Inertial Measurements of Free-Living Activities: Assessing Mobility to Predict Falls

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***Abstract*—An exploratory analysis was conducted into how simple features, from acceleration at the lower back and ankle during simulated free-living walking, stair ascent and descent, correlate with age, the overall fall risk from a clinically validated Physiological Profile Assessment (PPA), and its sub-components. Inertial data were captured from 92 older adults aged 78-95 (42 female, mean age 84.1, standard deviation 3.9 years). The dominant frequency, peak width from Welch's power spectral density estimate, and signal variance along each axis, from each sensor location and for each activity were calculated. Several correlations were found between these features and the physiological risk factors. The strongest correlations were from the dominant frequency at the ankle along the mediolateral direction during stair ascent (Spearman's correlation coefficient ρ = - 0.45) with anterioposterior sway, and signal variance of the anterioposterior acceleration at the lower back during stair descent (ρ = - 0.45) with age. These findings should aid future attempts to classify activities and predict falls in older adults, based on true free-living data from a range of activities.**

I. Introduction

The myriad of negative effects of falls on the falling older adult as well as their families and the wider community is now widely recognized [1]. Accurately identifying individuals at high risk of falling in the medium- to long-term future may lead to more timely intervention and fewer injurious falls. Thus, the field of fall prediction is burgeoning with research attempts towards improving fall risk assessments, intervention strategies and prevention plans.

Most fall risk assessments today are conducted in a clinical setting, employing a range of often qualitative and/or subjective techniques, to measure factors that increase the chance of a fall [2]–[4]. Researchers have seen potential in the ability of light-weight, affordable inertial measurement units (IMUs) to offer quantitative data for assessing the biomechanics of one's mobility, physical condition and propensity for idiopathic falls. There are a number of scientific and logistical advantages to predicting falls in older adults using (1) wearable inertial sensors, and (2) data from the everyday home setting instead of a clinical one. Issues of subjectivity, high personnel and equipment overhead or effort, plus the importance of assessing risk where falls commonly occur [5] are addressed by using wearable sensors; understanding the inertial activity at specific body locations may also assist in the personalization of intervention plans. Meanwhile, evaluation within one's natural setting can obviate confounding behavioral changes which occur during assessment in a clinical setting. By merging these two approaches, we may arrive at fall risk assessment methods that come closer to one's true risk.

Previous studies in using body-worn sensors to predict falls have shown promise, but the activities performed by subjects during assessment were often directed routines, such as the Timed Up and Go test (TUGT) [6], or used a defined length of walking [7]. The conflicting results between Greene *et al*. [6] and Laessoe *et al.* [7] raises questions over whether these short tests reveal one's true mobility in everyday life. Weiss *et al*. [5] and van Schooten *et al.* [8] recently conducted prospective studies which showed that utilizing waist acceleration measurements from daily gait in logistic regression models based on clinical risk measures improved estimations of fall risk. A pilot study by de Bruin *et al.* [9] which analyzed a range of activities of daily living (ADL) in older adults highlighted the importance of long term ADL monitoring. The usefulness of wearable IMUs were further probed in a large study by Aminian *et al*. [10], where foot clearance parameters were presented to open further avenues for assessing risky gait and fall risk.

This paper explores how simple features, derived from accelerations at the lower back and the ankle during simulated free-living activities, correlate with parameters of a clinical fall risk assessment. Both body sites were considered, as the sacrum is closer to one's center of mass but faces attachment difficulties due to subject body and behavior idiosyncrasies, while ankle accelerations may be affected by shoe type. The advantage of a semi-free-living setting at this stage is the ability to accurately verify activity classification and results of data analysis, which will ensure reliable segmentation of pure free-living data acquired from future home trials. Potentially pertinent features identified in this work will then be validated with increased significance in these home studies.

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II. METHODS

A. Subjects

Under University of New South Wales Institutional ethics approval HC12316, 92 subjects (42 female), aged 78 to 95 years (mean 84.1 years, standard deviation 3.9 years) were recruited from a cohort of participants enrolled in an existing study on memory and aging at Neuroscience Research Australia (NeuRA), Sydney, Australia. The participants were community-dwelling and retirement village residents living in inner and eastern Sydney; aged 65+ years; English-speaking; with a Mini-Mental State Examination (MMSE) score of 24 or above; no acute psychiatric condition with psychosis or unstable medical condition; not currently participating in a fall prevention trial. For a clinical measure of fall risk, all subjects were assessed using the Physiological Profile Assessment (PPA) prior to, or just following, their completion of the study protocol [2] – see section II.*F* for details.

B. Instrumentation

Three inertial measurement Opal sensors (APDM, Portland, OR, USA) were used to collect inertial data from each subject while they completed free-living activities (see section II.*C*). The devices were worn on the dorsal surface of the right wrist; above the lateral malleolus of the right ankle; and in the center of the lower back. They were attached securely by adjustable Velcro straps to the wrist and ankle, and by an adjustable clip-belt to the lower back.

Each Opal contained a triaxial accelerometer (± 6 g), a triaxial gyroscope (± 2000 deg/s) and a triaxial magnetometer (± 6 Gauss). Data were sampled at 128 Hz per channel in low-power logging mode, saved onto internal storage and processed post-experiment. Signals were synchronized with each other and the video offline.

C. Experimental Protocol: Free-Living Activities

Subjects were asked to complete a sequence of tasks based on ADL, at their own natural pace. They were able to terminate the sequence at any point for any reason; all but six of the 92 subjects completed the entire sequence. Activities were completed in meeting rooms, hallways and the foyer in the NeuRA building. The tasks (TABLE I.) were designed to incorporate a range of body positions, transitions between activities, static and dynamic states, and changes in height. Resting activities were inserted between more energetic activities to avoid exhausting the subjects.

Subjects were permitted to use stair bannisters and walking aids if present and according to personal preference.

TABLE I. SEQUENCE OF SIMULATED FREE-LIVING ACTIVITIES; SEGMENTS USED FOR ANALYSIS FOR THIS PAPER IN BOLD. VH = VERTICAL HEIGHT.

	Activity	Approx. Duration	Approx. Traversal
1	Stand-sit-lie-sit-stand, x2; sit at table; flick wall power switch; light switch	2 min	5 m^2
2	**Walk to kitchenette**	40 s	25 m
3	Fill cup with tap water, sit, drink (real or pretend), rinse cup, dry hands	75 s	6 m^2
4	**Walk to elevator**	35 s	30 m
5	Ride elevator up to Level 2	10 s	1 story
6	**Walk to end of hallway**	40 s	38 m
7	Stand and wait (>10 s)	>10 s	-
8	**Walk back to elevator**	40 s	38 m
9	Ride elevator up to Level 3	10 s	1 story
10	**Walk to end of hallway**	40 s	36 m
11	Sit down on couch (> 1 minute)	>1 min	-
12	**Walk back to elevator**	40 s	36 m
13	Elevator down to Ground; walk up short stairs (6 steps)	20 s	2 stories; 1 m VH
14	**Walk to end of hallway**	50 s	44 m
15	**Walk up longer stairs (9 + 10 steps)**	25 s	1 story
16	Walk to room, sit at table (>1 minute), walk back to longer stairs	>1 min	6 m; 6 m
17	**Walk down longer stairs**	20 s	1 story
18	**Walk back across hallway**	50 s	44 m
19	Walk down short stairs, to armchairs, sit (>20 s), back to home room, lie down (>10 s)	75 s	1 m VH; 10 m; 30 m

D. Data Processing

To focus on body accelerations by removing gravity and high-frequency noise [10], [11], calibrated accelerometer data were third-order Butterworth band-pass filtered between 0.25 Hz and 17 Hz in MATLAB (Natick, MA, USA).

Data from only the lower back and ankle, in purposeful walking on flat ground, stair ascent, and stair descent were investigated for this study. Purposeful walking was selected, distinct from loitering or weight-shifting. Bouts of walking were extracted between toe-off after the second step at the start of a bout, and the second-to-last step at the end of a bout, to exclude the accelerating and decelerating phases. Stair ascent and descent were marked between points of toe-off immediately after stepping up or downwards (Fig. 1).

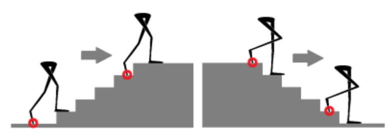

Fig. 1: Signal annotation point at toe-off (circled in red) for stair ascent (left) and descent: before second step onto, and final step off staircase, respectively.

E. Signal Features

Four parameters were extracted from the accelerometer data of each axis (AP = anterioposterior, ML = mediolateral, VT = vertical), on each device and for each activity. These were: the amplitude of the tallest peak (PkA) in the signal's power spectral density (PSD), representing the strength of the dominant frequency along that axis; the width of this peak of the PSD at half-height (PkW), representing frequency dispersion; the dominant frequency itself (PkF), encoding the cadence; and signal variance (Var), a measure of the acceleration range or activity vigor. The three spectral parameters were calculated using Welch's averaged periodogram PSD estimate, with a Hamming window size of 512 samples (or 256 for signals shorter than 512 samples) and 50% overlap, for each bout of walking or stair traversing – then averaged across bouts of the same activity type. Var was calculated for each sensor, axis and activity, using all bouts concatenated together. The features were selected due to their previous usage in fall prediction and activity classification [5], [12]. PkA features were removed from this paper due to high correlations with Var, and to reduce the number of comparisons performed.

F. Targets

Relationships between the signal features and nine targets were explored. These targets were seven sub-components of the PPA, age, and the overall PPA score. Within the PPA, five individual parameters of physiological performance were assessed to provide a composite estimate of physiological fall risk. They were: visual contrast sensitivity (using the Melbourne Edge Test), proprioception (using a lower-limb matching task), quadriceps muscle extension strength (assessed isometrically in the dominant leg while seated), reaction time (using a light stimulus and finger-press response), postural sway path length, and the extent thereof in the ML and AP axes (using a sway meter to record body displacements at the pelvis, standing on a foam mat with eyes open). In multivariate models, weighted contributions from these variables provided a fall risk score with 75% prediction accuracy in community settings [2]. Subjects with no score for a PPA component due to inability to complete the task or equipment failure were excluded from the corresponding analysis; this included one subject from all sway targets and an additional 33 from Sway Path.

G. Statistical Analysis

Correlations between signal features and fall risk targets were tested using Spearman's rank correlation coefficient ρ, a nonparametric measure of monotonic statistical dependence that allows for any nonlinear correlations which may exist. To illustrate confidence in these relationships, p-values using the star coding system were calculated, where * = ($p < 0.05$), ** = ($p < 0.01$), *** = ($p < 0.001$). This choice of p-value was made by convention and not with the intention of performing any hypothesis testing. No corrections for multiple comparisons were made, as we wished to minimize the chance of rejecting a true relationship.

III. Results

Correlation coefficients (ρ) with $p \leq 0.05$ are displayed in Fig. 2 to Fig. 4; 'LB' = lower back, 'An' = ankle; 'Knee' = quadriceps (knee extension) strength, 'Score' = overall PPA. Magnitudes of ρ are used to shade each cell. To save space, results are not shown for Vision and Proprioception (had poor correlations), hand Reaction Time (deemed of low relevance) and Sway Path (dependent on SwayAP and SwayML).

Walking: Var features correlated with all targets but knee strength (Fig. 2). Only ankle Var features correlated with either Sway score. Sway ML correlated somewhat with every Var feature from the ankle, but less so from the lower back. The highest ρ was between Var lower back VT and age ($\rho = -0.31$). PkW in VT and AP axes from both locations as well as PkF VT features correlated weakly with knee strength.

Stair Ascent: Stair ascent presented stronger correlations with both the overall PPA score and its sub-scores (Fig. 3) than normal walking (Fig. 2) and stair descent (Fig. 4). The highest correlation was between PkF ankle ML and sway AP ($\rho = -0.45$). The only noticeable correlations with knee strength were PkW and Var from the lower back VT, but not from the ankle. In contrast, every Var feature from the ankle correlated noticeably with sway in both directions, but not knee strength.

Stair Descent: Several PkF and Var features and only one PkW feature correlated with a PPA sub-score (Fig. 4). Relatively high ρ values were reported for correlations between both Var VT features and lower back AP, and age (all $|\rho| \geq 0.38$). All three features from the lower back ML correlated noticeably with sway AP; Var lower back ML was the only feature that correlated noticeably with the overall PPA score.

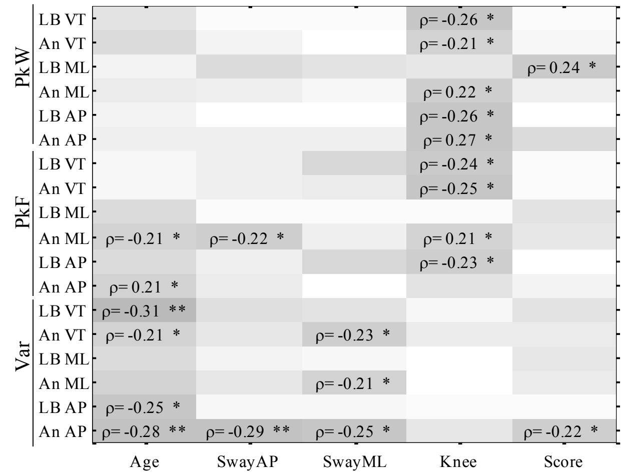

Fig. 2: Correlations for walking features vs. age, PPA and its sub-scores.

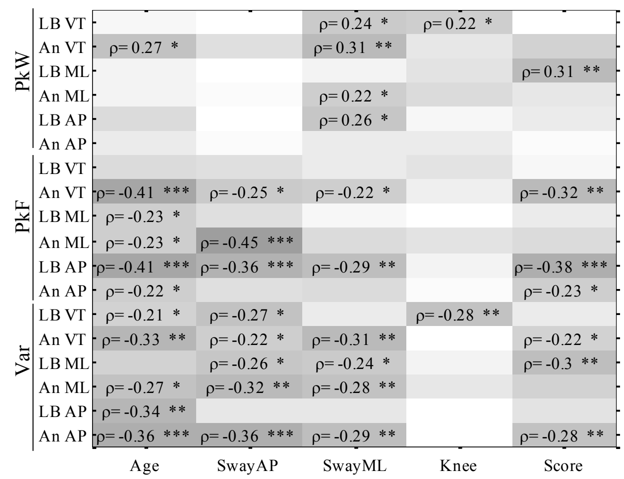

Fig. 3: Correlations for stair ascent features vs. age, PPA and its sub-scores.

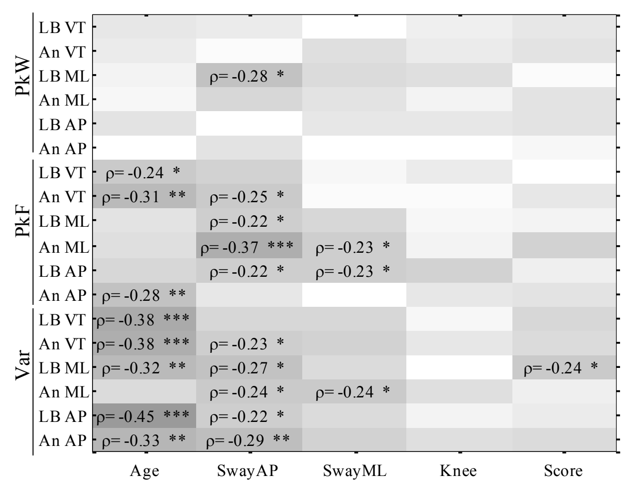

Fig. 4: Correlations for stair descent features vs. age, PPA and its sub-scores.

IV. DISCUSSION

Finding biomechanically sensible inertial predictors of falls from ADL is a complex issue. In this analysis, we found both similarities and obvious contrast between the nature of four sensor-derived features from different gait conditions, not previously addressed by Weiss *et al* [5]. The directions of correlations were usually representative of true relationships between gait factors and falls. Mathematically, Var increases with the amplitude of the periodic acceleration along any axis during gait. By interpreting the magnitude of the waveform as kinetic energy input, which in turn indicates movement vigor or confidence, it is unsurprising that Var features, from both locations, correlated negatively with PPA sub-scores (Fig. 2 to Fig. 4), whose values increase with frailty and fall likelihood.

In stair ascent and descent (Fig. 3, Fig. 4), the negative relationships found between PkF, which encodes cadence, and PPA (sub-)scores, suggest that the rate of stair traversal was slower for older subjects, with more sway and higher clinical fall risk. However, the fact that these correlations were only moderate, and that all PkF from normal walking had $|\rho| < 0.3$, suggests that the relationship between walking cadence, commonly assessed in gait analysis [7], and falls, is not straight-forward. In the literature, cadence has previously been shown to relate to fall history when derived from the TUGT [6], but failed to distinguish fallers from non-fallers in a 1-year prospective study [7]. This may be explained by the fact that the TUGT often requests maximal performance, unlike 'normal' walking in this study as well as that by Laessoe *et al*. [7]. Similarly, stair ascent and descent presented stronger correlations with PPA sub-scores than normal walking – with several $|\rho| > 0.3$ from stair ascent and descent, compared to none from walking. With stair traversal being a greater physical challenge than walking on flat ground, performance on stairs is more likely to demarcate differing physical abilities within a population.

PkW was described by Weiss *et al*. as a measure of frequency dispersion, reflecting a more variable gait pattern [5]. Its positive correlations at the lower back and ankle in stair ascent (Fig. 3) with ML sway and the PPA suggest that gait variability measured near the body's center of mass may indicate balance instability and thus a higher risk of falls, which agrees with Bosse *et al*. [13]. However, PkW also reported some weakly negative correlations (Fig. 2, Fig. 4) as well as positive correlations with knee strength (Fig. 2, Fig. 3), so any definitive conclusions ought to be drawn from further data collection and analysis.

Overall, no single correlation stood out (all $|\rho| < 0.5$), as expected: the uncontrolled nature of the experiment, in which we asked subjects to move as naturally as possible, would have introduced high variability not usually present in clinical data from strictly regulated activities. The unpredictable nature of everyday life is one of the complications of free-living assessment, but one can conversely argue the value of minimal imposition on subject behavior, as the final goal is to predict falls from true ADL. Conducting prospective studies to test but also validate sensor-based fall predictors in any fall risk study is thus a priority.

A limitation of the study was that the axes definitions were chosen to match the local sensor axes and not relative to true body planes. The ankle swings considerably during gait, alternating the predominant acceleration vector between our Y (AP) and X (VT) axes. Transforming to a subject body coordinate system would be a valuable next step. In addition, as the study was intended as an exploration for potential risk indicators before starting a larger home-based trial, no corrections were made for multiple statistical tests to discourage the occurrence of false negatives. Interdependence between features was also an issue as the signals came from the same source (body location and activities), justifying further studies to verify the significance of our results.

In conclusion, correlations have been found between some features derived from inertial-sensor measurements of simulated free-living and fall risk measures. Future work will involve completing the follow-up branch of the study for prospective fall data, and developing activity classification algorithms for monitoring in the true free-living environment, to then be used for fall prediction studies in future home trials.

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