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Evaluation of Functional Deficits and Falls Risk in the Elderly – Methods for Preventing Falls

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Abstract— **Falls in the elderly have a profound impact on their quality of life through injury, increased fear of falling, reduced confidence to perform daily tasks and loss of independence. Falls come at a substantial economic cost. Tools to quantify falls risk and evaluate functional deficits allow interventions to be targeted to those at increased risk of falling and tailored to correct deficits with the aim of reducing falls rate and reducing ones risk of falling. We describe a system to evaluate falls risk and functional deficits in the elderly. The system is based on the evaluation of performance in a simple set of controlled movements known as the directed routine (DR). We present preliminary results of the DR in a cohort of 68 subjects using features extracted from the DR. Linear least-squares models were trained to estimate falls risk, knee-extension strength, proprioception, mediolateral body sway, anteroposterior body sway and contrast sensitivity. The model estimates provided good to fair correlations with (r=0.76 p<0.001), (r=0.65 p<0.001), (r=0.35 p<0.01), (r=0.53 p<0.001) , (r=0.48 p<0.001) and (r=0.37 p<0.01) respectively .**

I. Introduction

Falls in the elderly are a major concern with a significant proportion of the elderly population falling at least once each year [1]. Not all falls result in injury, however falls may lead to increased fear of falling and restricted social and physical activity, which drastically reduces ones quality of life [2]. A rapidly ageing population, expensive medical care and overwhelmed healthcare systems drive the need to develop a means of identifying the at-risk population, delivering appropriate interventions and reducing the falls rate and risk within the elderly population.

Wearable sensor technology coupled with years of falls research enables the development of novel systems to reduce the rate and risk of falls the elderly. This paper describes such a system, using a single waist-mounted triaxial accelerometer (TA), to evaluate a simple set of controlled movement tasks, known as the directed routine (DR). Features obtained from the DR tasks, are used to model falls risk a set of physiological parameters – body sway, knee-extension strength, proprioception and contrast sensitivity [3] – deficits which are associated with increased falls risk.

Previous studies have looked to evaluate particular factors associated with falls risk, such as gait [4, 5], standing balance [6], sit-to-stand transfers [7] and the timed up-and-go test [8]. More recently, attention has been given to classifying elderly prone to falling [9-11]. Limited work has been done to model falls risk [12] and in particular develop systems suitable for unsupervised assessment [13]. In contrast, we aim to develop a system suitable for unsupervised assessment that quantifies falls risk and can identify particular functional deficits.

Subsequent sections present preliminary results to an investigation evaluating the use of the DR to evaluate falls risk and functional ability in a cohort of community-dwelling elderly subjects.

II. Methods

68 subjects (21 male, 47 female) aged 72 to 91 (mean ± standard deviation = 80.01±4.48) were evaluated by the Falls and Balance Research Group at the Prince of Wales Medical Research Institute Sydney, Australia. Participants were assessed over a number of physiological domains to provide a measure of falls risk, and were also evaluated by means of a DR using a waist-mounted ambulatory monitor. The University of New South Wales Ethics Committee approved the study, and informed consent was obtained from subjects prior to their participation.

A. *Evaluation of Fall Risk and Functional Ability*

Prior to DR assessment, subjects were evaluated for falls risk using Physiological Profile Assessment (PPA) [3]. The PPA is a validated falls risk assessment tool. The PPA evaluates falls risk by the performance of five physiological assessment tasks - body sway, proprioception, knee extension strength, contrast sensitivity and reaction time. The PPA has demonstrated accuracies in the range of 75%-79% predicting multiple fallers from non-multiple fallers. The PPA is used to provide a 'gold standard' measure of falls risk and functional ability.

B. *Directed Routine*

The DR is a set of movements designed to be performed in a controlled manner. The intention is for the movements to be performed unsupervised and as such, are simple, safe movements requiring minimal equipment. By controlling the way in which the movements are performed parameters

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extracted from the DR can be compared longitudinally. The DR comprises of the Alternate -Step Test (AST), Timed Up-and-Go Test (TUGT) and the Sit-to-Stand 5 (STS5).

1) Instrumentation

A waist-mounted triaxial accelerometer (TA), placed at the waist (TA), was used to measure accelerations at the waist over a set of movements that constitute the DR. The device streams acceleration data, with a sensitivity of ± 1.5g, at 40Hz for each axis via a Class 1 Bluetooth radio to a nearby laptop which logs the data. Via the laptop, an observer annotated the streaming data with time markers to capture the timing of particular events for each movement. Subjects were asked to attach the TA to their waist at the hip. Subjects who did not have a belt were provided with a Velcro strap on which to affix the TA.

2) AST

The AST is performed by alternately placing the whole of each foot onto and off of a platform 19cm high and 40cm wide, eight times as quickly as possible [14]. That is four times with each foot. An observer marked the data with start and end times as well as the times at which the subject returns each foot to the ground. Figure 1 shows a representative sample of the AST.

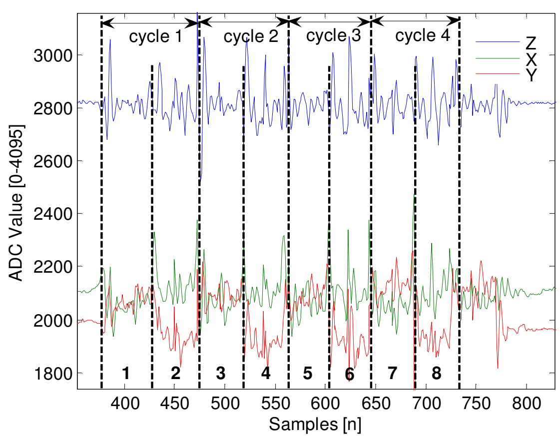

Fig. 1. Representative sample of the alternate step test showing the raw acceleration data for each axis as well as the observer placed time markers. The markers show the start and end time as well as the times at which the feet return to the ground.

3) TUGT

The TUGT is performed as follows - from a seated position, stand, walk three meters, turn around, walk back to the chair and return to a seated position. The subject is instructed to perform the TUGT as quickly as possible. An observer marked the start and end times, as well as, the time to reach the standing position, reach the three meter mark, turn around, reach the chair and returned to a seated position. Fig. 2 shows a representative sample of the TUGT.

4) STS5

The STS5 is performed by doing five sit-to-stand transfers, with arms folded, as quickly as possible [14]. An observer marked the start and end times as well as the times at which the subject returned to a seated position. Fig. 3 shows a representative sample of the STS5.

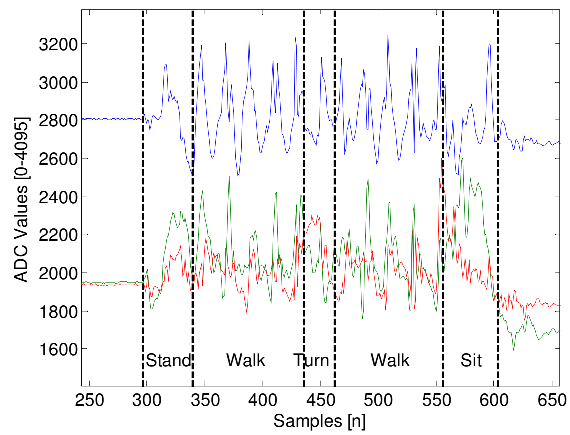

Fig. 2. Representative sample of the timed up-and-go test showing the raw acceleration data for each axis as well as the observer placed time markers. The markers show the start and end time, as well as the time at which the subject reached a standing position, reached the 3 m mark, turned around, reached the chair.

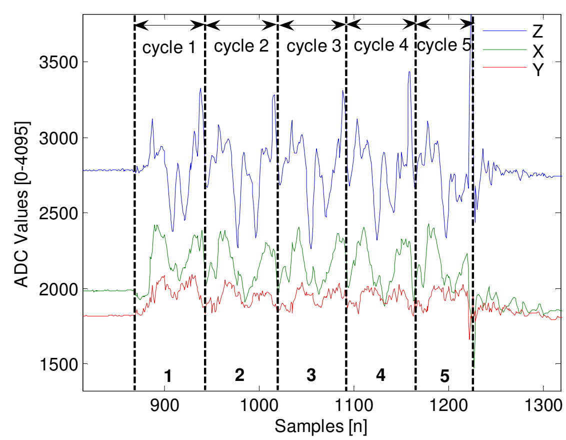

Fig. 3. Representative sample of the sit-to-stand five test showing the raw acceleration data for each axis as well as the observer placed time markers. The markers show the start and end time as well as the times at which the subject sits.

C. Feature Extraction

A variety of features were extracted from each DR assessment, 51 in total. For the sake of brevity, a description of the types of features considered is provided. Table I, further explains the particular features used in the models of falls risk and physiological risk factors.

Simple temporal features, such as total task duration, time to particular markers, or time between particular markers were extracted. For the quasi-periodic AST and STS5 tasks cycle times and cycle time variability were evaluated. Similarly derived features based on an estimate of energy using the Signal Magnitude Area (SMA) [12] were extracted. Additional ratios between maximum and minimum energy per cycle were evaluated. A dissimilarity metric was used to compare particular cycles within the AST and STS5. For example, the metric was used to evaluate the deviation within the left foot cycles and right foot cycles of the AST and compare all the cycles within the STS5. This metric looks to evaluate the average deviation of the cycles from a mean cycle waveform [12]. In addition, age, sex and reaction time were added to the pool of features.

TABLE I
DESCRIPTION OF FEATURES

Test	Feature ID	Feature	Description
TUGT	1	t_{SIT}	Time taken to sit down
	2	SVM_{RMS}	RMS force
	3	SMA_{total}	Total energy
AST	4	t_{TRAIL4}	Time taken to perform fourth step with the trailing foot
	5	t_{σ}	Standard deviation of cycle times
	6	$t_{NORM\sigma}$	Standard deviation of cycle times normalized to total duration
	7	$Diss_{Leading}$	Dissimilarity of leading foot cycles
	8	$Diss_{Trailing}$	Dissimilarity of trailing foot cycles
	9	$Diss_{Cycle}$	Dissimilarity of all AST cycles
	10	$SMA_{\sigma 2}$	Variability of energy expended per cycle
	11	$SMA_{\sigma 2 Trailing}$	Variability of trailing foot cycles
STS5	12	t_{TOTAL}	Total time to complete task
	13	$Diss_{Cycle}$	Dissimilarity of all STS5 cycles
	14	t_{CYCLE2}	Time to complete cycle two
	15	$SMA_{\sigma 2}$	Variability of energy expended per cycle
____	16	RTzscore	Reaction time standard score
	17	Age	Age of the subject
	18	Sex	Sex of the subject

D. Modeling Falls Risk and Functional Tests

Linear least squares models were trained to estimate falls risk, knee-extension strength, proprioception and body sway, obtained from the PPA, using the features described in Table I. In short, a floating forward-backward feature selection search algorithm was used to find an optimal subset of features, from a pool of fifty five features, by minimizing root-mean-squared error (RMSE) as evaluated by leave-one-out cross-fold validation. A full description of the model used can be found in [12].

III. RESULTS

Table II shows the performance of the trained models. The RMSE values knee-extension strength, proprioception, body sway and contrast sensitivity are in kilograms, degrees, millimeters and decibels respectively. The RMSE error, as a fraction of the standard deviation of the target variable, equals 0.65, 0.75, 0.93, 0.85, 0.87 and 0.94 for falls risk, knee-extension strength, proprioception, body sway mediolateral, body sway anteroposterior and contrast sensitivity, respectively.

TABLE II
MODEL PERFORMANCE RESULTS

Model	Performance			Selected Features
	r*	RMSE	p-value	
Falls Risk	0.76	0.62	$4.02x10^{-14}$	6, 7, 13, 15, 16
Knee Extension Strength	0.65	7.02	$1.97x10^{-9}$	2, 6, 11, 15 16, 17
Body Sway Mediolateral	0.53	12.10	$2.76x10^{-6}$	3, 5, 8, 9, 14, 15, 18
Body Sway Anteroposterior	0.48	8.08	$3.11x10^{-5}$	12, 16, 17
MET	0.37	2.19	$1.8x10^{-2}$	7, 9, 16, 17, 18
Proprioception	0.35	1.40	$3.00X10^{-3}$	1, 2, 4, 7, 10, 11

* Pearson's correlation coefficient

IV. DISCUSSION AND CONCLUSION

In contrast to previous studies [9, 10, 12, 13], we have described and demonstrated a system that both, evaluates falls risk and identifies deficits in functional ability in community-dwelling elderly using a simple ambulatory monitor. A number of studies have shown the effectiveness of exercise interventions, in reducing both the rate of falls and falls risk in the elderly [2, 15]. Single-component interventions, based on a particular exercise, and multiple-component interventions, using combinations of different exercises have proven successful [2]. Our system could be used to assist clinicians in prescribing exercise interventions by providing information on particular physiological deficits.

Limitations in the current system are particularly evident in the relatively large error of the models. Naturally, this is a result of the inability in the DR tasks to explain the variability in the factors contributing to falls risk. In part, this is due to selecting movements that can be safely performed unsupervised. Additionally, DR tasks were selected with the expectation they were associated with risk factors contributing to the falls risk score. As an example, the STS5, was expected to correlate quite well with knee-extension strength. Fig. 4 shows this clearly is not the case (r=-0.1519,p=0.2162). Another contributing factor is the choice of features. With the objective of an unsupervised assessment in mind, features were extracted that are impervious to variation in device placement. As such, simple temporal parameters and gross energy parameters were used. Ensuring a fixed TA placement and carefully selected DR tasks allows a broader range of features to be extracted to better explain falls risk and functional deficits and reduce model error.

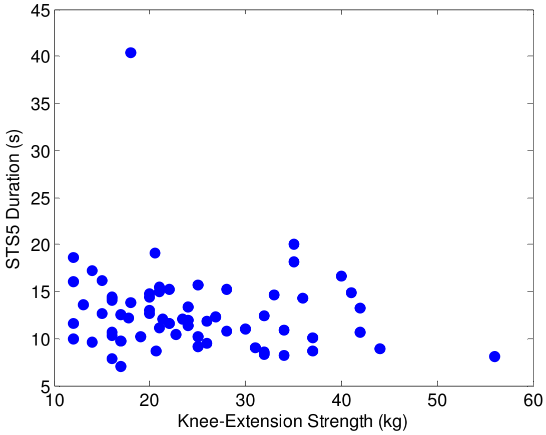

Fig. 4. Knee-extension strength versus STS5 duration for a cohort of 68 elderly subjects.

It should be noted reaction time scores, from the PPA, were included in the pool of features, as a reaction time assessment can easily be integrated into the TA thus allowing it to form part of the DR.

An interesting aspect of the DR is the possibility of evaluating physiological parameters such as body sway - which involves measuring the amount of mediolateral and anteroposterior movement, by way of a sway meter, while trying to maintain balance on a compliant surface with eyes open or closed [1] - using a simple set of movements suitable for unsupervised use.

Model performance, in particular model error, needs to improve to make the DR system usable. Despite the moderate performance of the models, this paper demonstrates the utility of a DR system to evaluate falls risk and functional ability in community-dwelling elderly to allow interventions to be delivered to those at increased risk for falls and tailored to correctly identified deficits.

Future work will involve selecting alternate movements and develop new features to improve model performance. Additionally, systems need to be developed to enable the DR to be performed unsupervised. That is, a means of administering the DR unsupervised, of verifying signal quality and to automatically segment the signals to extract the necessary features.

References

[1] S. R. Lord, C. Sherrington, and H. B. Menz, *Falls in Older People: Risk Factors and Strategies for Prevention*: Cambridge University Press, 2001.

[2] D. Gillespie Lesley, M. C. Robertson, J. Gillespie William, E. Lamb Sarah, S. Gates, G. Cumming Robert, and H. Rowe Brian, "Interventions for preventing falls in older people living in the community," 2009.

[3] S. R. Lord, H. B. Menz, and A. Tiedemann, "A Physiological Profile Approach to Falls Risk Assessment and Prevention," *Physical Therapy*, vol. 83, pp. 237-252, 2003.

[4] M. Sekine, T. Tamura, T. Fujimoto, and Y. Fukui, "Classification of walking pattern using acceleration waveform in elderly people," in *Engineering in Medicine and Biology Society, 2000. Proceedings of the 22nd Annual International Conference of the IEEE*, vol. 2, 2000, pp. 1356-1359 vol.2.

[5] T. Wark, M. Karunanithi, and W. Chan, "A Framework for Linking Gait Characteristics of Patients with Accelerations of the Waist," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2005, pp. 7695-7698.

[6] E. M. Ruth, C. L. Joost, H. V. Peter, and H. Hermie, "Standing balance evaluation using a triaxial accelerometer," *Gait & posture*, vol. 16, pp. 55-59, 2002.

[7] W. Janssen, J. Bussmann, H. Horemans, and H. Stam, "Analysis and decomposition of accelerometric signals of trunk and thigh obtained during the sit-to-stand movement," *Medical and Biological Engineering and Computing*, vol. 43, pp. 265-272, 2005.

[8] Y. Higashi, K. Yamakoshi, T. Fujimoto, M. Sekine, and T. Tamura, "Quantitative evaluation of movement using the timed up-and-go test," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 27, pp. 38-46, 2008.

[9] G. Daniele, M. Giovanni, C. Stefano, B. Francesco, and M. Velio, "Assessment of fall-risk by means of a neural network based on parameters assessed by a wearable device during posturography," *Medical engineering & physics*, vol. 30, pp. 367-372, 2008.

[10] M. H. Jeffrey, A. R. Dean, and K. E. Helen, "Gait variability and fall risk in community-living older adults: A 1-year prospective study," *Archives of physical medicine and rehabilitation*, vol. 82, pp. 1050-1056, 2001.

[11] B. Najafi, K. Aminian, F. Loew, Y. Blanc, and P. A. Robert, "Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly," *Biomedical Engineering, IEEE Transactions on*, vol. 49, pp. 843-851, 2002.

[12] M. R. Narayanan, M. E. Scalzi, S. J. Redmond, S. R. Lord, B. G. Celler, and N. H. Lovell, "A wearable triaxial accelerometry system for longitudinal assessment of falls risk," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2008, pp. 2840-2843.

[13] M. Marschollek, K.-H. Wolf, M. Gietzelt, G. Nemitz, H. Meyer zu Schwabedissen, and R. Haux, "Assessing elderly persons' fall risk using spectral analysis on accelerometric data - a clinical evaluation study," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2008, pp. 3682-3685.

[14] A. Tiedemann, H. Shimada, C. Sherrington, S. Murray, and S. Lord, "The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people," *Age Ageing*, vol. 37, pp. 430-435, 2008.

[15] M. E. Tinetti, "Preventing Falls in Elderly Persons," *N Engl J Med*, vol. 348, pp. 42-49, 2003.