Fall Detection: Threshold Analysis of Wrist-Worn Motion Sensor Signals

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Abstract. In this paper, we present a detection algorithm that accurately differentiates the event of a person falling from normal Activities of Daily Living (ADL). Our algorithm processes signals recorded from accelerometers built into wearable activity monitoring devices such as a Fitbit or Apple Watch that is worn on an individual's wrist. Given the potential danger of injury resulting from a fall, especially for the elderly population whom are more susceptible, an accurate fall detection algorithm could be the precursor to an autonomous emergency alert system that pages paramedics. Immediate medical intervention is critical for survival in urgent situations such as a stroke, cardiac event, or Traumatic Brain Injury (TBI); unfortunately, in many of these cases the individual may be unconscious and unable to intervene on their own behalf. With the advancement of geospatial technology, an algorithm that can distinctly detect the event of a fatal fall can automatically trigger a call for emergency medical services to the exact GPS coordinates of a mobile device or the wearable wrist device itself. We will explore the use of a combination of threshold-based and machine learning-based approaches to develop a refined fall-detection algorithm that builds upon previous research.

Keywords: fall detection · threshold analysis · Activities of Daily Living (ADL) · signal processing · Acceleration Vector Change (AVC) · Angular Velocity Vector Change (WVC) · K-Means Clustering · Support Vector Machines (SVM) · wrist-worn triaxial motion sensors ·

1 Introduction

The elderly are most prone to the dangers of falling that may significantly impair their daily lifestyle. Non-fatal falls often result in severe physical injuries such as broken bones, internal tissue damage, and head trauma. However, these falls for the elderly population can also result in persisting psychological fears due to post-traumatic stress and are at the highest risk of a reoccurring incident. The World Health Organization (WHO) report that fatality rates from falls are consistent with risk factors of advanced age and other associated predispositions such as: 1) reduced activity from physical depreciation; 2) chronic underlying medical conditions, including arthritis, neurological diseases, and cardiac diseases; 3) side effects from increased use of prescription medications, that can have compounding effects on the central nervous system; 4) hazardous environments; and 5) substance abuse.[1] Fall prevention has been investigated as a proposed solution, taking preemptive measures to reduce the number of falls, but accidental falls can not always be averted. In 2016, approximately 30,000 adults aged 65 years and older died as the result of fatal falls in the United States, the leading cause of injury-related fatalities within this age range.[3] The adjusted-age death rates for this senior population have increased by 31% from 2007 to 2016, with an estimated 43,000 deaths due to fatal falls in 2030 if these current rates remain stable.[3] Autonomous fall detection systems have since been developed with the intention of quickly identifying senior falls to provide immediate interventions if necessary in an effort to combat these increasing mortality rates.

The critical danger of a fall is being in a "long-lie" condition, in which the person remains on the ground for an extended period unable to help themselves up after a fall.[1] This may result in severe loss of self-confidence in fortunate situations of non-bodily harm, but in more grave cases potentially result in life-threatening complications such as a Traumatic Brain Injury (TBI) induced by head trauma from the fall. The Centers for Disease Control and Prevention (CDC) reported in 2014 that falls were the leading cause for TBI, accounting for roughly half (48%) of TBI-related emergency department visits.[2] Patients can suffer extended periods of unconsciousness in a critical "long-lie" condition in urgent cases of traumatic brain injuries, unable to help themselves or request for immediate assistance.

From a survey obtained on 125 subjects ages 65 and older, half of those who suffered a "long-lie" state for over an hour died within six months following the first reported fall.[14] Fall detection systems help address the concerns of "long-lie" falls by identifying when falls occur and dispatching immediate assistance in order to minimize the period of time individuals remain helpless. The first fall detection system proposed was a personal alarm system (PAS), in which a user-activated device could be worn as a wristband or necklace, but required the user to be conscious after a fall has occurred to press the button and alert an emergency help desk operator.[5] The issue with these initial systems is that they did not consider severe cases in which individuals lose consciousness and are unable to activate the alarm signal for assistance. Since then, novel autonomous fall detection systems have been introduced that do not require a user-activated alert signal; they can be categorized into: camera-based systems, ambient environment sensor-based systems, and wearable sensor-based systems.

Advancements in wearable sensors and system over the past decade has generated interest in using wearable technology to support clinical assessments of patients. Potential applications from these developments have shown promise in early diagnosis of cardiac diseases such as congestive heart failure, prevention of chronic conditions such as diabetes, improvement in clinical management of neuro-degenerative conditions such as Parkinson's disease, and the ability to promptly respond to emergency situations such as cardiac arrest or TBI.[2] Cur-

[1] `https://www.who.int/news-room/fact-sheets/detail/falls`
[2] `https://www.cdc.gov/traumaticbraininjury/get_the_facts.html`

rently, wearable technologies have been commercialized on the market as smartwatch accessories that include features for activity monitoring, physical fitness tracking, and global positioning systems (GPS). A 2019 survey conducted by the Pew Research Center reports that one in every five Americans (21%) are estimated to wear a smartwatch or fitness tracker regularly, producing massive amounts of data that can be used for healthcare research.[3] Considering how wide-spread the use of these devices are currently, we believe autonomous fall detection research primarily focused on sensor placements on the wrist will have the most potential as a universal real-world application to address concerns regarding the mortality rates from falls.

Unfortunately, prior research testing fall detection reliability have found that false positive rates are high when using a single wrist sensor.[6] Generally, torso, waist and head based sensors have proven to be more effective in detecting falls, but in this study, wrist-based sensors were still able to detect faster falls with some accuracy. While waist placement has the benefit of aligning to the human anatomy's center of gravity, sensor placement at the head has produced superior impact detection sensitivity. Triaxial accelerometer data from both sites produced efficient fall detection algorithms with a sensitivity around 97% and specificity of 100%, even with simple threshold-based algorithms.[10] Although evidence suggests that sensors placed at the head and waist yielded the most accurate predictions, we only investigate how wrist sensor data can be used to train an autonomous fall-detection algorithm for its potential application in smartwatch accessories.

The remainder of this paper is organized into the following sections. Section two will discuss related studies that have guided our work and analyzed the efficacy of previous implementations of autonomous fall-detection systems. Section three will discuss methodologies: how the data was collected along with its structures and processing methods, as well as a high-level overview of the machine learning concepts applied to develop our solution. Section four will present the results of our findings accompanied with tables and figures to summarize the analysis. Section five will wrap up our analysis with ethical considerations and potential implications of handling personal health data recorded from wearable wrist devices. Section six will summarize our main conclusions and potential ideas to refine our proposed solution.

Fall detection is a rich field with considerable depth and breadth. Much work has been done on all levels, from algorithms to detect falls from certain positions or heights to simply studying and defining movement in general.

2 Related Works

One of the most prominent studies for our purposes is the Burns study on fall-related deaths in the elderly.[3] This is the primary impetus for our project: fall-related deaths are common and preventable with timely intervention.

[3] `https://www.pewresearch.org/fact-tank/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/`

In [9], fall scenarios are categorized for evaluation purposes: namely forward, backward, and lateral. Fall-like scenarios such as syncope, where a fainted individual slips down a wall into a sitting position, are also mentioned. Such categorizations are later used in many studies for fall events.

Methods that use accelerometers to detect a fall typically analyze data about a person's acceleration before, during, and after the event. Terminology varies between studies, but most describe the segmentation in the following chronological order: a normal ADL period succeeded by a sudden spike in acceleration within a short time window, followed by a sudden deceleration on impact, followed by an extended period of no acceleration if the person is in a "long-lie" state. Events with slower falls or multiple impacts may have slightly different profiles of acceleration over time.[11]

Prior fall detection research suggests processing raw triaxial sensor measurements into magnitude signal vectors to reduce dimensionality. From the acceleration magnitude vector, an Acceleration Vector Change (AVC) feature can be extracted to capture motion intensity. Stronger motions will result in sudden, drastic changes in the acceleration signal and produce greater AVC values.[6] Gjoreski's various studies compared the effectiveness of different fall detection models trained using this feature at four positional sensors (wrist, head, waist, and thigh), finding a Random Forest model to perform the best overall with an accuracy of 80%. However, his research indicated that a Support Vector Machine (SVM) classifier was more accurate on just wrist sensor data.

In a different study using similar methods, Hussain et al. used a low-pass Butterworth filter to pre-process their data. A low-pass Butterworth filter is a common technique in signal processing, used to filter out noise components in a signal system. In our case, the noise would be gravity itself. If we represented our problem of discerning acceleration in an activity, ADL or otherwise, from gravity, we would represent it thusly:

$$acc_x = A_x + g$$

Where acc is the overall acceleration, A represents the activity-based acceleration and g represents gravity. A low-pass Butterworth filter would decompose this equation into A and g, and allow the researcher to determine if A represents a fall or an ADL. This enables researchers to a subject's effect on its acceleration in space. After pre-processing, the researchers compared various classifiers and their efficacy in predicting falls and found SVM to be the most accurate at 99.98%, further verifying the viability of SVM classifiers in detecting falls.[8]

3 Materials and Methods

Our study uses a subset of the UP-Fall Detection dataset to analyze acceleration and angular velocity signals measured on wrist-worn sensors to simulate smartwatch placement.

3.1 Data

The UP-Fall Detection dataset is used to analyze and compare the different methods for detecting falls through wrist sensors. The complete dataset is a collection of information from five wearable sensors, six infrared sensors, two cameras, and an electroencephalograph headset. Martínez-Villaseñor et al. publicly presented this multimodal dataset as a comprehensive database resource to assess the efficacy of novel fall detection methods in camera-based, ambient environment sensor-based, and wearable sensor-based systems.[12] Our study only uses a subset of the data to focus on the acceleration and angular velocity signals measured through the sensor worn at the wrist to simulate a smart watch placement. The accelerometer is measured in units of g, which is the force per unit of mass on Earth or 9.81 m/s^2. The gyroscope is measured in units of degree per second (deg/s).

Table 1. Description of Participating Subjects.

Subject ID	Age	Height (m)	Weight (kg)	Gender
1	18	1.70	99	Male
2	20	1.70	58	Male
3	19	1.57	54	Female
4	20	1.62	71	Female
5	21	1.71	69	Male
6	22	1.62	68	Male
7	24	1.74	70	Male
8	23	1.75	88	Male
9	23	1.68	70	Female
10	19	1.69	63	Male
11	20	1.65	73	Female
12	19	1.60	53	Female
13	20	1.64	55	Male
14	19	1.70	73	Female
15	21	1.57	56	Female
16	20	1.70	62	Male
17	20	1.66	54	Female

They used a Mbientlab MetaSensor to collect the raw data from a triaxial accelerometer and gyroscope at a sampling rate of 100 Hz. The data collection process spanned across four weeks in the summer of 2018 and was conducted on the third floor of the Faculty of Engineering building at Universidad Panamericana in Mexico City.[12] Their study enlisted 17 healthy young adults to perform 11 different physical activities. The volunteers consisted of nine males and eight females ranging from 18-24 years old with the average height of 1.66 meters and the average weight of 66.8 kilograms. The only participant that was left-hand dominant was Subject three. Table one provides a description for each subject that participated in the study.

Each subject performed three trials for every activity. The physical activities were selected to simulate six typical human activities of daily living and five common types of falls. The action of picking up an object was specifically tested since it is an activity that is commonly mistaken for a fall, and was performed once within a ten second interval per trial. The jumping activity was measured in 30 seconds intervals, while the other activities of daily living were all measured in 60 second time frames. The simulated falls were measured within ten second time frames with only one a single fall executed in each trial. Table two provides a summary of each activity's description and duration for each trial.

Table 2. Description of Activities Performed by Each Subject.

Activity ID	Description	Duration (s)
1	Falling forward on hands	10
2	Falling forward on knees	10
3	Falling backwards	10
4	Falling sidewards	10
5	Falling from seated position on chair	10
6	Walking	60
7	Standing	60
8	Sitting	60
9	Picking an object up	10
10	Jumping	30
11	Lying	60

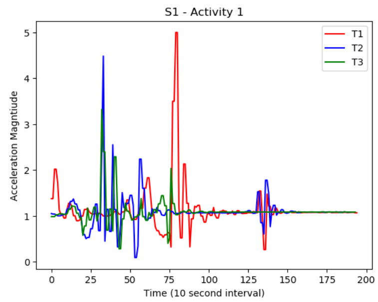
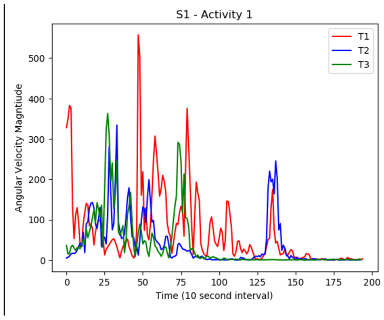
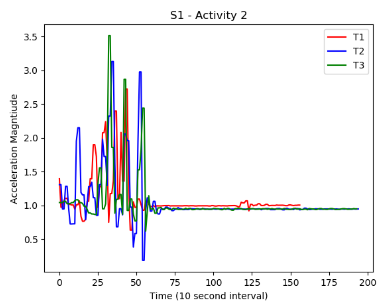
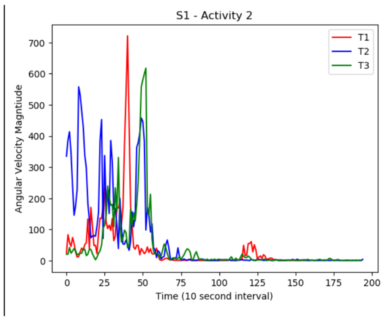
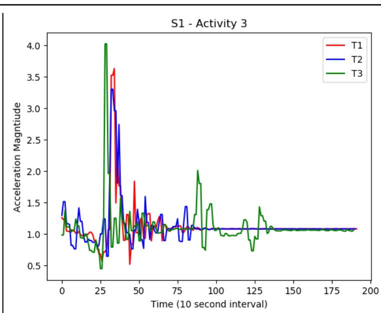
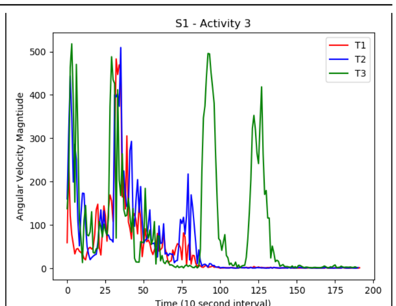
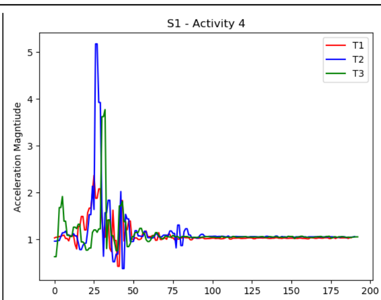
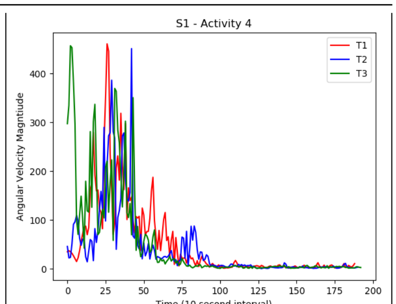
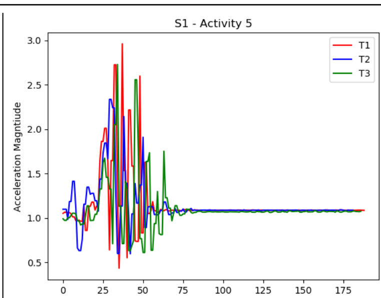
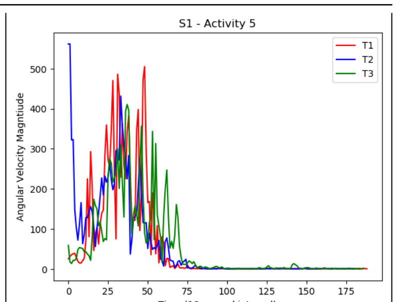
Table three shows the magnitudes of Subject one's acceleration and angular velocity signals from the wrist sensor for each simulated fall trial (activities one through five). The original accelerometer and gyroscope wrist sensor data was provided on along the x, y and z axis. These triaxial measurements were processed into a single magnitude vector for acceleration (a) and angular velocity (w) at each sensor measurement sample as shown in table three. The magnitude signals for each simulated fall trial performed by Subject one (activities one through five) are provided as examples. This processing step was done to reduce the data dimensions and identify potential sensor threshold values that can distinguish falls from ADLs through the following representation:

$$\mathbf{a} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

$$\mathbf{w} = \sqrt{w_x^2 + w_y^2 + w_z^2}$$

The acceleration and angular velocity magnitude vector signals present as time series data of each simulated fall trial over the data collection interval. We

Table 3. Sensor Signal Magnitudes of Simulated Falls for Subject 1

Activity ID	Acceleration (g)	Angular Velocity (deg/s)
1		
2		
3		
4		
5		

use the peak value from these plot as potential threshold values to distinguish a fall from activities of daily living. However, the peaks occur at different maximum values for the five different types of simulated falls. The lower acceleration peaks for activities two and five with values of 3.0 and 3.5 appear to be a result of smaller distance displacements. The subject falls onto their knees from a standing position in activity 2 and falls from a seated position in activity five. In these two cases, the vertical displacement of the wrist sensor are smaller compared to the other falling simulations in which the subject falls from a standing position to the ground.

We also define threshold values with vector changes of the acceleration and angular velocity magnitude signals. Instead of training the sensor to detect when a certain magnitude is measured, the model learns to detect motion intensity through magnitude changes. The Acceleration Vector Change (AVC) and Angular Velocity Vector Change (WVC) features are defined as:

$$AVC = \sum_{i=1}^{n} \frac{|\mathbf{a}_{\boldsymbol{i}} - \mathbf{a}_{\boldsymbol{i-1}}|}{T_n - T_0}$$

$$WVC = \sum_{i=1}^{n} \frac{|\mathbf{w}_{\boldsymbol{i}} - \mathbf{w}_{\boldsymbol{i-1}}|}{T_n - T_0}$$

The absolute value of the summed differences between consecutive magnitude signals is divided by trial sampling period to produce the vector change value of a signal, where $\mathrm{T_0}$ is the timestamp of the first data sample in a trial and $\mathrm{T_n}$ is the last. When the sensors are not experiencing motion, the vector change for consecutive measurements will remain be constant. When motion is detected, the vector change value will measure the intensity of the motion with larger changes indicative of more forceful activity.

These processing steps resulted in 559 data instances that describe every trial executed by each of the 17 subjects for the 11 activities; two data points are missing because subject eight is missing sample signals for trials two and three in activity eleven. The raw triaxial sensor measurements, maximum magnitude values per trial, and signal vector changes were tested as candidate threshold values in our model.

3.2 Methods

We compare the competing preprocessing methods by feeding the different features into our classification pipeline. K-means clustering identifies the acceleration and angular velocity threshold values that distinguish falls from other activities through centroid Euclidean distances. These distances are leveraged as class labels for falls and ADLs in a binary classification task using Support Vector Machines (SVM).

K-Means Clustering Eleven clusters were initially tested to simulate the 11 different experimental activities, but these clusters did not provide clear separation between the different activities. Since specific values could not be identified for each activity, generalized threshold values for falls and ADLs were identified using two cluster centroids in the k-means clustering algorithm. Figure one presents the results of the clustering analysis with two identified centroids displaying separation between the simulated falls and ADLs. Since the sensor experiences more force during the event of a fall, the k-means centroid for falls (red data points) has larger threshold values for acceleration and angular velocity compared to ADLs (green data points) as expected. The vector change threshold values from the fall cluster are 6.891 g for acceleration and 897.310 deg/s for angular velocity. The vector change threshold values from the ADL cluster are 0.955 g for acceleration and 241.720 deg/s for angular velocity.

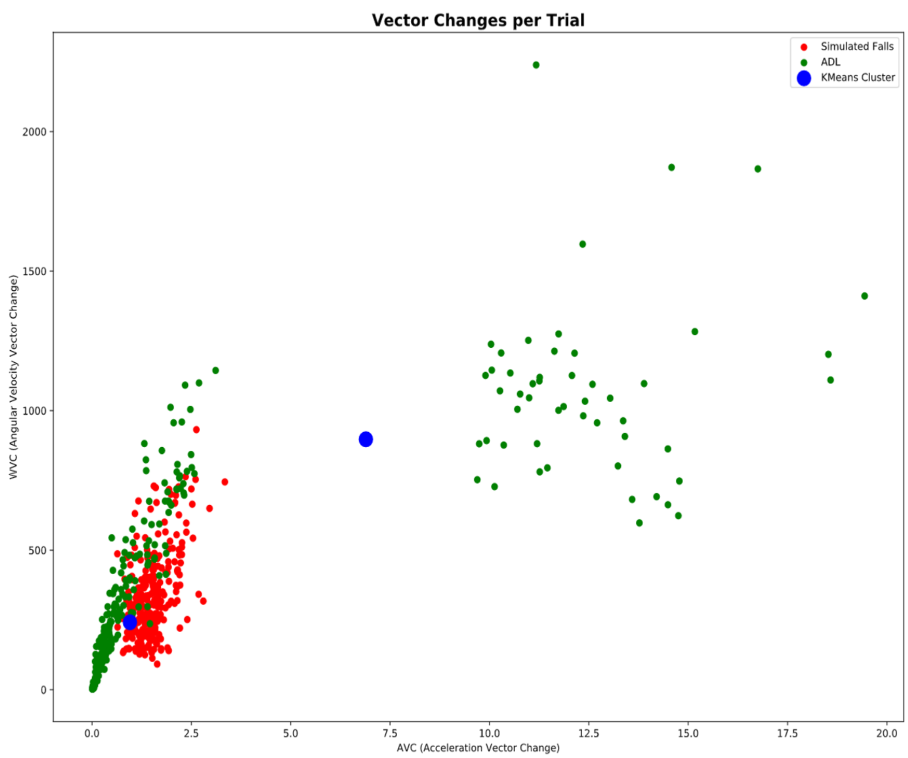


Fig. 1. : K-Means Fall and ADL Class Centroids for AVC & WVC thresholds

In addition to acceleration and angular velocity changes, the threshold analysis also tests raw sensor measurements on individual axes and maximum magnitude signals as well. Principal Components Analysis (PCA) is used to reduce the triaxial measurements to a smaller feature set representing the signals measured by the accelerometer and gyroscope in each trial. Alternatively, maximum magnitude signals from each trial were extracted as another processing technique to reduce data dimensionality and represent potential thresholds for each of the two sensors. Table four summarizes the centroid distance extracted from k-means clustering for each of the competing threshold types. These centroid distances represent threshold values that are used as input labels for distinguishing falls from activities of daily living in a SVM classifier.

Table 4. Summary of Magnitude Threshold Values to be Tested in Classifier

Threshold Type	Acceleration Threshold (g)	Angular Velocity Threshold (deg/s)
Triaxial Measurements (PCA)	2.530 (Fall) 1.554 (ADL)	648.035 (Fall) 259.401 (ADL)
Maximum Magnitude	3.502 (Fall) 2.331 (ADL)	694.076 (Fall) 292.689 (ADL)
AVC & WVC	6.891 (Fall) 0.955 (ADL)	897.310 (Fall) 241.720 (ADL)

Support Vector Machine Classification Support Vector Machines is a supervised machine learning technique that projects labeled training data onto a higher dimensional space. A decision boundary is then defined to linearly separate categorical class labels by maximizing its orthogonal distances from support vectors. In two dimensions the decision boundary can be defined as a line, but in n-dimensions it is best defined as a hyperplane with (n-1)-dimensions. Support vectors are the data instances closest to the defined closest to the boundary line on each side of the class labels.

With non-linearly separable data, transformation kernel tricks are employed to map the data into a different dimensionality space so that the SVM algorithm can better identify a hyperplane capable of linearly separating classes. A variety of kernels (i.e., linear, sigmoid, polynomial, Gaussian) are tested on the k-means feature space to evaluate the best parameters for the binary classification of falls from activities of daily living. Accuracy, recall, precision, and F_1 score are used as comparative metrics to quantify the performance of competing models. In order to leverage the k-means labeling of fall and ADL threshold values, the centroid distance vectors from the different data processing methods were fed into a Support Vector Classifier (SVC) as input criteria.

4 Results

The raw triaxial measurements provided two distance vectors per axis for a total of six vectors. PCA was applied to the six feature vectors to reduce the data dimensionality of the binary classification task to two components. These principal component values were then used to compute 2 k-means centroid distances for fall and ADL class labels in an SVM classifier tested with different kernels. The results are represented in the 3D scatterplot shown in Figure two.

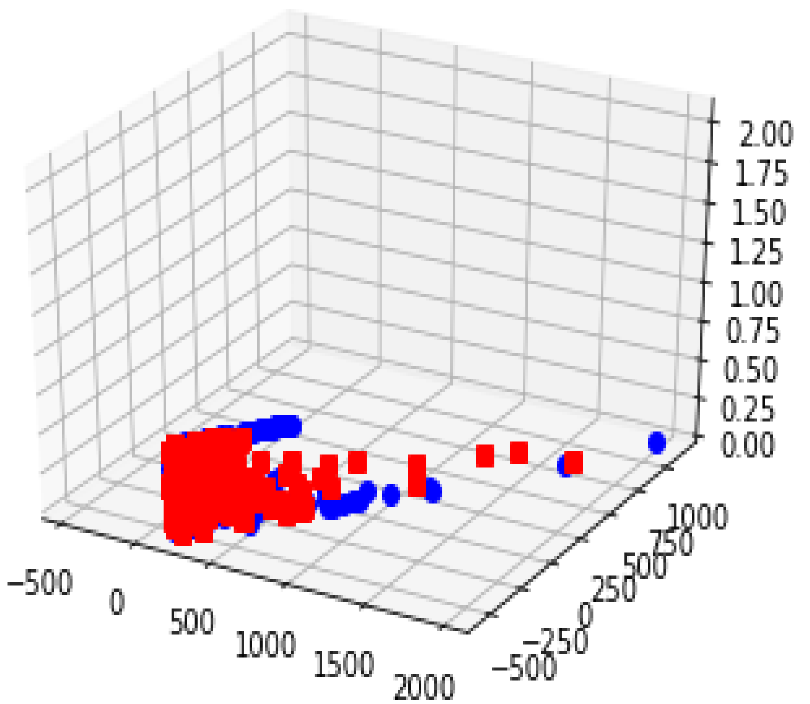


Fig. 2. : 3D PCA Decision Boundary of Triaxial Distance Components

Many of the predictions are clustered around a single point in space and are not easily separated linearly by projecting to a higher dimensional plane. This is reflected in the low accuracy around 50 percent regardless of the kernel selected for SVM classification. Given this low performance and lack of response to parameter tuning, maximum magnitude signals from each trial were instead used as a processing step to extract threshold values for classification.

Linear, sigmoid, polynomial, and Gaussian kernels were again tested on the maximum magnitude signals. These values provided higher accuracy than the

PCA components of raw triaxial sensor measurements with the linear kernel yielding the most significant performance in comparison to the other kernels at 67%. The linear kernel yielded the most significant performance improvement in comparison to the other kernels and the raw triaxial sensor measurements. Figure three shows the hyperplane decision boundary from the SVM classifier on maximum magnitude signal thresholds using a linear kernel.

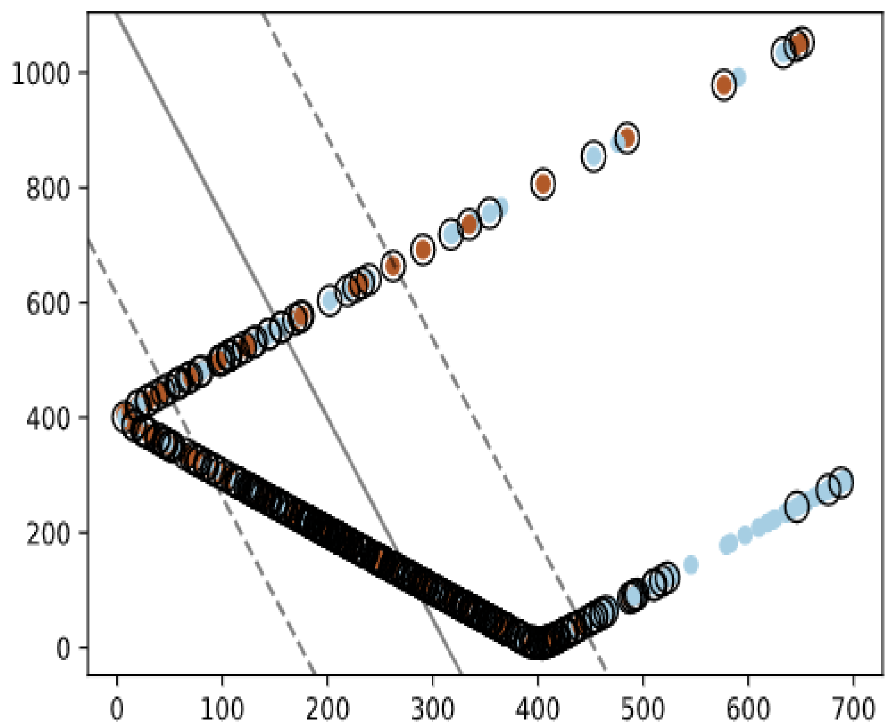


Fig. 3. : Linear SVM Classifier of Maximum Magnitude Thresholds

Many of the data points appear to be clustered in an elbow shape around the origin, with most representing the majority class. This likely accounts for the improvement in accuracy, but does not significantly increase the precision. To account for some of these issues, we shifted our threshold analysis to vector change features from the accelerometer and gyroscope sensors to better measure motion intensity. Acceleration Vector Change (AVC) and Angular Velocity Vector Change (WVC) values per trial were pushed through the classification pipeline to identify class labels through k-means and predict fall instances from ADLs in a binary SVM classifier.

Figure four shows that the k-means centroid classification task using vector change features produces a much narrower hyperplane, along with the same elbow shape seen in the previous classifier. The vectors are much more closely clustered around the hyperplane as well. Unlike the previous classifier, the linear separation is more clear between the ADL vectors and the fall vectors. This will yield higher accuracy, and more importantly, higher precision on the classification task. The outliers are still present but are on the correct side of the decision boundary. One concern with the narrowness of the hyperplane is the possibility of misclassification in the case of vectors that are slightly further away from the support vectors. We will want to examine recall to ensure this is not a potential weakness.

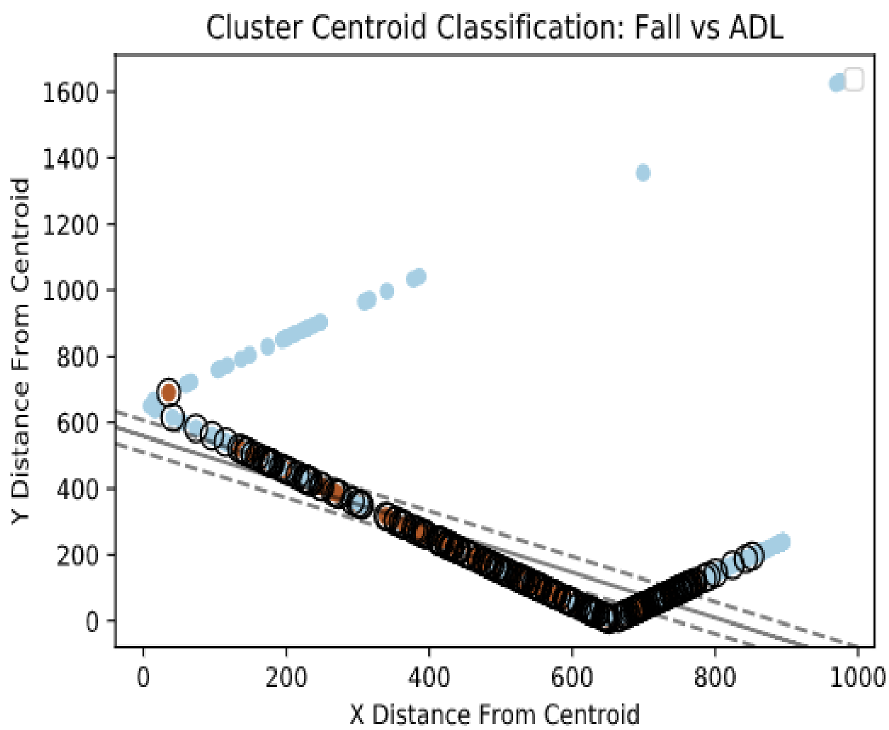


Fig. 4. : Linear SVM Classifier of AVC and WVC

Despite the presence of outliers, this vector change model performed the best with an overall accuracy of 78.4%. The linear decision plot appears similar to the magnitude model, but predict ADL labels further away from the decision boundary. This aligns with what is seen in the cluster plot, and could explain the increase in accuracy from the previous model. A final comparison of the performance metrics from our top-competing models is shown in table five.

Table 5. SVM Classifier Accuracy for AVC Distance By Kernel

Pre-Processing	Kernel Type	Accuracy	Precision	Recall	F_1 Score
AVC	Linear Kernel	78.400%	74.200%	82.800%	78.300%
Magnitude Threshold	Linear Kernel	67.000%	63.800%	69.00%	66.300%
Magnitude Threshold	Gaussian Kernel	58.900%	58.500%	43.700%	50.000%

The linear kernel SVM classification on k-means centroid distances of vector change features showed significant improvement across all metrics from previous models. This model appears to address some of the precision issues in current fall detection algorithms on solely wrist sensor data with a competitive measure of 74.2% indicating low false positive rates. Precision weighs the costs of false positive predictions (i.e., predicting an activity of daily living to be a fall). Recall weighs the costs of false negative predictions (i.e., predicting a fall to be an activity of daily living). At 82.8% recall, our model performs even better in regards to actually identifying relevant instances as falls and not mislabelling them as an ADL. The F_1 score metric is the harmonic mean of precision and recall, meaning it weighs model performance with false positive and false negative costs over true negative predictions. The F_1 Score of 78.3% is comparable to the overall classification accuracy of 78.4%, indicating a balanced model that is accurate, precise, and generalizable.

5 Discussion

As mentioned in the results, our final 3-phased threshold analysis model approach (AVC to K-Means to SVM) had an accuracy of about 78 percent. Although there is sparse research on the efficacy of existing fall detection systems outside laboratory settings, owing to manufacturers being reticent to releasing that information, many consumer studies report similar accuracy to our result. However, unlike these products our model is much more precise, at 74 percent.

A potential concern was noted when plotting the decision boundary - the possibility of misclassification due to narrowness in the hyperplane. Although the data on which we trained the model produced a good recall score (over 82%) it is worth exploring some possible strategies to make the model more adaptable and resilient. Outliers were observed in the formed AVC and WVC k-means centroid clusters. These data points with larger vector change values for acceleration and angular velocity were identified to be from trials of activity ten as shown in figure five. Activity ten from the data iss jumping, which consists of continuous acceleration changes over the trial period. Given the nature in which

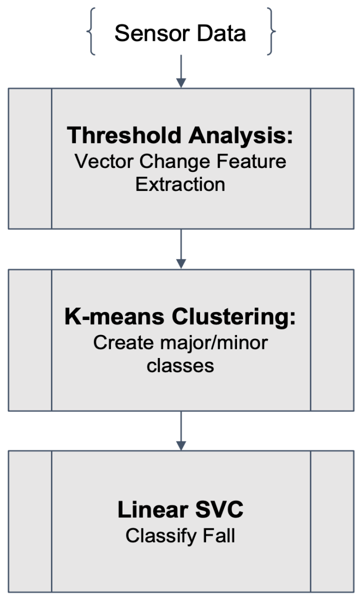


Fig. 5. : 3-Phased Model Approach

vector changes were calculated over the entire trial period, a jumping activity would generate large a vector change value due to continuous motion over a 30 second window and manifest as outliers in the data.

In order to address this issue, an optimal window for vector change thresholds needs to be defined so that motion intensity can be better measured in small time frames. In this way, threshold values can better capture large, sudden changes in acceleration and angular velocity vectors that are more characteristic of fall events. This is an important distinction as the stimulated falls (activities one through five) are sampled in 10 second trial periods compared to the the majority of stimulated ADLs (activities six through eleven) are mostly sampled in 30 or 60 second trial periods. An optimal sampling window for vector change thresholds would improve signal processing by ensuring that sudden, large vector changes measured by the sensor can be attributed to intense motions rather than continuous motion.

Prior research investigated the use of Butterworth filters to remove noise such as gravitational acceleration from the raw triaxial sensor signals as an effective signal processing technique.[8] With noise effectively filtered from these signals, an acceleration component characteristic of just the detected motion can be isolated and provide vector change thresholds that are more representative of pure human motion.

A knowledge-based multiphase fall model approach has been researched to address many of the technical challenges of an autonomous fall detection system and yielded overall performances of 99.79% sensitivity, 98.74% specificity, 99.05%

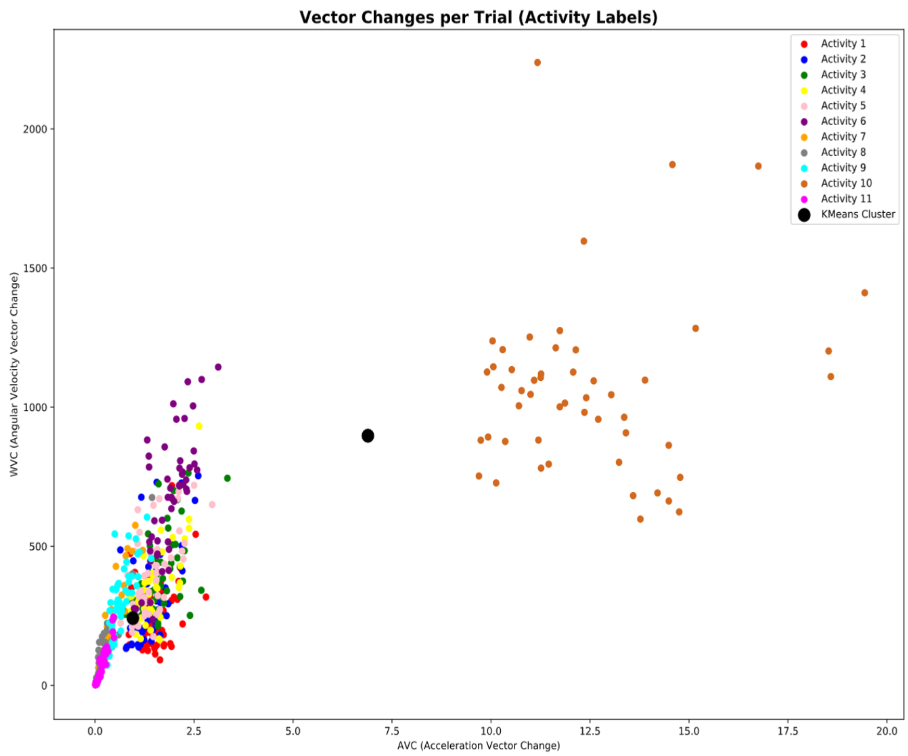


Fig. 6. : AVC & WVC highlighted by activity

precision, and 99.33% accuracy.[7] The multiphase approach introduces free fall, impact and rest phases to characterize a fall. These three phases characterize a window of a drastic increase in acceleration, succeeded by a rapid decrease in acceleration, and ends with an extended period of constant acceleration. In the free-fall phase, the acceleration vector change signal should mimic gravitational acceleration and could be extracted using Butterworth filters as previously discussed. The impact phase can be characterized as a large, negative vector change within a small time window. The rest phase should be attributed with a vector change value of 0 over a few seconds. Applying vector change features and machine learning based approaches to this multiphase model potentially offers a potentially viable solution to an autonomous fall detection system developed from threshold analysis of wrist sensor data.

As a real-world application, our model can be integrated into modern-day wearable technologies such as smartwatches to leverage their built-in Global Positioning System (GPS). In the event a fall results in incapacitation, the autonomous fall detection system can dispatch emergency medical services to the pinpoint location of the device. The imprecision of existing systems is a barrier for such a development, and we believe introducing a more precise model such as ours will ensure broader adoption by rectifying this issue.

5.1 Ethics

One major ethical consideration, both within this analysis and others on fall detection, is bias within the data. Pre-existing publicly available datasets often contain data sourced from healthy adults who predominantly skew younger and male.[4] Studies that generate their own data frequently recruit people of similar demographics because of the health and safety concerns posed by attempting to source data from the elderly.[6] Any data that is generated by older adults is often limited to ADLs as opposed to falls. Although volunteers are often coached to simulate fall behavior in a similar fashion to the elderly, factors like predefined movements, test environments that do not well approximate where the elderly are most likely to fall, and the presence of safety precautions like mattresses could all result in simulated fall data that does not actually match the reality.[4] Kangas et al. demonstrate that the profiles for a small number of real-life falls look similar to those of simulated ones.[10] However, we caution against assuming this extends to other simulated data and recommend more investigation into the possible influence of demographic bias and safety measures.

Another potential ethical consideration is privacy. In a similar fashion to how personalized medicine tailors to individual patients, a user-centric model that trains on the wearer's baseline ADL movements has been suggested to perform better than a generalized one.[13] Manufacturers of wrist wearables could allow users to opt-in to providing their real-life ADL data to refine the generalized model that the user-centric model works with. However, this introduces realistic concerns over whether user information is properly removed or anonymized in the event of data breaches.

6 Conclusion

Our study uses a subset of the UP-Fall Detection dataset to analyze acceleration and angular velocity signals measured on wrist-worn sensors to simulate smartwatch placement. We designed a threshold-based model on a binary classification task to distinguish falls from activities of daily living. We found that vector change features capturing the collective sum of differences between consecutive signals in time provided the most accurate model. The Acceleration Vector Change (AVC) and Angular Velocity Vector Change (WVC) features were inputted into a K-Means Clustering algorithm to identify two k-means centroids: one for falls and one for activities of daily living (ADL). The centroid distances represent the threshold values that AVCs and WVCs must reach to classify a fall. The two centroids with AVC and WVC distances were fed into a Support Vector Machine (SVM) classifier with a linear kernel and yielded an accuracy of 78.4%.

Due to the use of the trial period as the processing time window for vector change features, activities consisting of continuous motions created outliers in the data. Activity 10, jumping, from the dataset was the example previous discussed. Thus, the processing time window should be lowered to an optimal period that better capture sudden, large changes in the acceleration and angular velocity magnitude vectors. Smaller time windows will provide a better representation of vector changes for individual motions rather than continuous.

Previous research on fall detection systems lend insight into techniques that can further refine our proposed model. Signal processing techniques such as Butterworth filters have been used to remove background noise from the triaxial accelerometer and angular velocity sensors to extract a signal that is more characteristic of pure human motion. A knowledge-based multiphase model characterizing distinct free fall, impact, and rest states for fall detection systems has provided extremely accurate results across performance metrics.

The objective of our proposed solution for novel autonomous fall detection systems is to provide a model that can be applied to wrist-wearable technologies with accelerometer and gyroscope sensors. We must caution extrapolating this model to the senior population as it was only trained on a sample population of young, healthy adults aged 18-24 years old. Many current commercialized smartwatch devices also have built-in GPS that our application can further take advantage of by dispatching local paramedics to an exact location if a fall is detected in order to minimize the dangers of a "long-lie" condition.

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