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Distinguishing Near-Falls from Daily Activities with Wearable Accelerometers and Gyroscopes using Support Vector Machines

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***Abstract*— Falls are the number one cause of injury in older adults. An individual's risk for falls depends on his or her frequency of imbalance episodes, and ability to recover balance following these events. However, there is little direct evidence on the frequency and circumstances of imbalance episodes (near falls) in older adults. Currently, there is rapid growth in the development of wearable fall monitoring systems based on inertial sensors. The utility of these systems would be enhanced by the ability to detect near-falls. In the current study, we conducted laboratory experiments to determine how the number and location of wearable inertial sensors influences the accuracy of a machine learning algorithm in distinguishing near-falls from activities of daily living (ADLs).**

I. INTRODUCTION

Falls are the leading cause of injuries in older adults with a substantial impact on health and healthcare costs. Approximately one in three persons over the age of 65 falls at least once each year [1-3]. An individual's risk for falls depends on his or her frequency of imbalance episodes, and ability to recover balance following these events [4-6]. For example, investigators have found that older adults who report multiple "near-falls" (missteps or stumbles) are more likely to go on to fall [7]. An accurate quantification of near-falls during daily activities could assist clinicians in assessing balance and developing strategies to prevent future falls [7, 8]. However, our current knowledge of near-falls in older adults is based on self-reports, which are often unreliable and likely underestimate the true occurrence of such events [6, 9].

Wearable inertial sensors, such as miniature accelerometers and/ or gyroscopes represent a promising technology for objectively quantifying balance, mobility and falls in older adults. Sensor hardware is rapidly advancing in terms of size, accuracy and cost. However, challenges remain in developing software to derive accurate, reliable and clinically relevant outcomes from sensor data. At present, the primary application for these systems is to detect the occurrence of a fall and alert care providers to this event [1, 10, 11].

Our goal is to enhance the utility of wearable fall monitoring systems beyond fall detection, to distinguish near-falls from activities of daily living (ADLs). In particular, the current paper describes efforts to test, through laboratory experiments, how the number and location of sensors (3D accelerometers and gyros) influence the accuracy of a machine learning algorithm in distinguishing near-falls from ADLs.

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II. METHODOLOGY

A. Participants

Ten healthy adults participated in this study, ranging in age between 22 and 32 years. All subjects were students at Simon Fraser University (SFU), recruited through advertisements posted on university notice boards. All participants provided informed written consent and the experiment protocol was approved by the research and ethics committee at SFU.

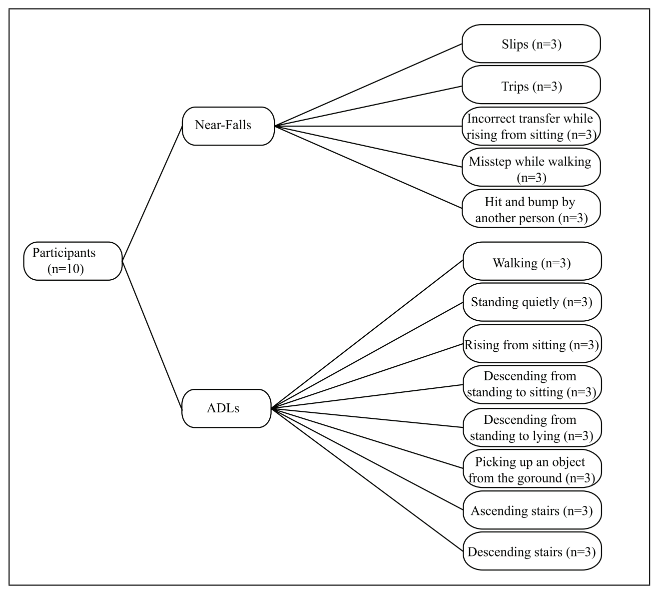

Fig. 1. Experiment protocol, indicating various types of near-falls and Activities of Daily Living (ADLs) simulated by each participant.

B. Experimental Design

During the experiment, participants underwent five types of near-falls and eight different activities of daily living (ADLs) (Fig. 1). These near-fall scenarios were selected as being representative of those emerging as most common from a study analyzing video-captured real life falls in long term care. All participants viewed falls from this library were then asked to act out the scenarios [12]. All near-fall trials were performed on a 30 cm thick gymnasium mattress, into which we inserted a 13 cm top layer of high density

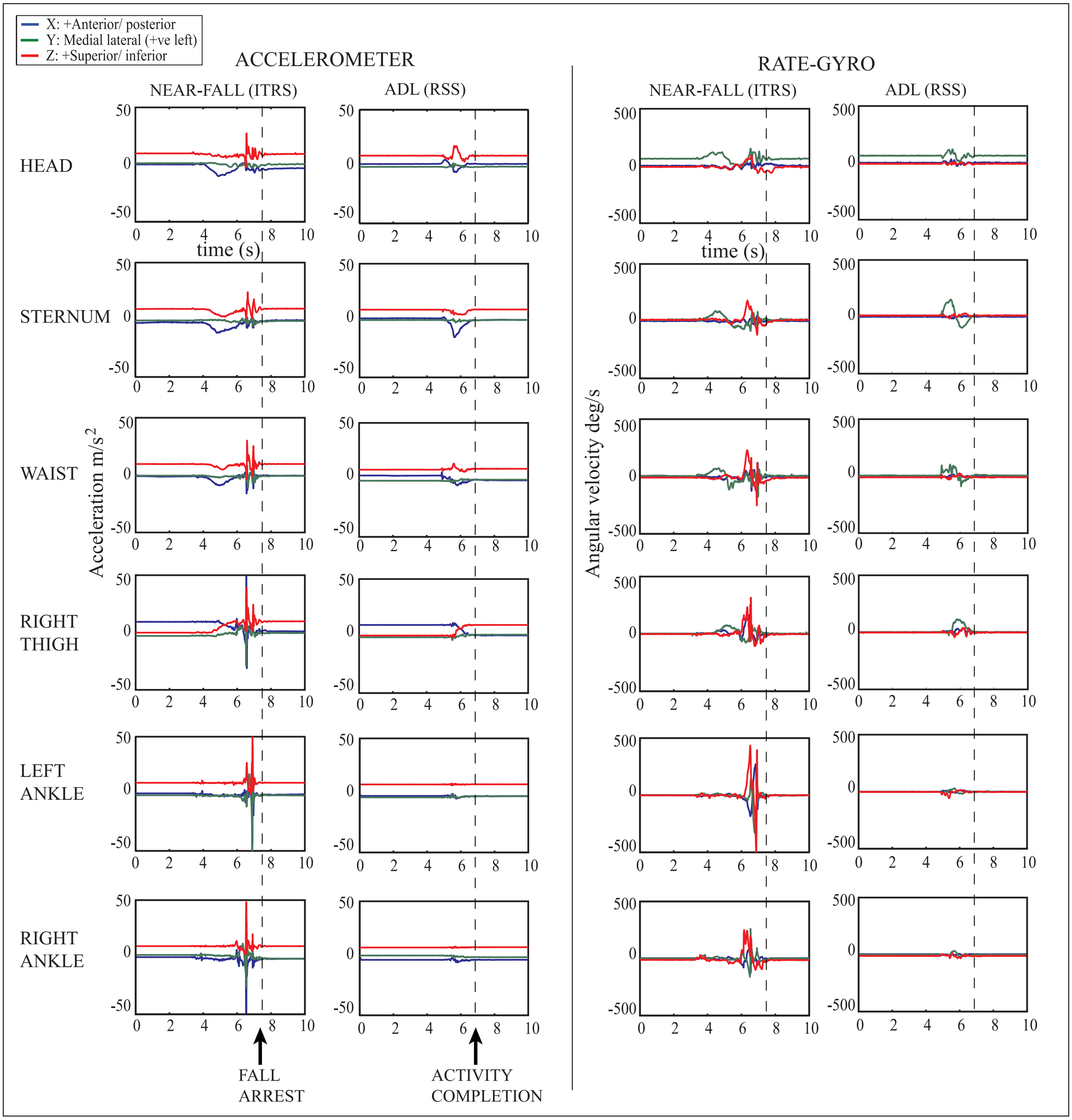

Fig. 2. Acceleration and rate-gyro traces in X, Y and Z direction from a typical participant in near-fall (Incorrect Transfer while Rising from Sitting (ITRS)) and ADL (Descending from Standing to Sitting (DSS)). The two vertical dotted lines show the completion of fall arrest in near-falls and the completion of activity in ADL.

ethylene vinyl acetate foam so the composite structure was stiff enough to allow for stable standing and walking, but soft enough to reduce the impact force to a safe level in case of a fall. In the near-falls, the participants were subjected to five different scenarios: (i) slips, (ii) trips, (iii) incorrect transfer while rising from sitting to standing (iv) misstep while walking, and (v) hit and bump by another person. For ADLs, eight scenarios were included: (i) walking, (ii) standing quietly, (iii) rising from sitting, descending from (iv) standing to sitting and (v) standing to lying, (vi) picking up an object from the ground, (vii) ascending and (viii) descending stairs. All participants performed three trials in each category. Accordingly, over the ten participants, a total of 150 near-falls and 240 ADLs were recorded.

C. Data Acquisition

In each trial, we used seven inertial sensors (triaxial accelerometers having a range of ±6g and triaxial gyros having a range of ±1500 deg/s, APDM, Inc. Opals) worn bilaterally on ankles and thighs, and at the waist, sternum and head recording at 128 Hz to acquire synchronized measures of the 3D accelerations and angular velocities.

III. DATA ANALYSIS

Data analysis focused on determining how the number and location of sensors influenced the ability of our classification algorithm to distinguish near-falls from ADLs. In the single sensor category, head, sternum, waist and both thigh sensors were included but not right or left ankle, based on the consideration that asymmetry in foot movements could necessitate bilateral placement in any real life application of our sensor technology. Moreover, in all three or more sensor categories, only one of the thigh sensors (i.e. right thigh) was used in the analysis. Thigh sensors are particularly useful for identifying transitions in movement, for example, descending from standing to sitting or lying position and vice versa, and one thigh sensor is deemed sufficient to capture such transition movements [13].

For each trial, we identified the approximate instant of fall-arrest (for near-fall trials) and activity completion (for ADL trials) by visual inspection of the sensor data. We then selected a 2.5 s time window prior to this instant to calculate the means and variances of the X, Y and Z signals for each accelerometer and gyroscope sufficient to capture the near-fall event from the initiation to arrest phase (Fig 2).

We used the Support Vector Machine (SVM) implementation in LIBSVM [14] with Radial Basis Function (RBF) kernel to distinguish near-falls from ADLs. The features (i.e. means and variances) were then split into training and testing sets of equal size by choosing the data from the first five subjects for training and the following five for testing. The SVM constructs a hyper-plane or a set of hyper-planes in a high or infinite-dimensional space, which can be used for classification. However, the effectiveness of the SVM depends on the selection of kernel and the kernel's parameters. In this study we used SVMs with RBF kernel which required two parameters, C and γ. The best combination of C and γ was selected by a grid-search with exponential growing sequences of C and γ (i.e. $C \in \{2^{-5}, 2^{-4}, \dots, 2^{14}, 2^{15}\}$; and $\gamma \in \{2^{-15}, 2^{-14}, \dots, 2^{2}, 2^{3}\}$). Each combination of parameter choices was checked using a 10-fold cross-validation and the parameter with the best cross-validation accuracy was picked. The final model, which was used for classifying test data, was then trained on the whole training set using the selected parameters. The procedure was conducted on the data from each sensor, and for each possible combination of 2, 3, 4, 5 and 6 sensors. In each case, we then calculated the sensitivity and specificity as:

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative} \qquad (1)$$

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive} \qquad (2)$$

TABLE I
SENSITIVITY AND SPECIFICITY OF 3D ACCELEROMETER AND RATE-GYRO ARRAYS IN SEPARATING NEAR-FALLS FROM ACTIVITIES OF DAILY LIVING

Sensor Combination	No. of FP	No. of FN	Sensitivity	Specificity
Single sensor				
Head	11	7	90.66	90.83
Sternum	6	9	88.00	95.00
Waist	5	15	80.00	95.83
L.thigh	11	3	96.00	90.83
R.thigh	1	6	92.00	99.16
Two sensors				
L.foot+R.foot	2	3	96.00	98.33
L.thigh+R.thigh	7	2	97.33	94.16
R.thigh+Waist	0	18	76.00	100.00
R.thigh+Sternum	1	12	84.00	99.16
R.thigh+Head	3	12	84.00	97.50
Waist+Sternum	3	7	90.66	97.50
Waist+Head	6	20	73.33	95.00
Sternum+Head	5	11	85.33	95.83
Three sensors				
L.foot+R.foot+R.thigh	1	3	96.00	99.16
L.foot+R.foot+Waist	1	0	100.00	99.16
L.foot+R.foot+Sternum	1	0	100.00	99.16
L.foot+R.foot+Head	5	2	97.33	95.83
R.thigh+Waist+Sternum	1	10	86.66	99.16
R.thigh+Waist+Head	2	18	76.00	98.33
R.Thigh+Sternum+Head	3	7	90.66	97.50
Four sensors				
L.foot+R.foot+R.thigh+Waist	1	2	97.33	99.16
L.foot+R.foot+R.thigh+Sternum	1	1	98.66	99.16
L.foot+R.foot+R.thigh+Head	1	0	100.00	99.16
L.foot+R.foot+Waist+Sternum	1	0	100.00	99.16
L.foot+R.foot+Waist+Head	2	0	100.00	98.33
L.foot+R.foot+Sternum+Head	1	0	100.00	99.16
R.thigh+Waist+Sternum+Head	2	20	73.33	98.33
Five sensors				
L.foot+R.foot+R.thigh+Waist+Sternum	1	1	98.66	99.16
L.foot+R.foot+R.thigh+Waist+Head	0	0	100.00	100.00
L.foot+R.foot+R.thigh+Sternum+Head	1	1	98.66	99.16
Six sensors				
L.foot+R.foot+R.thigh+Waist+Sternum+Head	2	1	98.66	98.33

False Positive (FP) = ADLs, incorrectly identified as near-falls
False Negatives (FN) = Near-falls, incorrectly identified as ADLs

IV. RESULTS

We found that our SVM algorithm showed good sensitivity and specificity in distinguishing near-falls from ADLs with various sensor combinations (Table 1). With a single sensor, the sensitivity and specificity of the system was at least 88% except for the waist sensor, which had 80% sensitivity.

With two sensors, the least number of false positives (FP) and false negatives (FN) was provided by the left ankle + right ankle combination, which distinguished near-falls and ADLs with 96% sensitivity and 98% specificity.

With three sensors, the highest sensitivity and specificity was provided by (a) left foot + right foot + sternum and (b) left foot + right foot + waist. Both combinations showed 100% sensitivity and 99% specificity.

The best overall performance was observed with the five sensor combination of left foot + right foot + right thigh + waist + head, which did not result in any false positive or false negative, and provided 100% sensitivity and specificity in distinguishing near-falls and ADLs. Sensitivity and specificity were no better with four and six sensor combinations than with three.

V. DISCUSSION

In this study, we conducted lab based experimental trials with young adults to examine the utility of a wearable sensor array for distinguishing near-falls from ADLs. Our results indicated that the data from various combinations of three or more sensors, when input in our Support Vector Machine algorithm, provided sensitivity and specificity higher than 99% in distinguishing near-falls from ADLs. We also found that sensor placement at the feet considerably decreased false negatives indicating that lower extremity body kinematics was essential to identify near-falls.

There are important limitations to this study. First, our participants were healthy young adults, and they were aware of the external perturbations being applied to disturb their balance. An important unanswered question is the extent to which our classification procedure and results will transfer to unexpected near-falls in real-life scenarios by older adults, including those with specific disease conditions or neuromuscular impairment. Ultimately, this issue can only be addressed by testing the system with older adults as they go about their daily activities. However, several aspects of our experimental design enhance the validity of our results for older adults. Most importantly, before commencing a given series of trials, each of our participants studied representative video clips of real-life falls experienced by older adults residing in long-term care, and were instructed to "act out" a similar fall and near-fall [12]. Despite the inevitable variability in the acting style of participants, we believe this approach substantially enhanced the validity of our results for older adults.

Second, given the current size of self-contained wearable 3D sensors with on-board data storage and power supply (which are at least the size of large wrist watches), there is a legitimate concern that routine wear may be met with low user compliance in the target population. However, given the rapid rate of miniaturization of these components, one might expect that sufficient performance will soon be achieved with units the size of plasters.

This study demonstrates the utility of a wearable sensor system in distinguishing near-falls from ADLs with high accuracy. Incorporation of this application in fall monitoring systems should substantially enhance their utility for health professionals in assessing and monitoring the effectiveness of strategies in reducing fall risk.

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