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Classification Between Non-Multiple Fallers and Multiple Fallers Using a Triaxial Accelerometry-Based System

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***Abstract*—Falls are a prominent problem facing older adults and a common cause of hospitalized injuries. Accurate falls-risk assessment and classification of falls-risk levels will provide useful information for the prevention of future falls. This study presents a triaxial accelerometer (TA) based two-class classifier, which discriminates between multiple fallers and non-multiple fallers, using a directed-routine (DR) movement test. One-hundred-and-twenty-six features were extracted from the accelerometry signals, recorded during the DR tests using a waist mounted TA, from 68 subjects. A linear multiple regression model was employed to map a subset of these features to an estimate of the number of previous falls experienced in the preceding twelve months. A simple threshold is applied to this estimated number of falls to create a basic linear discriminant classifier to separate multiple from non-multiple fallers. The system attained an accuracy of 71% in classifying the exact number of falls experienced in the last 12 months and 97% in identifying multiple fallers.**

I. Introduction

Falls are a prevalent issue confronting many older adults in developed countries, especially those over 65 years of age. Falls can cause serious injury requiring hospitalization. Clinical research has shown that a high falls-risk is a consequence of many factors, some of which include: body balance; vision; reaction time; proprioception; and lower limb strength [1]. Of course, there are other extrinsic factors related to the subject's environment which are more difficult to quantify. An accurate falls-risk assessment and classification of falls-risk levels would provide useful information relating to these intrinsic falls-risk factors and help with the prevention of future falls through the use of appropriate intervention strategies.

Accelerometers, which can be used to measure body movement when a person performs daily activities, have been widely used to identify falls events or near falls and stumbles [2]–[4]. Recent research has also focused on utilizing this technology for falls-risk assessment, to provide an accurate prediction of falls events in the near future [5]–[7]. The value of using a wearable sensor system to estimate falls risk is that it can be deployed unsupervised in the home environment, to either enable the screening of larger populations, or to provide long-term monitoring, which might allow the efficacy of falls-risk reduction interventions to be assessed remotely and frequently.

In a study by Narayanan *et al.*, a falls-risk estimation model was developed using 54 features extracted from a directed-routine (DR) scripted sequence, which consists of a timed up-and-go test (TUGT), a sit-to-stand movement with five repetitions (STS5), and an alternate step test (AST) movement. These features are mapped to a clinical falls-risk score (physiological profile assessment (PPA) [8]) with a reasonable correlation of 0.81 [5]. Further research by our group has made substantial improvements to this result, through the addition of 72 frequency domain features to the existing 54 used by Narayanan *et al.*, resulting in a correlation of 0.99 with the PPA gold standard [7]. This result is obtained using fully automated signal analysis, developed by Redmond *et al.* [9], which improves on the manual signal segmentation used by Narayanan *et al.*.

Rather than mapping to the PPA score, which is an intermediate estimate of falls-risk, this study aims to estimate the number of falls that a subject suffered over the previous 12 months. While this is not a prospective study, whereby the number of falls in the coming twelve month is predicted, it serves as a proof of principle for the feasibility of such a prediction scheme. The same methodology was employed as was previously used in [5] and [7] to create a simple two-class classifier model to distinguish between multiple fallers and non-multiple fallers (which means one or no falls). All 126 time and frequency domain features extracted from the DR are used in a linear model to map to the target falls history (number of falls in the last 12 months). Applying a threshold to the output of this linear model creates a simple linear discriminant classifier. The performance of the automatic segmentation algorithm developed by Redmond *et al.* is also assessed and compared to a manual segmentation method [9]. The performance of each DR subtest (TUGT, AST and STS5) is also analyzed separately, to investigate their relative importance in the classification scheme.

II. Methods

A. Instrumentation and subjects

A triaxial accelerometer (TA) was attached to the waist at the anterior iliac crest to measure body movement during the DR. The sampling frequency was 40 Hz for each of the three channels. The sensitivity was $\pm$ 1.5 G (where G=9.81 m/s/s). The accelerometry data were streamed live to a PC using a class 1 Bluetooth radio.

Sixty-eight subjects (including 47 female, 21 male) aged from 72 to 91 years, were randomly recruited from a falls clinic at the Prince of Wales Medical Research Institute, Sydney, Australia. A clinical falls-risk assessment (PPA) was performed on each subject prior to their execution of the DR tests. This is the same dataset used by Narayanan *et al.* [5].

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Each of the subjects was already involved, for varying durations, in an independent 12 month prospective falls-risk trial, during which a comprehensive falls event diary was documented; the resulting falls event counts used in this paper correspond to the total for the entire 12 month period of that parallel study.

B. Directed routine

The DR is a set of predefined movement tests which are easily performed in unsupervised settings. Three different tests are included in the DR; namely, the TUGT, AST and STS5, which have been shown to be significantly correlated to falls-risk factors [1], [5], [7], [10].

The TUGT test involves standing up from a chair, walking straight for 3 m, turning around, walking back to the chair and sitting down. The AST test involves placing one foot on a raised platform (19 cm high and 40 cm wide) and then back down on the floor, then placing the other foot on and quickly off the platform, repeating this for four times, as quickly as possible. The STS5 consists of five sit-to-stand movements with arms folded in front of the chest, being performed as fast as possible.

C. Signal segmentation

Two segmentation methods were used in this study. The manual segmentation is identical to that used by Narayanan *et al.*, whereby an observer presses a keyboard to denote the occurrence of fiducial events during the DR assessment [5]. Automatic segmentation algorithms, developed by Redmond *et al.*, are also employed to investigate the feasibility of a completely automated and unsupervised assessment [9].

Key markers in the three tests were defined as follows:

1) TUGT markers: The time when the subjects start and finish the TUGT test, t^{TUGT}_{start}, t^{TUGT}_{end}; the time when they have stood up, t^{TUGT}_{stand}; the time when they have walked 3 m, t^{TUGT}_{3m}; the time when they have turned around, t^{TUGT}_{turn}; the time when they have walked back to the chair, t^{TUGT}_{chair}.

2) AST markers: The time when the subjects start to lift the leading foot (assumed to be the left foot) from the ground, t^{AST}_{l1}; the time when they start to raise the trailing (right) foot from the ground, t^{AST}_{r1}; the same time markers in the following three repetition, t^{AST}_{l2}, t^{AST}_{r2}, t^{AST}_{l3}, t^{AST}_{r3}, t^{AST}_{l4}, t^{AST}_{r4}; and the time when they finish the AST test, t^{AST}_{end}.

3) STS5 markers: The time when the subjects start each sit-to-stand cycle, $t^{STS5}_{i} (i \in \{1, ..., 5\})$; the time when they finish the last cycle, t^{STS5}_{end}.

D. Feature extraction

One-hundred-and-twenty-six features were generated either from the accelerometry signals of the DR tests (123 features), or from the physiological data (3 features), which might be related to one's risk of falling. Of the 123 features extracted from the accelerometry signals, 51 were temporal and energy-related features, and 72 were spectral features, which were extracted from the frequency spectra of all three directions (x, y and $z-$axis) and an acceleration magnitude signal [7].

The estimated gravitational acceleration component was estimated by low-pass filtering at 0.1 Hz and was subtracted from the original signals to generate the body acceleration (BA) components, before feature extraction proceeds. Table I shows a complete list of features. An overall description of the features follows below.

Temporal features include: the total duration of each whole test, $\{1, 34, 84\}$; the duration between two successive markers, marked as $\{2, ..., 6, 35, ..., 42, 85, ..., 89\}$; the estimated stepping frequency, $\{7\}$; the SD of successive time differences in repeating movements and the normalized SD of the same value, $\{43, 44, 90, 91\}$; dissimilarity measures between cycles of the AST and STS5, $\{45, 46, 47, 92\}$. Refer to Narayanan *et al.* for more details on the calculation of these features [5].

Energy-related features include: the root-mean-square (RMS) of the signal vector magnitude (SVM) for the entire test duration, $\{8, 48, 93\}$, the signal magnitude area (SMA) over various time intervals, and additional analysis of the SMA between different cycles, $\{9, 49, ..., 59, 94, ..., 99\}$. The SVM signal was obtained from the square root of the sum of the squared value of $x_{BA}[i]$, $y_{BA}[i]$, and $z_{BA}[i]$ (x_{BA}, y_{BA}, and z_{BA} are the BA components of the acceleration signals in anteroposterior, mediolateral and vertical directions). The SMA features were calculated as the sum of the absolute value of x_{BA}, y_{BA}, and z_{BA}, over the duration of the targeted segment of the test.

Spectral features were extracted from the spectra of four signals: x_{BA}, y_{BA}, z_{BA} and the SVM signal, for each DR test. A discrete Fourier transform was performed to calculate the spectrum of each signal, $F_x(j\omega)$, $F_y(j\omega)$, $F_z(j\omega)$, $F_{SVM}(j\omega)$. A search for the fundamental frequency ω_1 was performed on the spectra ($\omega_1 > 2\pi(0.15)$ rad/s), selecting the value which maximized the sum of the magnitude spectrum at the first six harmonics. To quantify the periodicity characteristic of each signal, the sum of the magnitude of the first six harmonics were divided by the sum of the magnitude of the remaining area between these harmonic peaks, to give features $\{10, ..., 13, 60, ..., 63, 100, ..., 103\}$; the ratio of the magnitude under each harmonic to the sum of the magnitude spectrum at the first six harmonics and the ratio of the magnitude under the even harmonics to the magnitude under the odd harmonics, was also calculated to give features $\{14, ..., 33, 64, ..., 83, 104, ..., 123\}$.

In addition to the features extracted from the TA signals, three non-TA based physiological features were considered; namely, age, gender (binarized), and reaction time (RT) z-score (obtained from the PPA assessment) to give features $\{124, 125, 126\}$.

E. Falls prediction model and two-class classifier

A linear multiple regression model is used to estimate the number of previous falls experienced by each subject. Features extracted from the TA signals (with the possible addition of age, sex and RT z-score) are weighted and mapped to the target value: the number of falls in the last 12 months. The i^{th} subject has a row vector, $\mathbf{x}_i^T$, which consists of a

TABLE I
SUMMARY OF THE 126 CANDIDATE FEATURES WHICH MAY CORRELATE WITH FALLS-RISK.

Feature no.	Feature name
1 - 6	TUGT total time duration and time intervals between each two consecutive markers
7	TUGT f_{step}
8, 9	TUGT RMS of high-pass filtered SVM and TUGT SMA
10 - 13	TUGT first 6 harm. freq. ratio of SVM, x_{BA}, y_{BA}, z_{BA}
14 - 17	TUGT fund., 2nd, 3rd, 4th harm. magnitude ratio of SVM
19 - 22	TUGT fund., 2nd, 3rd, 4th harm. magnitude ratio of x_{BA}
24 - 27	TUGT fund., 2nd, 3rd, 4th harm. magnitude ratio of y_{BA}
29 - 32	TUGT fund., 2nd, 3rd, 4th harm. magnitude ratio of z_{BA}
18, 23, 28, 33	TUGT even to odd harm. magnitude ratio of SVM, x_{BA}, y_{BA}, z_{BA}
34 - 42	AST total time duration and time intervals between each two consecutive markers
43, 44	Standard deviation and normalized SD of AST time differences
45, 46	AST dissimilarity of leading foot steps and trailing foot steps
47	AST dissimilarity of leading/trailing step pairs
48, 49	AST RMS of high-pass filtered SVM and AST SMA
50, 51	AST SMA of weakest cycle and strongest cycle
52	AST max. - min. cycle SMA
53	AST SMA ratio between strongest and weakest cycle
54	AST SMA variance per cycle
55, 56	AST SMA of leading foot cycles and lagging foot cycles
57	AST SMA ratio of leading/trailing leg energy
58, 59	AST SMA variance for leading foot cycles and trailing foot cycles
60 - 63	AST first 5 harm. freq. ratio of the SVM, x_{BA}, y_{BA}, z_{BA}
64 - 67	AST fund., 2nd, 3rd, 4th harm. magnitude ratio of SVM
69 - 72	AST fund., 2nd, 3rd, 4th harm. magnitude ratio of x_{BA}
74 - 77	AST fund., 2nd, 3rd, 4th harm. magnitude ratio of y_{BA}
79 - 82	AST fund., 2nd, 3rd, 4th harm. magnitude ratio of z_{BA}
68, 73, 78, 83	AST even to odd harm. magnitude ratio of SVM, x_{BA}, y_{BA}, z_{BA}
84 - 89	STS5 total time duration and time intervals between each two consecutive markers
90, 91	Standard deviation and normalized SD of STS5 time differences
92	STS5 dissimilarity of sit-to-stand cycles
93, 94	STS5 RMS of high-pass filtered SVM and STS5 SMA
95, 96	STS5 SMA of the weakest and the strongest cycle
97	STS5 max. - min. cycle SMA
98	STS5 SMA ratio between strongest and weakest cycles
99	STS5 SMA variance per cycle
100 - 103	STS5 first 4 harmonics frequency ratio of SVM, x_{BA}, y_{BA}, z_{BA}
104 - 107	STS5 fund., 2nd, 3rd, 4th harm. magnitude ratio of SVM
109 - 112	STS5 fund., 2nd, 3th, 4th harm. magnitude ratio of x_{BA}
114 - 117	STS5 fund., 2nd, 3rd, 4th harm. magnitude ratio of y_{BA}
119 - 122	STS5 fund., 2nd, 3rd, 4th harm. magnitude ratio of z_{BA}
108, 113, 118, 123	STS5 even to odd harm. magnitude ratio of SVM, x_{BA}, y_{BA}, z_{BA}
124 - 126	Age, Sex, RT z-score

selected subset of features from the feature list. A matrix, $\mathbf{X}$, contains the N row vectors, $\mathbf{x}_i^T$, for $i \in \{1, ..., N\}$, from $N \leq 68$ subjects included in the model training set. The N estimated number of previous falls, $\hat{\mathbf{f}}$, are calculated as $\hat{\mathbf{f}} = \mathbf{X}\mathbf{w}$, where $\mathbf{w}$ is a column vector which contains weights assigned to each feature. The vector $\mathbf{w}$ is calculated so as to minimize the root-mean-squared-error (RMSE) between the estimated falls-risk values, contained in the vector $\hat{\mathbf{f}}$, and the number of previous falls, contained in the vector $\mathbf{f}$. The closed-form solution is given by $\mathbf{w} = \mathbf{X}^{+}\mathbf{f}$, where $\mathbf{X}^{+}$ represents the pseudo-inverse of the matrix $\mathbf{X}$. This linear model produces a non-integer estimate of an integer number of falls, $\hat{f}$. To estimate the number of falls, all estimates are rounded to their nearest integer, with all values less than zero rounded up to zero.

Two classes of fallers were considered. Subjects suffering two or more falls were defined as multiple fallers, and others were non-multiple fallers. Before rounding to an integer number of falls, a threshold of 1.5 was applied to $\hat{f}$ to categorize the subjects into two groups. The accuracy of this classifier was calculated as the ratio of the number of subjects being correctly classified as a fraction of the total number of subjects.

F. Cross validation and feature selection

Leave-one-out cross validation was employed in the classifier validation. Each subject was used for testing once, while the remaining data were used to train the model. A sequential forward floating search (SFFS) algorithm was used to select the optimal subset of features from the candidate feature pool [11]. The selected feature set will give the smallest RMSE value between the true falls history and the estimated falls event count, as estimated using cross validation. Furthermore, the predictive power of features from each DR subtest are analyzed in isolation, with or without the addition of the three physiological features.

III. RESULTS

Table II shows the performance of the linear model in estimating previous falls history, using either manual or automatic signal segmentation before feature extraction. The performance when inclusion or exclusion of the three physiological features is also listed. The near optimal subset of selected features is listed in the order that they were recruited by the SFFS algorithm. The accuracies of the two-class classifier and the accuracies in estimating the number of previous falls are also listed in Table II.

Table III shows the confusion matrix obtained when the estimated number of falls are rounded to the nearest integer, using manual segmentation and using all candidate TA-based features. In addition, Table IV summarizes the confusion matrix for the two-class classifier when discriminating between non-multiple fallers and multiple fallers. A scatter plot of the estimated number of falls (before rounding) against the true falls history record is also shown in Fig. 1.

IV. DISCUSSION AND CONCLUSION

A two-class classifier has been generated using a linear multiple regression model, which uses features derived from accelerometry signals acquired during the execution of a DR assessment. The number of falls occurring in the previous 12-month period has been retrospectively estimated for 68 elderly subjects and compared to a gold standard.

Table II shows that when using all 126 candidate features, the model has an excellent accuracy in classification between non-multiple fallers and multiple fallers when using manual signal segmentation (97%) and automatic segmentation algorithms (90%). It should be noted the groups are heavily unbalanced with only 9 of the 68 subjects falling into the multiple faller category.

TABLE II
PERFORMANCE MEASURES FOR THE TWO-CLASS CLASSIFIER AND THE THE CLASSIFIER IN ESTIMATING PREVIOUS FALLS HISTORY.

Segmentation method	Candidate features	Selected features	Accuracy of the two-class classifier	Accuracy in estimating the number of falls
Manual	TUGT, AST & STS5 features*	{120, 18, 89, 101, 109, 57, 39, 123, 40, 23, 15, 61, 112, 48, 69, 113, 31, 60, 45, 97, 53, 68, 4, 56, 50}	97%	71%
Manual	TUGT features*	{18, 27, 14, 24, 25}	87%	44%
Manual	AST features	{67, 59, 55, 47, 62, 36, 38, 48, 83}	91%	47%
Manual	AST & non-TA features	{67, 59, 55, 47, 62, 124, 36, 39, 38}	90%	47%
Manual	STS5 features	{120, 101, 109, 119, 114}	87%	50%
Manual	STS5 & non-TA features	{120, 101, 109, 119, 114, 124, 112, 118, 103}	85%	44%
Automatic	TUGT, AST & STS5 features*	{120, 18, 36, 39, 55, 110, 119, 81, 89, 65, 80, 62}	90%	58%
Automatic	TUGT features*	{22, 3, 1, 21}	85%	47%
Automatic	AST features*	{55, 59, 72}	87%	44%
Automatic	STS5 features*	{120, 104, 102, 88, 119, 113, 87}	84%	51%

*Performance and the selected features remained the same when supplementing with non-TA features.

TABLE III
CONFUSION MATRIX OF ESTIMATED NUMBER OF FALLS (ROUNDED) AGAINST TRUE PREVIOUS FALLS HISTORY, USING ALL TA-BASED FEATURES AND MANUAL SEGMENTATION. ACCURACY: 71%.

		True previous falls history					
		0	1	2	3	4	All
Estimated falls	0	35	4	0	0	0	39
	1	11	8	1	0	0	20
	2	0	1	4	2	0	7
	3	0	0	0	1	1	2
	4	0	0	0	0	0	0
	All	46	13	5	3	1	68

TABLE IV
CONFUSION MATRIX OF THE TWO-CLASS CLASSIFIER (NON-MULTIPLE FALLERS VS. MULTIPLE FALLERS), USING ALL TA-BASED FEATURES AND MANUAL SEGMENTATION

		True previous falls history		
		Non-multiple	Multiple	All
Estimated	Non-multiple	58	1	59
	Multiple	1	8	9
	All	59	9	68

While manual segmentation proved superior for this task, the selected near optimal feature subsets show some consistency between the two segmentation methods. The first two selected features $\{120, 18\}$ (from 126 candidate features) were the same under both segmentation schemes. These two features $\{120, 18\}$ are the second harmonic magnitude ratio in the vertical direction of STS5, and the even to odd harmonic magnitude ratio of the SVM signal in TUGT, respectively.

The performance when using only features from one DR subtest, with or without non-TA features, are also shown in Table II. It is seen that each of the DR subtests give similar accuracies for both classification tasks, with the two class problem showing accuracies in the range of 84% to 91%.

A careful examination of the selected features reveals that the spectral features appear most often across all subsets. The first selected feature was a spectral feature in nearly all cases; except when using only the AST subtest with automatic segmentation, where feature 55 was chosen first and is the SMA of leading foot cycles.

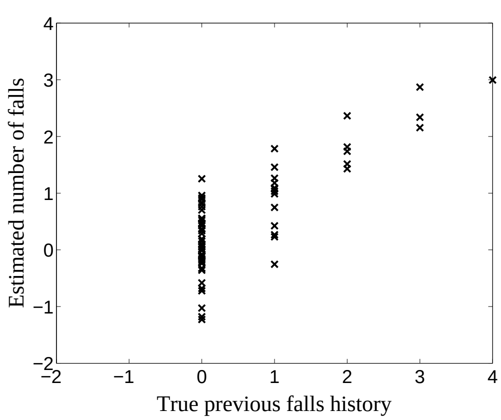

Fig. 1. Scatter plot of the estimated number of falls against true previous falls history.

It is also interesting to note that in most cases, when non-TA features were included in the candidate features, none of the three physiological features were selected, except when they were with AST features or with STS5 features separately (both under manual segmentation). In these cases, the only physiological feature selected was age, with the implication that more elderly subjects would have higher falls-risk levels than younger subjects, which is unsurprising. Interestingly, the RT z-score, which is usually considered to be more indicative of falls-risk in the elderly, was never selected from any feature set which was considered.

A major limitation of this study lies in the fact that it is a retrospective analysis which attempts to estimate previous falls history. It should not be seen as an accurate prediction of future falls, as the collected data may belie intervention (which occurred prior to subjects performing the DR), or previous falls-related injuries or fears. However, it serves as a strong incentive to perform a prospective study to examine if this prediction accuracy is repeated when predicting future falls.

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