/retest reliability [5] that may make it a suitable test for inclusion in a longitudinal falls risk monitoring protocol; however, Thrane et al. [8], in a large-scale retrospective study, suggested that the TUG test is not sensitive enough for use as a clinical tool. The TUG test is normally used by a clinician or a physiotherapist in a geriatric clinic. It is not currently known, which specific portions or segments of this test provide its predictive power for falls; however, individual segments of the TUG test have been found to have an association with falls risk. For example, Dite and Temple [9] identified certain turn measures that discriminate between groups of older adults with and without a history of falls and had good sensitivity for identifying multiple fallers. Furthermore, the sit-to-stand transition and variabilities in temporal gait parameters [12] have been associated with falls risk.

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Quantitative assessment of gait and turning during the TUG test may allow for more objective and sensitive determination of falls risk. Recent research has raised the possibility of using inertial sensors for quantitative evaluation of movement and falls risk. A system that could robustly and reliably provide an accurate estimation of an elder’s falls risk would be of enormous clinical benefit. Higashi et al. [13] employed body-worn gyroscopes to evaluate the movement in hemiplegic patients with pathological gait while performing the TUG test. Similarly, Zampieri et al. [14] used body-worn gyroscopes to examine gait during the TUG test in patients with Parkinson’s disease. Skrba et al. [15] used automatically extracted video-based parameters to quantify turning and walking in 63 elderly adults while performing the TUG. Giansanti [16] used a wearable device containing a triaxial accelerometer and gyroscope to distinguish 100 elderly fallers with documented balance problems (Tinetti scale level 3) from 100 controls while performing a number of balance tests. Najafi et al. [11] used triaxial accelerometer recordings made during the sit–stand and stand–sit transitions to provide a quantitative assessment of falls risk in 11 elderly patients when compared to the Tinetti balance scale. Similarly, in a recent study by Narayanan et al. [17] on 68 elderly patients, results showed that a number of features extracted from triaxial accelerometer recordings map to a clinically validated measure of falls risk; the physiological profile assessment.

This study aims to show that body-worn kinematic sensors can be used to objectively quantify the TUG test and provide a comprehensive, quantitative analysis of timing, gait, and stability for each of the segments of the TUG test. We will use the derived parameters to develop logistic regression models for retrospectively estimating falls risk in community-dwelling elderly adults.

### II. Dataset

The gait and balance of 349 (103 M, 246 F) community-dwelling elderly adults were evaluated in the TRIL clinic, St James’ hospital, Dublin, Ireland. These data were acquired as part of larger study on aging (www.trilcentre.org). The data analyzed consisted of 207 subjects with a self-reported history of falling in the past 5 years, henceforth, known as “fallers” and 142 “nonfallers” (where falling is defined as an unexpected loss of balance resulting in coming to rest on the floor, the ground, or an object below the knee level [18]). The mean age of the participants at the time of evaluation was 72.4 ± 7.4, the mean weight 73.7 ± 14.5 kg. Table I provides demographic information for the dataset broken down by falls history.

<table>
<thead>
<tr>
<th></th>
<th>Fallers</th>
<th>Non-Fallers</th>
</tr>
</thead>
<tbody>
<tr>
<td>N (M/F)</td>
<td>44/163</td>
<td>59/83</td>
</tr>
<tr>
<td>Mean Age (yrs)</td>
<td>74.0±7.3</td>
<td>70.1±6.9</td>
</tr>
<tr>
<td>Mean Height (cm)</td>
<td>163.6±9.0</td>
<td>168±8.9</td>
</tr>
<tr>
<td>Mean Weight (kg)</td>
<td>70.6±13.5</td>
<td>78.8±14.6</td>
</tr>
</tbody>
</table>

This study aims to show that body-worn kinematic sensors can be used to objectively quantify the TUG test and provide a comprehensive, quantitative analysis of timing, gait, and stability for each of the segments of the TUG test. We will use the derived parameters to develop logistic regression models for retrospectively estimating falls risk in community-dwelling elderly adults.

### III. Method

#### A. Data Acquisition

Kinematic data from each patient were acquired using two SHIMMER kinematic sensors (http://shimmer-research.com) [19], which were attached, to the anterior of each shank, oriented to capture movement about the anatomical mediolateral (ML) axis, by means of elasticized bandages, placed at roughly the midpoint of the shank. TUG was performed as follows: the participant was asked to get up from a standard chair (46 cm high seat, 65 cm arm rests), walk 3 m, turn at a designated spot on the mat (the experimental setup is illustrated in Fig. 1, the designated turning point is marked with a red “x”), return to the seat and sit down. The time taken to complete the task was recorded by the clinician using a stopwatch. The time was measured from the moment the clinician says “go” to the moment the participant sits back on the chair (this time is referred to hereafter as the manual TUG time). Each patient was evaluated using the manual TUG and also the Berg balance scale (BBS) [20] in order to provide two standard measures of falls risk for each patient that can be compared to our method.

Each kinematic sensor contained both a triaxial accelerometer and an addon triaxial gyroscope board and was programmed to sample each axis at a rate of 102.4 Hz using custom-developed TinyOS (http://www.tinyos.net/) firmware.

Kinematic and video data were synchronously acquired in real time using a custom-built application developed using the BioMOBIUS software development environment (http://www.biomobius.org) and stored in the native “EBF” format. Data were acquired through BioMOBIUS on a Dell Precision 490 PC, with 2 GB RAM and an Intel Xeon CPU.

The video data for each patient’s TUG test were visually inspected to ensure only data from valid TUG tests were included in the analysis. Video and sensor data were also edited...
synchronously within BioMOBIUS to ensure only data relevant to the TUG were included in each file. The kinematic data for each test were then exported to text format for subsequent offline analysis.

B. Preprocessing

All postprocessing and analysis were carried out offline using the MATLAB (http://www.mathworks.com/ (Natick, VA) programming environment. The raw accelerometer and gyroscope data were calibrated to derive the acceleration and angular velocity vectors with respect to the sensor unit coordinate axis [21]. Before further processing, the raw gyroscope signal was low-pass filtered with zero-phase fifth-order Butterworth filter with a 50.2 Hz corner frequency (corner frequency, \( f_c = (f_s/2) − 1 \), where \( f_s \) is the sampling rate).

C. TUG-Derived Parameters

A number of parameters were derived from the left and right shank angular velocity signals in each of the sagittal, lateral, and vertical sensor axes in order to capture the timing and movement properties of each patient while performing the TUG test. The derived variables fall into following two categories.

1) Temporal gait parameters.
2) Angular velocity parameters.

1) Temporal Gait Parameters: Temporal parameters of gait were derived using a previously reported method [22] that applies an adaptive algorithm to determine heel-strike (HS) and toe-off (TO) events times from the ML angular velocity of each shank.

The present algorithm compares well to a marker-based motion capture system and a force plate [22] for temporal gait analysis. The algorithm was found to be robust to different walking characteristics and speeds as well as noise in the angular velocity signal due to artifact. Temporal gait parameters are calculated from the gait characteristic points: HS and TO. An artifact rejection routine is employed to remove spurious temporal parameters that are calculated from “bad” or artifactual angular velocity data. This routine is also designed to account for missing and extra HS and TO points detected by the adaptive algorithm as reported in [22].

Fig. 2 shows a sample of the ML shank angular velocity signal derived from the gyroscope from a subject while performed the TUG test. The midswing, HS and TO points for each gait cycle along with the turning point are marked.

Each kinematic sensor is positioned such that its measuring axis is aligned with the ML axis of the shank of the leg. In order to ensure the angular velocity signal derived from the gyroscope has the correct polarity (see Fig. 4), the “skewness” of the signal (a measure of the asymmetry of the signal) is calculated for each walk. If the skewness is less than zero, the gyroscope signal is inverted to ensure correct polarity of the signal.

The HS and TO characteristic points derived from the angular velocity signals from each shank were used to calculate the standard temporal gait parameters listed as follows.

1) Stride time (s).
2) Swing time (s).
3) Stance time (s).
4) Step time (s).
5) Double support (%).
6) Single support (%).

Stride time is defined as the time from initial contact (HS) of one foot to initial contact of the same foot. The stance time is defined as the time between a HS and TO point on the same foot. Similarly, swing time is defined as the time between a TO point and the HS point on the same foot. Step time is calculated as the time between the HS point on one foot and the HS point on the other foot. Double support is defined as the percentage of each gait cycle during which both feet are in contact with the ground (where the gait cycle time is the time between successive right HSs). The single support for the left foot equals the swing duration of the right foot and vice versa [23] expressed as a percentage of the gait cycle time. In this study, the data for all strides from left and right shanks for each temporal gait parameter were merged.

The coefficient of variation (CV) for each of the temporal gait parameters was calculated (to provide a measure of gait variability [24]) as the ratio of the standard deviation to the mean of each parameter, expressed as a percentage.

A number of additional temporal parameters are introduced in this study, designed to capture the timing characteristics of the various phases of TUG were calculated.

1) TUG recording time (s).
2) Walk Time (s).
3) No. of gait cycles.
4) No. Steps taken during walk.
5) Cadence (steps/min).
6) Turn time (s).
7) Return time (s).
8) Walk-turn time ratio.

The TUG recording time is simply the duration of the edited data recording for each TUG test. The walk time is related to the manually timed TUG time; however, it is calculated as the
time between the first HS or TO point detected by the algorithm during the TUG to the last HS or TO points detected. Cadence (steps per minute) can then be calculated as 60 times the number of steps taken while performing the TUG divided by the walk time (time taken to take the steps identified during the TUG)

\[
\text{Cadence} = 60 \times \left( \frac{\# \text{ Steps}}{\text{WalkTime}} \right)
\]

The number of gait cycles is calculated as the number of right HS points detected from the angular velocity signal during the TUG test minus one (i.e., the number of complete gait cycles). The turn time represents the approximate time during the TUG test at which the turn occurs, i.e., the subject turns and starts proceeding back toward the starting point. Empirical tests determined that the amplitude of the ML angular velocity signal corresponding to the midswing point of the gait cycle is lower during turning than walking (see Fig. 3); this was confirmed by simultaneous examination of the video data. Similarly, empirical tests also determined that the vertical angular velocity signal shows a large positive peak, which may correspond to foot clearance during the turn). The turn time is then calculated for each shank as the median of the occurrence times of each of the detected gait points (TO, HS, midswing) for each walk. The turn time is then calculated as the time taken from the turning point to return to the starting position. The walk-turn time ratio is defined as the ratio of the time to turn to the time from turn (unity means the same time taken to walk to and from the turn). No analyses of the strides per post-turning were included owing to the limited number of strides usually contained within a TUG test.

2) Angular Velocity Parameters: A number of novel parameters were derived directly from the angular velocity signal in the ML, anteroposterior (AP), and vertical (V) directions to capture characteristics of this signal during the TUG test in three dimensions. They include parameters to detect and analyze the speed and timing of the turn during the TUG test.

1) Mean, minimum, and maximum angular velocity value during walk (deg/s).
2) Mean, minimum, and maximum angular velocity times height (deg. m/s).
3) Range of midswing point amplitude (deg/s).
4) Mean amplitude of mid-swing points.
5) Turn angular velocity (deg/s).

The means across both shanks of the mean, maximum, and minimum value of the angular velocity signals in the ML, AP, and V directions during the TUG test were used to characterize the properties of the angular velocity signal during the TUG for each subject.

The mean, max, and min values of each of the angular velocity signals in each plane are also multiplied by the height (in meters) of each subject in order to obtain a variable approximately proportional to the linear velocity of the shank (as linear velocity equal radius times angular velocity where the radius is the leg length and height is assumed to be approximately proportional to the leg length). The mean amplitude of the midswing points is the mean of each of the midswing points detected in the ML angular velocity signal while the range of midswing points is defined as the difference in amplitude (in deg/s) between the largest and smallest midswing points on the angular velocity signal derived from each shank and is intended to capture variability in leg movement. The turn angular velocity is the mean amplitude (taken across both shanks) of the angular velocity signal at the turn point for each shank. The CV is also calculated for each angular velocity parameter in order to provide a measure of variation during the TUG.

D. Statistical Analysis

1) Falls Risk Estimation Model: For continuous data, the Mann–Whitney version of the Wilcoxon rank–sum test was used to test for statistical differences between subjects who experienced a fall and those who did not across the entire sample in order to identify those variables of specific importance (see Table III).

Following this initial nonparametric screening, logistic regression was used to test the predictive properties of each parameter, automatically derived during the TUG test. The entire sample was stratified by gender and age because the association between females who are over 75 years of age and frailty has been shown to be stronger than those in males [25]. The number of males with no history of falling in the dataset was deemed insufficient to generate robust logistic regression models of males in two age categories. As a result, three separate logistic regression models were generated.

1) Males.
2) Females under 75 years of age.
3) Females over 75 years of age.

The large quantity of gyroscope derived variables (\(N = 44\)) meant that it was necessary to group or “block” variables in terms of general characteristics before performing the analysis.
A series of logistic regression analyses with falls history as the dependent variable was carried out separately to the originally cross-sectional analysis (see Table I). Working with each block we performed a logistic regression analysis on each individual independent variable plus all two-way interactions and retained only those which were significant ($p < 0.05$) in each block.

The significant variables from each block were combined into a final model. Through logistic regression all nonsignificant variables were eliminated.

For comparison purposes, logistic regression models were also created in each of the three patient groups as aforementioned using only the values for each patient for manual TUG and BBS scores. These models were used as references models for comparison against the three models discussed in Table II.

2) Model Performance Metrics: In order to ensure an unbiased estimate of each model’s falls prediction performance, cross validation was employed. In each stratified sample, male ($N = 77$, fallers = 32, nonfallers = 45), female < 75 ($N = 119$, fallers = 72, nonfallers = 47) and female $\geq 75$ ($N = 68$, fallers = 45 and nonfallers = 23) a randomized 80% sample was taken to train the model with the significant variables identified in Table III and tested against the remaining 20%. Due to the low numbers we constrained the randomization to ensure the prevalence of fallers within the 20% test was of an adequate level. This was completed 10 times with a different 80:20 mix each time for each of the three models. Accuracy (Acc), sensitivity (Sens) and specificity (Spec) were the numerical metrics employed to quantify the performance of each validation. Sensitivity is defined as the proportion of fallers (as labeled by the geriatrician evaluating the subject in the TRIL clinic) correctly identified by the model. Similarly, specificity is defined as the proportion of nonfallers that are correctly identified by the model. Accuracy is then defined as the overall percentage of patients correctly classified. Receiver operating characteristic (ROC) curves were generated for each logistic regression model using the test set probability outputs obtained by cross validation. The area under the ROC curve was also used as an index of each statistical model’s performance. The area under the ROC curve is equivalent to the Mann–Whitney version of the two sample nonparametric Wilcoxon rank–sum statistic [26].

IV. RESULTS

Each patient was assessed using two standard falls risk assessment tools (manual TUG and BBS). The mean manual TUG time in patients with a history of falls was $11.5 \pm 5.2$ s, while the mean Berg balance score for the same group was $49.8 \pm 7.0$. Patients with no history of falls had a mean manual TUG time of $8.5 \pm 2.6$ s and Berg balance score of $54.0 \pm 3.1$. The Berg score and manual TUG time for the dataset were negatively correlated ($\rho = -0.76$, $p < 0.001$). The mean TUG time in our dataset showed strong variations with age. Fig. 4 shows the variation of the manually recorded TUG time with age for fallers and nonfallers.

Data for temporal gait parameters, stride, stance, swing, and step times, were merged for the left and right shank for each patient. However, in order to test for gait asymmetry, an additional rank–sum test was used to evaluate left and right leg data separately. Right stance time showed a significant difference between fallers and nonfallers ($p < 0.05$), the remaining parameters did not.

Numerical results for each of the parameters (introduced in section 3.3) were derived automatically from the kinematic sensors and are tabulated in Table III. Out of the 44 reported parameters, 29 (as shown in Table III) are shown to provide significant discrimination between fallers and the nonfallers. Table III also shows the correlation of each reported parameter with the BBS score and manual TUG time. The correlations for all parameters highlighted in bold are significant to $p < 0.05$.

Fig. 5 shows class specific histograms for a number of parameters derived from the gyroscope. Some separation in the means is evident in the return time and the mean vertical angular velocity $\times$ height variables.

Table IV provides the cross-validated retrospective falls risk estimation results from each of the gyroscope parameter-based models. The male model yielded a sensitivity of 71.5% and a specificity of 89.0%, the female $\geq 75$ model yielded a sensitivity of 82.9% and a specificity of 72.8% and finally the female < 75 model yielded a sensitivity of 77.5% and a specificity of 66.0%. The mean accuracy (for all 3 logistic regression models) was 76.8%, while the mean sensitivity and specificity were 77.3% and 75.9%, respectively. The mean ROC curve area for the gyroscope parameter-based models was 0.81 whereas the ROC curve area for logistic regression models based purely on the manual TUG and BBS scores were 0.66 and 0.69, respectively.

The top panel in Fig. 6 shows the ROC curves for each of the three gyroscopes derived logistic regression models while the bottom panel shows the ROC curves constructed for the models derived from the gyroscopes parameters compared to those derived solely from the manual TUG time and BBS score, these curves provide a graphical illustration of the performance of the system when compared to standard falls risk assessments.
<table>
<thead>
<tr>
<th>Variable</th>
<th>All subjects</th>
<th>Males</th>
<th>Females &lt;75</th>
<th>Females ≥75</th>
<th>( p ) BBS</th>
<th>( p ) mTUG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk time (s)</td>
<td>8.2±3.4</td>
<td>7.9±3.5</td>
<td>7.3±3.4</td>
<td>8.5±3.3</td>
<td>0.09</td>
<td>0.39</td>
</tr>
<tr>
<td>Return time (s)</td>
<td>4.4±2.0</td>
<td>4.3±1.9</td>
<td>3.9±1.9</td>
<td>5.2±2.0</td>
<td>0.09</td>
<td>0.39</td>
</tr>
<tr>
<td>No steps</td>
<td>12.8±3.8</td>
<td>12.6±3.0</td>
<td>12.0±3.0</td>
<td>12.4±3.0</td>
<td>0.10</td>
<td>0.38</td>
</tr>
<tr>
<td>Turn time (s)</td>
<td>3.8±1.5</td>
<td>3.6±1.0</td>
<td>3.4±1.0</td>
<td>4.6±1.5</td>
<td>0.10</td>
<td>0.38</td>
</tr>
<tr>
<td>Min ML velocity x Height</td>
<td>-181.7±34.4</td>
<td>-180.3±31.1</td>
<td>-187.6±37.4</td>
<td>-186.5±36.1</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td>TUG recording time (s)</td>
<td>15.6±6.5</td>
<td>15.0±5.3</td>
<td>14.4±5.5</td>
<td>17.6±6.5</td>
<td>0.53</td>
<td>0.67</td>
</tr>
<tr>
<td>Min AP velocity x Height</td>
<td>-347.0±69.1</td>
<td>-338.1±53.0</td>
<td>-375.0±65.6</td>
<td>-358.0±62.3</td>
<td>0.40</td>
<td>0.52</td>
</tr>
<tr>
<td>No. gait cycles</td>
<td>5.2±1.9</td>
<td>4.7±1.4</td>
<td>4.0±1.8</td>
<td>5.1±1.9</td>
<td>0.09</td>
<td>0.39</td>
</tr>
<tr>
<td>Max V velocity x Height</td>
<td>195.9±75.7</td>
<td>207.6±75.3</td>
<td>190.5±74.0</td>
<td>202.2±74.0</td>
<td>0.37</td>
<td>0.48</td>
</tr>
<tr>
<td>Mean AP velocity x Height</td>
<td>30.4±13.7</td>
<td>30.6±17.4</td>
<td>24.7±14.4</td>
<td>35.5±12.8</td>
<td>0.41</td>
<td>0.52</td>
</tr>
<tr>
<td>Max ML velocity x Height</td>
<td>202.0±50.4</td>
<td>329.7±19.0</td>
<td>303.2±45.6</td>
<td>289.4±24.3</td>
<td>0.45</td>
<td>0.52</td>
</tr>
<tr>
<td>Max speed (steps/min)</td>
<td>24.8±10.0</td>
<td>29.0±11.0</td>
<td>24.9±9.2</td>
<td>29.2±10.6</td>
<td>0.36</td>
<td>0.48</td>
</tr>
<tr>
<td>Min V velocity x Height</td>
<td>-140.4±53.4</td>
<td>-173.4±72.0</td>
<td>-146.4±52.2</td>
<td>-167.2±103.1</td>
<td>0.29</td>
<td>0.41</td>
</tr>
<tr>
<td>Min AP velocity (deg/s)</td>
<td>-111.3±21.9</td>
<td>-109.8±17.3</td>
<td>-115.1±23.0</td>
<td>-106.9±20.4</td>
<td>0.42</td>
<td>0.50</td>
</tr>
<tr>
<td>Max V velocity (deg/s)</td>
<td>15.3±6.9</td>
<td>16.8±7.0</td>
<td>15.2±6.6</td>
<td>17.5±6.2</td>
<td>0.35</td>
<td>0.46</td>
</tr>
<tr>
<td>Max ML velocity (deg/s)</td>
<td>119.6±34.1</td>
<td>135.9±36.4</td>
<td>121.9±36.3</td>
<td>113.1±32.9</td>
<td>0.35</td>
<td>0.46</td>
</tr>
<tr>
<td>Mean AP velocity (deg/s)</td>
<td>24.1±8.1</td>
<td>22.7±10.0</td>
<td>25.7±8.6</td>
<td>25.5±9.1</td>
<td>0.41</td>
<td>0.50</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>99.2±19.3</td>
<td>96.8±17.0</td>
<td>100.2±16.1</td>
<td>102.6±16.0</td>
<td>0.44</td>
<td>0.63</td>
</tr>
<tr>
<td>Mean AP velocity (deg/s)</td>
<td>46.5±15.0</td>
<td>54.2±17.0</td>
<td>48.7±15.0</td>
<td>52.5±15.3</td>
<td>0.39</td>
<td>0.45</td>
</tr>
<tr>
<td>Mean V velocity (deg/s)</td>
<td>-95.5±30.7</td>
<td>-95.3±46.9</td>
<td>-88.2±31.2</td>
<td>-103.0±24.0</td>
<td>0.28</td>
<td>0.38</td>
</tr>
<tr>
<td>AP angle velocity max Height</td>
<td>347.3±115.2</td>
<td>328.4±111.1</td>
<td>363.4±119.9</td>
<td>326.6±106.8</td>
<td>0.36</td>
<td>0.45</td>
</tr>
<tr>
<td>Max ML velocity (deg/s)</td>
<td>178.8±29.5</td>
<td>195.5±43.1</td>
<td>186.6±32.8</td>
<td>170.7±32.7</td>
<td>0.41</td>
<td>0.46</td>
</tr>
<tr>
<td>Mean ML velocity (deg/s)</td>
<td>28.5±9.0</td>
<td>27.8±9.3</td>
<td>29.9±9.5</td>
<td>26.9±7.7</td>
<td>0.37</td>
<td>0.41</td>
</tr>
<tr>
<td>Mean mid-swing points (deg/s)</td>
<td>133.5±24.6</td>
<td>132.5±21.6</td>
<td>139.7±32.8</td>
<td>135.8±25.5</td>
<td>0.47</td>
<td>0.52</td>
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<tr>
<td>Max AP velocity (deg/s)</td>
<td>212.4±66.8</td>
<td>235.6±76.4</td>
<td>222.5±62.5</td>
<td>206.7±64.8</td>
<td>0.34</td>
<td>0.42</td>
</tr>
<tr>
<td>Range of mid-swing points (deg/s)</td>
<td>117.7±30.5</td>
<td>125.4±17.1</td>
<td>113.6±32.5</td>
<td>120.8±30.0</td>
<td>0.22</td>
<td>0.28</td>
</tr>
<tr>
<td>Mean Double support (%)</td>
<td>0.41±0.2</td>
<td>0.50±0.2</td>
<td>0.40±0.2</td>
<td>0.50±0.2</td>
<td>0.10</td>
<td>0.14</td>
</tr>
<tr>
<td>Mean step time (s)</td>
<td>0.74±0.1</td>
<td>0.70±0.1</td>
<td>0.61±0.1</td>
<td>0.70±0.1</td>
<td>0.16</td>
<td>0.26</td>
</tr>
<tr>
<td>Mean stance time (s)</td>
<td>0.8±0.1</td>
<td>0.8±0.2</td>
<td>0.8±0.1</td>
<td>0.8±0.2</td>
<td>0.24</td>
<td>0.39</td>
</tr>
<tr>
<td>Mean single support (%)</td>
<td>0.8±0.1</td>
<td>0.8±0.1</td>
<td>0.8±0.1</td>
<td>0.8±0.1</td>
<td>0.36</td>
<td>0.39</td>
</tr>
<tr>
<td>CV single support (%)</td>
<td>22.9±15.7</td>
<td>21.2±16.6</td>
<td>21.4±16.2</td>
<td>22.7±13.1</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>CV ML velocity (deg/s)</td>
<td>130.6±27.0</td>
<td>129.2±36.0</td>
<td>131.2±28.3</td>
<td>130.5±24.9</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>Mean stride time (s)</td>
<td>1.2±0.2</td>
<td>1.2±0.2</td>
<td>1.2±0.1</td>
<td>1.2±0.2</td>
<td>0.29</td>
<td>0.42</td>
</tr>
<tr>
<td>CV V angular velocity (deg/s)</td>
<td>132.6±23.1</td>
<td>129.7±27.9</td>
<td>134.2±24.4</td>
<td>133.2±21.4</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>CV Double support (%)</td>
<td>80.7±26.6</td>
<td>94.2±22.8</td>
<td>79.9±26.3</td>
<td>75.6±23.4</td>
<td>0.16</td>
<td>0.23</td>
</tr>
<tr>
<td>Walk-turn-time ratio</td>
<td>1.2±0.3</td>
<td>1.1±0.2</td>
<td>1.1±0.3</td>
<td>1.1±0.3</td>
<td>0.21</td>
<td>0.26</td>
</tr>
<tr>
<td>Mean swing time (s)</td>
<td>0.5±0.1</td>
<td>0.5±0.1</td>
<td>0.5±0.1</td>
<td>0.5±0.1</td>
<td>0.13</td>
<td>0.04</td>
</tr>
<tr>
<td>CV swing time (s)</td>
<td>28.1±19.9</td>
<td>31.0±22.0</td>
<td>27.7±17.8</td>
<td>30.6±21.6</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>CV AP velocity (deg/s)</td>
<td>136.8±26.3</td>
<td>135.7±26.0</td>
<td>132.4±20.5</td>
<td>135.2±23.5</td>
<td>0.07</td>
<td>0.06</td>
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<tr>
<td>CV stride time (s)</td>
<td>24.9±13.2</td>
<td>24.3±14.7</td>
<td>23.2±14.1</td>
<td>23.4±12.3</td>
<td>0.14</td>
<td>0.20</td>
</tr>
<tr>
<td>CV step time (s)</td>
<td>42.2±21.0</td>
<td>40.3±22.9</td>
<td>42.7±17.0</td>
<td>41.5±23.0</td>
<td>0.13</td>
<td>0.16</td>
</tr>
<tr>
<td>CV stance time (s)</td>
<td>43.3±19.3</td>
<td>45.0±20.4</td>
<td>43.7±19.8</td>
<td>39.7±21.0</td>
<td>0.22</td>
<td>0.27</td>
</tr>
<tr>
<td>Turn angular velocity (deg/s)</td>
<td>24.0±50.9</td>
<td>26.3±56.3</td>
<td>24.0±49.6</td>
<td>23.4±57.8</td>
<td>0.06</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Results in bold were found to provide significant discrimination between fallers and non-fallers (p<0.05). Correlation between each parameter and BBS score (\( \rho \) BBS) and the manual TUG time (\( \rho \),mTUG) are also shown.
V. DISCUSSION

This study illustrates how inertial sensors can be used for accurate cross-sectional falls risk assessment from a protocol based on the TUG test. Results of this study show that clinically useful parameters can be derived automatically from triaxial gyroscopes placed on each shank. A mean test accuracy of 76.8% was achieved for retrospectively estimating falls risk in a cohort of 349 community-dwelling elderly adults; this exceeded the performance obtained (using the same cohort of patients) from two standard falls risk assessments; namely, manual TUG and BBS score, yielding a mean test set accuracy of 60.6% and 61.4%, respectively.

Three logistic regression models were developed in order to retrospectively estimate falls risk. By stratifying model variables by age and gender, it emerged that although 29 of the 44 reported variables showed significant discrimination between fallers and nonfallers, not every variable was significant in each of the three groups suggesting that there exist different properties of movement between fallers and nonfallers in each of the three groups. For example gait variability-based parameters such as swing time variability and single support variability are shown to have a strong impact on falls risk in females ≥ 75 and interestingly both variables were found to have a strong interaction effect with patient’s age in this grouping. Similarly, step time variability and single support variability have a bearing on the falls risk for females < 75. Examination of temporal gait parameters for left and right shanks showed there was a significant difference in right stance time between fallers and nonfallers but this finding was not reproduced in left stance time. The difference in stance time may be attributed to differences in turning strategies between the faller and nonfaller populations, while the differences between left and right stance time could be attributed to a larger proportion of the cohort favoring turning in one direction over the other, rather than fundamental differences in gait symmetry.

Variables related to gait velocity such as cadence, number of gait cycles, and return time were strongly associated with falls risk for males. Interestingly, the time taken for the subject to walk back to the chair from the turn (return time) was found to have a very strong bearing on the falls risk for men in the population whereas the time taken for the patient to walk to the turn (turn time) did not have as strong a relationship with falls risk. This implies that male fallers have a tendency to walk slower after the turning phase of the TUG than male nonfallers.

In the “females under 75” model, age is also showing significance (p < 0.05), this model suggests that the older the female is, the greater her risk of falling. In addition to this there are three two-way interaction effects; the first being that between step time variability and single support variability, the results suggest that a female that has low step time variability but large single support variability may be at greater risk of falling. The second interaction involves mean vertical angular velocity and max vertical angular velocity where subjects that possess extremes in both variables, e.g., low in both or high in both, may have a higher risk of falling than those that reside in the middle.

The final model includes all males in the dataset. Unfortunately, due to limited sample size it was not possible to stratify the male patients by age. However, it is anticipated that a larger cohort of community-dwelling elderly males would yield interesting results on the effect of age on the reported gyroscope derived TUG parameters. The male model is made up of one main effect and four two-way interaction effects. Return time is the main effect and is highly correlated with manual TUG (ρ = 0.89, p < 0.001). The longer it takes a male subject to return to the chair after the estimated turn, the higher the risk
of falling. The first interaction effect between weight and mean ML angular velocity suggests males who are heavier and have a high mean ML angular velocity may be at an increased risk of falling. The second interaction is between cadence and range of midswing points that may suggest those males who walk with high cadence and have a low range of midswing points as well as those who walk with low cadence and have a high range of midswing points may be at an increased risk of falling. The third interaction is between turn angular velocity and gait cycles may suggest that males with low turn angular velocity and a high number of gait cycles may be at an increased risk of falling. Finally, the interaction between weight and mean ML angular velocity $\times$ height infers that those subjects who are light weight and have a high value for mean ML angular velocity $\times$ height may be at an increased risk of falling.

A large body of previous research in this area has focused on how parameters derived from inertial sensors correlate with established clinically validated falls risk assessments [16], [17]. Correlation analysis on the present dataset found that manual TUG time was negatively correlated with the BBS score ($\rho = -0.76, p < 0.001$). A number of gyroscope derived variables were strongly correlated with the manual TUG time including: return time ($\rho = 0.89, p < 0.001$), time of turn ($\rho = 0.83, p < 0.001$), and walk time ($\rho = 0.90, p < 0.001$). Other parameters that were found to have a strong association with falls risk did not show a strong correlation with the Berg score and manual TUG, suggesting that may contain complementary information about the properties of standing, turning, and walking associated with falls that are not captured by the BBS and manual TUG tests.

The gyroscope-derived parameters reported in this study were temporally based; traditional temporal gait parameters along with novel angular velocity-based parameters were used to examine the timing and angular velocity properties of turning and walking. Recent research suggested that spatial parameters of gait variability such as step width variability are strongly linked with future falls [27], [28]. Future research will investigate methods to obtain robust spatial measures of gait from body-worn kinematic sensors. The time to complete the sit-to-stand and stand-to-sit transitions has been associated with a risk of falls [11], the TUG test contains one of each transition type so the addition of two kinematic sensors (one each worn on the torso and thigh) or the addition of a pressure sensor to the chair could allow parameters derived from the sit-to-stand and stand-to-sit transitions to be included in future falls risk estimation models.

One obvious limitation of this study is the retrospective design. Thrane et al. [8] suggested that retrospective evaluation of falls risk using the TUG test may over estimate the ability of TUG to predict falls risk. In future study, we intend examining the performance of our tool in prospectively predicting falls using a longitudinal study design. One further limitation is that no alpha correction was applied to the significance values reported in Table III. We felt that such a correction was not warranted given the exploratory nature of the study.

Objective assessment of falls risk using a standardized protocol as reported here, has potential to improve the quality of care offered to community-dwelling elderly adults at risk of falling and allow more timely intervention to prevent future falls. Furthermore, the reported tool has potential for use in a supervised monitoring protocol where deterioration in a subjects gait and balance would be noted as a change over time in their gyroscope

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### Table IV
Comparison of Gyroscope Based Falls Prediction Models to BBS Score and Manually Timed TUG for Retrospective Prediction of Falls in Three Categories (Males, Females $< 75$ and Females $\geq 75$ Years of Age)

<table>
<thead>
<tr>
<th>Gyroscope</th>
<th>BBS</th>
<th>TUG</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Male</strong></td>
<td><strong>Female (Age $&lt; 75$)</strong></td>
<td><strong>Female (Age $\geq 75$)</strong></td>
</tr>
<tr>
<td>Acc (%)</td>
<td>80.0</td>
<td>72.5</td>
</tr>
<tr>
<td>Sens (%)</td>
<td>71.5</td>
<td>77.5</td>
</tr>
<tr>
<td>Spec (%)</td>
<td>89.0</td>
<td>66.0</td>
</tr>
<tr>
<td>ROC area</td>
<td>0.84</td>
<td>0.73</td>
</tr>
</tbody>
</table>

---

Fig. 6. (Top) ROC curves for output of model for all three retrospective falls prediction models derived from gyroscope variables. The male only model had an ROC curve area of 0.84 while the female under and over 75 models had ROC curve areas of 0.73 and 0.86 respectively. (Bottom) ROC curves for output of cross-validated logistic regression models derived from gyroscope variables, the manually timed TUG time and the BBS score. The gyroscope derived model had an ROC curve area of 0.81 while the TUG- and BBS-based logistic regression models had ROC curve areas of 0.66 and 0.65, respectively.
derive parameters obtained while completing the TUG. This could form part of a continuous falls risk assessment protocol, deployed in-home or in a primary care facility.

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