A Wearable Triaxial Accelerometry System for Longitudinal Assessment of Falls Risk

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Abstract—Falls-related injuries in the elderly population are a major cause of morbidity and represent one of the most significant contributors to hospitalizations and rising health care expense in developed countries. Many laboratory-based studies have described falls detection systems using wearable accelerometry. However, only a limited number of reports have tried to address the difficult issues of falls detection and falls prevention in unsupervised or free-living environments. We describe a waist-mounted triaxial accelerometry (Triax) system with a remote data collection capability to provide unsupervised monitoring of the elderly. The basis of the monitoring is a self-administered directed-routine (DR) comprising three separate tests measured by way of the Triax. We present an initial evaluation of the DR results in 36 patients to detect early changes in functional ability and facilitate falls risk stratification. Extracted features considered alone show a correlation with falls risk of approximately $\rho=0.5$. Estimation of falls risk using a linear least squares model provides a root-mean-squared error of 0.69 ($p=0.58, p<0.0002$).

I. INTRODUCTION

Falls and their related injuries are a significant problem for the elderly, being the principal cause of injury related hospitalization in the over 65 age group in Australia [1,2]. Moreover, the aged population in developed countries is consistently increasing, causing a mounting burden on the health care system. As such, considerable recent research has been directed towards methods to identify specific deficits in functional ability and to evaluate falls risk. This study aims to devise and evaluate a directed-routine (DR) comprising three separate tests measured by way of the Triax. We present an initial evaluation of the DR results in 36 patients to detect early changes in functional ability and neurological deficits.

The DR refers to a set of movements and assessment tasks that can ostensibly be performed unsupervised. It includes the Alternate Step Test (AST), Sit-to-Stand with five repetitions (STS5), and the Timed Up-and-Go Test (TUGT) [3] that have been shown to be correlated with falls risk. The DR tasks are performed periodically and used to longitudinally track functional ability, balance, and motor neurological deficits.

At a pre-determined interval that can be adjusted remotely, an elderly subject conducts a DR by pressing the start button on the Triax. The unit sounds a set of audio cues to guide the subject through each of the DR movements. The raw ambulatory data is stored in XML format and streamed to a portal via Bluetooth where it is collected and synchronized with a central data server at routine intervals (typically once a day). Clinical parameters for each movement are extracted and appended to the longitudinal record for the respective subject. A Web-interface allows clinicians or caregivers with appropriate permissions to login and view their subjects’ longitudinal records thus facilitating the early detection of changes in the patients’ falls risk parameters.

While many studies have investigated falls risks in controlled, laboratory settings [4-6], very few [7] have extended or performed this investigation in the free-living environment. In this study, a cohort (n=36) of elderly participants performed a DR at the Falls Clinic of the Prince of Wales Medical Research Institute, Sydney, in order to evaluate the ability of the DR to be used as self-administrable assessment in a community-dwelling or home environment. The data was manually annotated with event markers indicating key events during each directed test. A number of timing and waveform related features were extracted from the data and their correlation with a clinical ‘gold-standard’ estimate of falls risk was assessed. In addition a feature selection search was performed to identify the near-optimal subset of features for utilization in a linear weight model to estimate falls risk.

II. METHODS

A. Physiological Profile Assessment

Prior to assessment with the Triax, the subject is first tested using an augmented version of the Physiological Profile Assessment (PPA) [8] and the Abbreviated Mental Test (AMT). The aforementioned tests represent a validated tool for quantifying risk of falling based on a combination of physiological measures, such as visual contrast sensitivity, knee extension strength, proprioception, reaction time and postural sway. The use of the PPA and AMT tests produces a ‘gold-standard’ falls risk score that categorizes subjects from very low risk (-5), up to marked risk (5).
B. Directed Routine

Following assessment using the PPA and AMT tests, the subject is asked to perform a series of three tasks, whose performances can be notionally characterized by the Triax and represent a measure of functional mobility, balance and lower limb strength. These tests were chosen due to their short administration time and they do not require specialized equipment, making them suitable for use in clinical settings.

The Triax is placed on the subject’s waist near the ischial spine. The signals from $x$, $y$ and $z$ axis are low-pass filtered with a $10^{th}$ order low-pass Butterworth filter, with a cut-off of 2 Hz, as we expect few movements to contain information of interest above 2 Hz. The magnitude acceleration vector, used for all analysis in this paper, is then calculated as $a = \sqrt{x^2 + y^2 + z^2}$.

1) Timed Up-and-Go Test (TUGT): The TUGT is an indicator of basic mobility, and measures the time required for a person to rise from a chair, walk 3 m, turn around ($180^\circ$), walk back to the chair and sit down.

As shown in Fig. 1, an observer has marked the data stream, denoting the time when the subject starts to rise from the chair, the time when the subject reaches the standing position, the time when the subject reaches the 3 m mark, the time taken to turn around, the time when the subject reaches the chair and the time taken to sit.

2) Sit to Stand 5 (STS5): The STS5 test is often used as a measure of lower limb strength and it consists of performing five sit to stand movements as quickly as possible. The subject is asked to stand without using their arms for support.

The markers (Fig. 2) denote the start of each sit to stand cycle, as well as the final reseating of the subject.

3) Alternative Step Test (AST): The AST is a measure of functional ability to perform walking and stair climbing tasks, since it involves shifting weight from one foot to the other, and hence is a measure of mediolateral stability. The subject stands in front of a raised platform (19 cm high and 40 cm wide) and alternatively places the whole left foot on the platform and then replaces it on the floor. They then place the whole right foot on top of the platform and then back to the floor. This is then repeated four times, as fast as possible. The start/end of each step is marked (Fig. 3).

III. Feature Extraction

We extract from the data, for each of the three tests, a number of features which we hope are correlated with the falls risk, and will ultimately enable us to estimate falls risk. The following sections describe these features in detail. In addition, subject age is also considered a feature of interest.

A. TUGT

The duration of the time between each marker, and the total duration of the test are the features of interest.

B. STS5

The total time from the commencement of the standing movement until the subject is reseated at the end of the test, and the standard deviation of the five sit-to-stand cycle durations (absolute and normalized by the total duration of the active part of the test) are extracted from the signal. The average variation in the dynamics of each cycle is calculated...
in order to check if there is a correlation between the repeatability of the movement and the risk of falling.

The segments of data in each sit-to-stand cycle are linearly warped in time, using a linear interpolation and resampling, so that each segment has 100 sample points. The five time-aligned segments are averaged to obtain an estimate of the mean signal morphology template. The mean of the standard deviation of these five signals at each sample point is then found and divided by the standard deviation of the mean template. This ratio is indicative of the average deviation of the signal from the mean morphology as a fraction of the overall signal variance during the active part of the test.

C. Alternative Step Test (AST)

The total time taken to complete the task and the standard deviation of the times taken (absolute and normalized by the total duration of the active part of the test) to complete the eight steps, alternating between left and right foot, are considered performance metrics.

Again, time-warping the segments for each stepping action, we investigate the average dissimilarity between steps: examining the variation in left foot movements, right foot movements, and the entire left foot and right foot movement cycle.

IV. LINEAR MODEL

An estimation of the falls risk has been implemented using a linear least squares model. The model requires a matrix, \( X \), where each of the \( N \) rows contains a number of features, extracted from each of the \( N \) subjects, and a vector, \( r \), containing the \( N \) ‘gold-standard’ falls risk scores for each subject. The set of weights, \( w \), are chosen to minimize the squared error between an estimate of the falls risk, \( \hat{r} \),

\[
Xw = \hat{r},
\]

and the ‘true’ falls risk, \( r \). The solution to this problem is

\[
w = X^{+}r,
\]

where \( X^{+} \) is the pseudo-inverse of \( X \).

V. PERFORMANCE MEASURES

A. Correlation Statistics

Pearson’s correlation coefficient was calculated to assess the relationship between the features extracted from the mobility tests and the risk of falling. The statistical significance of each correlation value is also quoted.

B. Root Mean Square Estimation Error

1) Leave-one-out cross-fold validation: The linear least squares model is trained using data from 35 of the 36 subjects. Data from the \( i^{th} \) subject is withheld for testing after the model is trained. Once the model has been trained, the calculated weights, \( w_i \), are used to estimate the falls risk for the \( i^{th} \) subject, \( \hat{r}_i \), as

\[
\hat{r}_i = x_i w_i,
\]

where \( x_i \) represents the set of features for the \( i^{th} \) subject.

The cycle is repeated 36 times, withholding a different subject each time. The root-mean-squared error is calculated as a measure of performance:

\[
rmse = \sqrt{\frac{\sum_{i=1}^{36}(\hat{r}_i - r_i)^2}{36}}
\]

2) Feature Selection: A floating forward-backward feature selection search algorithm was employed to search for the near-optimal subset of features which minimizes the root-mean-squared error (rmse) as calculated using cross-validation [9]. The algorithm sequentially selects the best feature from an unselected pool of features, and adds this to the selected set of features, provided the addition of this feature reduces the rmse. After the selection of each feature, the removal of a feature from the selected set of features is also considered.

VI. RESULTS

36 subjects, 25 female and 11 male, aged 72 to 86 years (mean 78.8, standard deviation 3.87) performed the DR. 16 features were extracted from the mobility tests and the subject’s age is also considered as a feature of interest.

A. Correlation Statistics

Table I shows Pearson’s correlation coefficient between the 17 features and the falls risk determined by the PPA.

Of particular interest are the time taken to reach the three meter mark in the TUGT (\( p=0.52, p=0.001 \)), the time to reach the chair in the TUGT (\( p=0.48, p=0.003 \)), the total duration of the TUGT (\( p=0.47, p=0.004 \)) and the absolute standard deviation of the AST (\( p=0.47, p=0.004 \)), which show the most significant (\( p<0.005 \)) correlation. Moderate associations are also present for the time taken to stand or sit in the TUGT, the total duration of the STS5 and standard deviation of the cycles in the STS5, the total duration of the AST and also for the age parameter.

<table>
<thead>
<tr>
<th>Test</th>
<th>Feature</th>
<th>( \rho )</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TUGT</td>
<td>Total duration</td>
<td>0.47</td>
<td>0.004**</td>
</tr>
<tr>
<td></td>
<td>Time to stand</td>
<td>0.34</td>
<td>0.043*</td>
</tr>
<tr>
<td></td>
<td>Time to reach the 3 m mark</td>
<td>0.52</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>Time to turn around</td>
<td>0.26</td>
<td>0.122</td>
</tr>
<tr>
<td></td>
<td>Time to reach the chair</td>
<td>0.48</td>
<td>0.003**</td>
</tr>
<tr>
<td></td>
<td>Time to sit</td>
<td>0.41</td>
<td>0.013*</td>
</tr>
<tr>
<td>STS5</td>
<td>Total duration</td>
<td>0.34</td>
<td>0.044*</td>
</tr>
<tr>
<td></td>
<td>Stand dev time to take 1 cycle</td>
<td>0.42</td>
<td>0.011*</td>
</tr>
<tr>
<td></td>
<td>normalized by total duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dis-similarity cycle</td>
<td>0.25</td>
<td>0.134</td>
</tr>
<tr>
<td>AST</td>
<td>Total duration</td>
<td>0.39</td>
<td>0.017*</td>
</tr>
<tr>
<td></td>
<td>Stand dev time to take 1 step</td>
<td>0.16</td>
<td>0.343</td>
</tr>
<tr>
<td></td>
<td>normalized by total duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stand dev time to take 1 step</td>
<td>0.47</td>
<td>0.004**</td>
</tr>
<tr>
<td></td>
<td>normalized by total duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dissimilarity right foot</td>
<td>0.25</td>
<td>0.147</td>
</tr>
<tr>
<td></td>
<td>Dissimilarity left foot</td>
<td>0.30</td>
<td>0.074</td>
</tr>
<tr>
<td></td>
<td>Dis-similarity cycle</td>
<td>0.18</td>
<td>0.299</td>
</tr>
</tbody>
</table>

\*(p\text{-value}<0.05) \*\* \(p\text{-value}<0.005\)
B. Linear Weight Model Estimation Error

The feature selection search algorithm selected three features from the 17 available to minimize the \( \text{rmse} \): the time to reach the three meter mark in the TUGT test, the absolute standard deviation of the time to complete each cycle in the AST test, and the age. Fig. 4 shows the falls risk estimated by the linear least squares model, using the three selected features and the leave-one-out cross-fold validation. Also shown is the line of best fit. The correlation between the estimated falls risk and the ‘gold-standard’ falls risk score is 0.58 (\( p=0.0002 \)) and the \( \text{rmse} \) is 0.69.

![Fig. 4: Correlation between the falls risk estimated by the linear least squares model, using the three selected features and the leave-one-out cross-fold validation, and the falls risk determined by the Physiological Profile Assessment. The red line represents the line of best fit. The correlation coefficient is 0.58 with a significance of \( p=0.0002 \). Root-mean-squared error is 0.69.](image)

VII. DISCUSSION AND CONCLUSION

We have investigated the usefulness of a Triax in estimating falls risk in the home environment. The accelerations exhibited by 36 elderly subjects, wearing a waist-mounted Triax, while completing three mobility tests were recorded. 16 timing and waveform related features were extracted in a semi-manual fashion from these signals, combined with the subjects’ age, and then compared, using Pearson’s correlation coefficient, to the gold-standard falls risk as determined using a PPA test. A linear least squares model, utilizing cross-fold validation and feature selection, was also employed to search for the near-optimum feature subset to estimate falls risk.

Correlation analysis proved three features: time taken to reach the three meter mark in the TUGT (\( p=0.52, p=0.001 \)), the absolute standard deviation of the AST (\( p=0.47, p=0.004 \)) and the total duration of the TUGT (\( p=0.47, p=0.004 \)) showed reasonable and statistically significant agreement with the falls risk.

The first two aforementioned features, along with the subject’s age were chosen as the best features for estimating falls risk, using a linear least squares model. Since the time to reach the 3 m mark and the total duration in the TUGT are strongly correlated (\( p=0.93, p<0.0001 \)) the exclusion of the total duration feature is understandable. While other features also show a modest correlation with falls risk, it is instructive to note that these features are clearly not robust across subjects since their addition to the three ‘best’ features only serves to degrade the estimation model’s performance. We note that none of the STS5 features were selected to estimate falls risk. Again, examining the correlation between features of the TUGT, AST and the STS5, we observe a strong correlation between the total duration of the TUGT and STS5 tests (\( p=0.86, p<0.0001 \)) and the standard deviation of the time to complete each cycle in the AST and the STS5 (\( p=0.82, p<0.0001 \)).

The segmentation of the acceleration signals here has been performed manually, through the addition of markers by an observer, in order to provide a proof of concept for the usefulness of Triax recordings in estimating falls risk. However, the translation of these tests to an unsupervised directed routine in the home environment will require an automatic segmentation of the data after it has been returned to the central server.

Previous studies have demonstrated the ability of accelerometry signals to measure various indicators of falls risk [4,5]. However, nearly without exception, these studies have concentrated on the clinical assessment of falls risk in contrast to the unsupervised DR approach described herein.

Future work will entail devising signal processing algorithms to automatically segment the acceleration signals and also the investigation of new features to aid the falls risk estimation process. Since the use of the Triax will enable us to obtain estimates of falls risk at regular intervals over an extended period of time, these longitudinal recordings may also provide interesting information relating to increasing risk of falls over time.

REFERENCES


