The Effect of Window Size and Lead Time on Pre-Impact Fall Detection Accuracy Using Support Vector Machine Analysis of Waist Mounted Inertial Sensor Data

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Abstract— **Falls are a major cause of death and morbidity in older adults. In recent years many researchers have examined the role of wearable inertial sensors (accelerometers and/or gyroscopes) to automatically detect falls. The primary goal of such fall monitors is to alert care providers of the fall event, who can then commence earlier treatment. Although such fall detection systems may reduce time until the arrival of medical assistance, they cannot help to prevent or reduce the severity of traumatic injury caused by the fall. In the current study, we extend the application of wearable inertial sensors beyond post-impact fall detection, by developing and evaluating the accuracy of a sensor system for detecting falls prior to the fall impact. We used support vector machine (SVM) analysis to classify 7 fall and 8 non-fall events. In particular, we focused on the effect of data window size and lead time on the accuracy of our pre-impact fall detection system using signals from a single waist sensor. We found that our system was able to detect fall events at between 0.0625-0.1875 s prior to the impact with at least 95% sensitivity and at least 90% specificity for window sizes between 0.125-1 s.**

I. INTRODUCTION

Falls are the leading cause of injury among older adults in Canada, including over 90% of hip fractures [2], [10] and wrist fractures [7], and a large percentage of head and spine injuries [6]. About 30% of older adults living in the community and 60% of individuals living in a residential care environment will experience at least one fall each year [11]. Hip fractures are the most significant injury related to falls, with approximately 23,000 annual cases in Canada, and medical costs in excess of $1 billion [8].

Wearable kinematic sensors such as accelerometers and gyroscopes represent a promising technology for preventing and mitigating the effects of falls in older adults. One of the key issues in preventing fall related injuries is to detect a fall in its descending phase with a sufficient lead time in order to deploy protective equipment (such as inflatable hip protectors, helmets, etc.) to cushion the fall prior to impact [12]. Wu and Xue [13] proposed a pre-impact fall detection technique by thresholding the vertical velocity profile of the waist worn accelerometer, and showed that with vertical velocity threshold set at -1 m/s their algorithm was able to detect all falls with at least 70 ms lead time with only three false positives found during approximately 13 hours of data. Similarly, Nyan et al. [5] showed 100% sensitivity with approximately 200 ms lead time by locating sensors at the sternum, waist and under the arm. However, Nyans threshold algorithm resulted in 16% of the activities of daily living (ADLs) being misclassified as falls.

Our study diverges from traditional threshold-based methods by using a machine-learning pre-impact fall detection method – support vector machines (SVM) – for better adaptability and reliability. Furthermore, our study uses a wide variety of fall and daily activity scenarios to more rigorously test the accuracy of our SVM algorithm across a combination of varying lead times and window sizes, using a single waist mounted tri-axial accelerometer and gyroscope.

II. METHODS

A. Participants

Ten healthy adults (ranging in age between 22 and 32 years) participated in the study. 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 experimental protocol was approved by the research and ethics committee at SFU.

B. Experiment Design

We examined a library of video sequences of 227 real-life falls in older adults, acquired as part of an ongoing project by our research team to examine the mechanisms of falls in long-term care facilities [9]. We found that 75% of falls were collectively due to the following seven causes: (i) slips, (ii) trips, (iii) hit or bump by an object or another person, (iv) collapse or loss of consciousness, (v) misstep or cross-step while walking and (vi-vii) incorrect shift of bodyweight while sitting down on or rising from a chair. We included all seven of these types of falls in our laboratory experiment. During all fall trials, the floor was covered with 30 cm thick gymnasium mats into which we inserted a 12 cm thick top layer of high-density ethylene acetate foam. The composite structure was stiff enough to allow for stable standing and walking while still soft enough to reduce the impact force to a safe level in case of a fall.

In addition to fall trials, eight activities of daily living (ADLs) were recorded which included: (i) walking, (ii)

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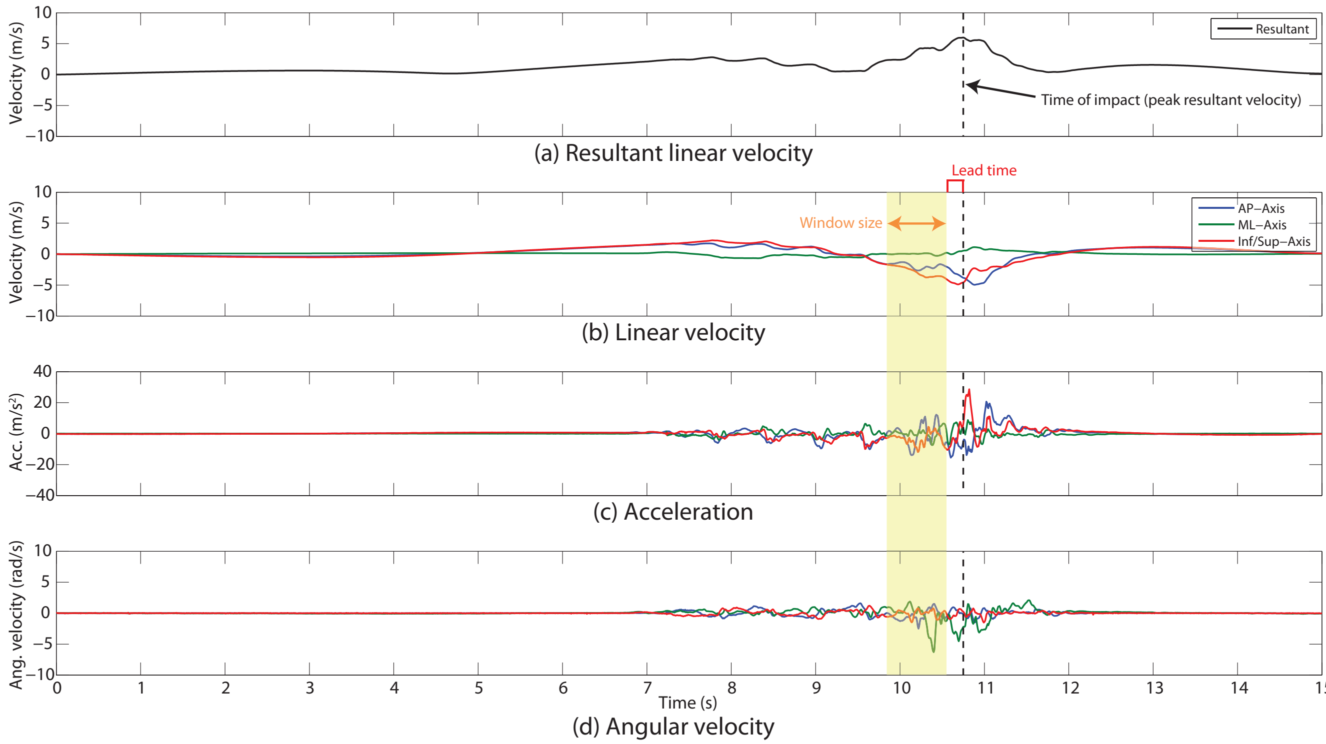

Fig. 1. Waist sensor signals for a sample slip fall trial. (a) Time of impact (dashed line) is estimated by finding the time of peak resultant linear velocity (obtained from numerical integration of the resultant acceleration signal), and the window location (shaded region, not shown to scale) is shifted by the lead time (not shown to scale) ahead of the time of impact. Mean and variance features are calculated within the window for each of the anteroposterior (AP), mediolateral (ML), and inferior-superior (Inf/Sup) axes of the (b) linear velocity, (c) acceleration and (d) angular velocity signals. Note that the peak linear velocity does not always coincide with peak acceleration.

standing quietly, (iii) rising from sitting, descending from (iv) standing to sitting and from (v) standing to lying, (vi) picking up an object from the ground, (vii) ascending and (viii) descending stairs. All participants performed each fall and ADL category three times. Accordingly, over ten participants, a total of 210 fall trials and 240 ADL trials were acquired.

C. Data Acquisition

In each trial, we recorded body kinematics using a single tri-axial accelerometer and gyroscope (ranges of ± 6 g and ± 26.18 rad/s respectively, Opal model, APDM Inc., Portland, OR) worn on a belt at the anterior aspect of the waist. Data were recorded at 128 Hz for a duration of 15 s per trial and streamed directly to a computer for storage and subsequent analysis.

D. Data Analysis

Our data analysis focused on determining how the various window size and lead time combinations influenced the accuracy of our pre-impact fall detection algorithm (Fig. 1). We used seventeen different data window sizes in combination with eighteen lead times to evaluate their effect on the sensitivity and specificity of the algorithm. The window sizes used varied from 0.125 s to 1.125 s with an increment of 0.0625 s, while the lead times varied from 0.0625 s to 1.125 s with the same increment.

In order to determine the base window location for fall trials, we estimated the instance of the body impacting the floor due to a fall by finding the time of peak resultant velocity from the waist sensor [3]. The resultant peak velocity was calculated through numerical integration of the high-pass filtered (cut-off frequency of 0.25 Hz to remove gravity signal) resultant acceleration signal. We then shifted the base window location a fixed amount back from the impact timepoint according to the chosen lead time (Fig. 1a). For increasing window sizes, we shifted the start time point of the base window back in time by the corresponding amount.

For ADL trials, we visually identified the start and end time points of activity motion from the sensor signals, and then set the base window location at a random position within that time frame. ADL window start and end time points were shifted symetrically from that base window as window sizes were increased. Lead times were not used in the analysis of ADL trials, as they do not contain a timepoint of interest analagous to the fall impact time.

Within each window we calculated the means and variances of X-, Y- and Z-axis accelerations, velocities and angular velocities to form the 18 features for use in our Support Vector Machine (SVM) analysis (Fig. 1b-d). We used the SVM implementation in LIBSVM [1] with a Radial Basis Function (RBF) kernel for pre-impact fall detection. The features (i.e. means and variances) were then split into training and testing sets of equal size by choosing the data

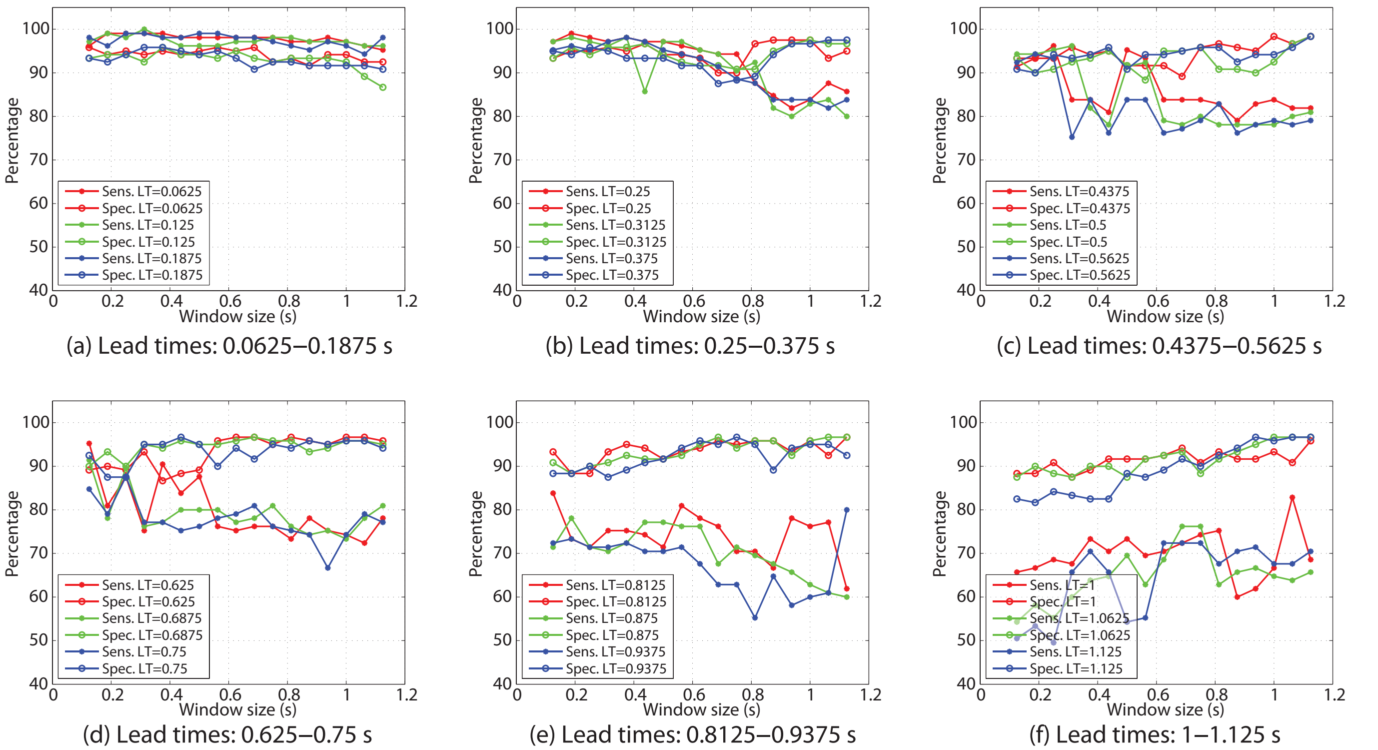

Fig. 2. Overall sensitivity and specificity of trial classification for each combination of window size and lead time. Subfigures (a-f) show results for triplets of increasing lead time size. Note that sensitivity and specificity are relatively stable across all window sizes for the three smallest lead times between 0.0625-0.1875 s (a), with sensitivity consistently above 95%. For larger lead times (b-f), sensitivity and specificity varied dramatically depending on window size, indicating the algorithm performance was less robust for these cases.

from the first five subjects for training and the following five for testing. The best combination of the two RBF kernel parameters C and γ was selected by a grid-search with exponential growing sequences (i.e. $C \in \{2^{-5}, 2^{-4}, \ldots, 2^{14}, 2^{15}\}$; and $\gamma \in \{2^{-15}, 2^{-14}, \ldots, 2^{2}, 2^{3}\}$). Each combination of parameter choices was tested 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 entire training set using the selected parameters. The process of training and testing the SVM model was repeated for every combination of window size and lead time.

After creating classification sets of test data for all window size and lead time combinations, we evaluated algorithm performance by calculating the sensitivity and specificity of each classification set. To assess typical algorithm performance per trial, we calculated the mean and standard deviation of each trial's classification sensitivity (for fall trials) or specificity (for ADLs) across all combinations of window size and the three smallest lead times (0.0625-0.1875 s).

All data analysis was performed in MATLAB (R2013a, The MathWorks Inc.).

III. RESULTS

Overall sensitivity and specificity of trial classification for each combination of window size and lead time are shown in Fig. 2. We found that our algorithm yielded relatively stable sensitivity and specificity values across all window sizes for the three smallest lead times between 0.0625-0.1875 s (Fig. 2a), with sensitivity consistently above 95% and with specificity above 90% (for window sizes 1 s or smaller). For larger lead times (Fig. 2b-f), sensitivity and specificity varied dramatically depending on window size, indicating algorithm performance was less robust for these cases.

Table I shows the individual trial means and standard deviations (SDs) of classification sensitivity (for falls) and specificity (for ADLs), as calculated across combinations of all window sizes and the three smallest lead times. Our algorithm typically had very high classification sensitivity (means >97% and SDs <4%) for all fall trials, with the exception of incorrect transfer while rising from sitting (ITRS) which had a mean sensitivity of 93.5% and SD of 7.5%. Classification specificity for ADLs was very high (means >97% and SDs <4%) for rising from sitting to standing (RSS), descending from standing to sitting (DSS), and standing quietly (SQ); moderately high (means >94% and SDs <5%) for normal walking (NW), ascending stairs (AS), and descending stairs (DS); but were relatively low and/or variable for descending from standing to laying (DSL, mean of 93.2% but SD of 9.1%) and picking up an object from the ground (POG, mean of 85.6% and SD of 11.3%).

IV. DISCUSSION

In this study we evaluated for the first time, to the best of our knowledge, the effect of data window size and lead time on pre-impact fall detection accuracy using data from a

TABLE I

INDIVIDUAL TRIAL MEANS AND STANDARD DEVIATIONS (SD) OF CLASSIFICATION SENSITIVITY (FALLS) AND SPECIFICITY (ADLS)[a].

	Falls								ADLs							
	CS	HB	ITDS	ITRS	LCC	Slip	Trip		NW	AS	DS	RSS	DSS	DSL	SQ	POG
Sens. (%)	99.3	100.0	97.4	93.5	98.2	99.3	99.9	Spec. (%)	94.5	96.3	94.6	99.7	97.8	93.2	100.0	85.6
SD (%)	2.0	0.0	4.0	7.5	3.5	2.4	0.9	SD (%)	4.6	4.7	4.6	1.3	3.7	9.1	0.0	11.3

[a]Descriptive statistics calculated by including all combinations of window sizes from 0.125-1.125 s and lead times from 0.0625-0.125 s (0.0625 s increments), as shown in Fig. 2a. CS = cross-step, HB = hit or bumped, ITDS = incorrect transfer while descending from standing, ITRS = incorrect transfer while rising from sitting, LCC = loss of consciousness or motor control, NW = normal walking, AS = ascending stairs, DS = descending stairs, RSS = rising from sitting to standing, DSS = descending from standing to sitting, DSL = descending from standing to laying down, SQ = standing quietly, POG = picking up an object from the ground.

waist-mounted inertial sensor. Furthermore, we employed a machine learning algorithm (SVM), as opposed to traditional threshold based techniques, to allow for more adaptability and robustness across subject and motion variability.

Based on the analysis of data collected in lab experiments with young adults, our system provided at least 95% sensitivity and at least 90% specificity for combinations of window size from 0.125-1 s and lead time from 0.0625-0.1875 s. However, we found that for lead times 0.25 s or greater, sensitivity and specificity varied dramatically with choice of window size, indicating poor robustness of the classification performance. Therefore, we would recommend the use of a target lead time around 0.1875 s or less, and window size 1 s or less for robust pre-impact fall detection.

Furthermore, we believe estimating the time of initial impact for fall trials based on the instant of peak resultant linear velocity is a more intuitively precise method than based on peak acceleration as done prevously, since the largest accelerations would typically occur shortly after impact [3].

There are several limitations of our study. Due to safety concerns, all fall and ADL trials were performed by young adults under controlled laboratory conditions and atop gymnasium mats. While there are important differences between falling patterns from typical laboratory studies of young subjects compared to real-life falls among older adults [4], we attempted to minimize these differences by having our subjects simulate a variety of falls most commonly observed among older adults [9]. Also, our analysis did not attempt to analyse sensor signals by sliding a sampling window along the datastream, as would be necessary in a real-time implementation for triggering device deployment, however, our study design allowed for a controlled method of testing the effects of window size and lead time. Finally, our system provided relatively low overall specificity, likely due to our wide range of ADLs tested (with individual specificities ranging from 85.6%-100%) and a modest testing sample from five subjects. Future work is required to compare the accuracy of machine learning versus threshold-based approaches on the same data set. While current performance is too low for practical use in device deployment, it may be improved in the future through the use of larger training datasets of falls and ADLs recorded from older adults, or with the use of complementary signals from other physiological sensors.

Our results provide a template for future developement of a robust pre-impact fall detection system, which is necessary for the developement of 'smart' next generation inflatable hip protectors or helmets for improved force attenuation and user acceptance.

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