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

Joseph Caguioa[1], Andy Nguyen[1], Michael J. Wolfe[1], and Jacquelyn Cheun[1]

Master of Science in Data Science, Southern Methodist University, Dallas TX 75275
USA {jcaguioa, andynguyen, mwolfe, & jcheun}@smu.edu

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 · Activities of Daily Living (ADL) · signal processing

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.[13] 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.[9] 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 be broken down into two sections: a discussion of related studies that have guided our work and analyzed the efficacy of previous implementations of autonomous fall-detection systems, and an explanation of the methods we will use to develop our solution. Section three will discuss methodologies: how the data was collected along with its structures and attributes, as well as a discussion on the different approaches utilized in our analysis and a high-level overview of the machine learning concepts applied in our algorithms. Section four will present our findings along with relevant visualizations, the results of our research, and a comparative analysis of the competing models. Section five will wrap up our analysis with ethical considerations of handling personal health data recorded from wearable wrist devices as well as potential implications and next steps. 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.

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

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.

In [8], 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.[10]

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.[7]

3 Materials and Methods

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.[11] 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.[11] 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.

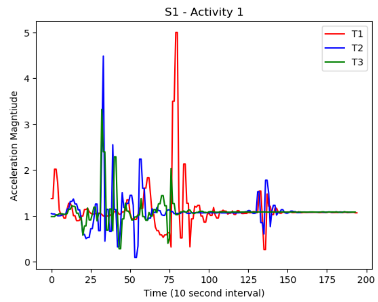
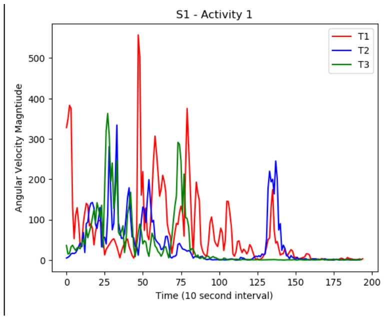
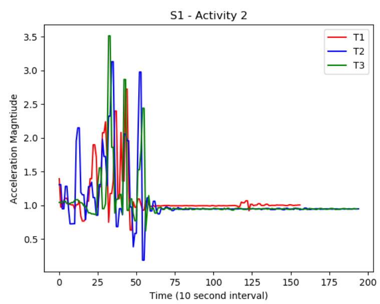
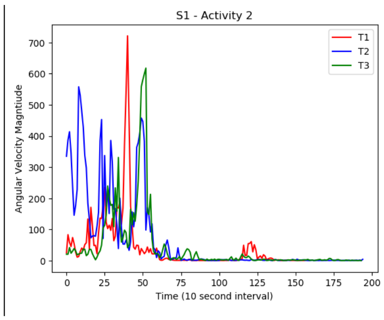
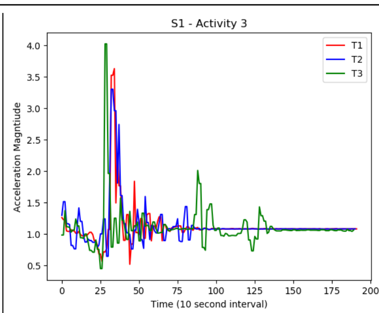
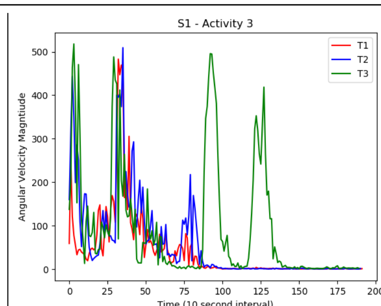
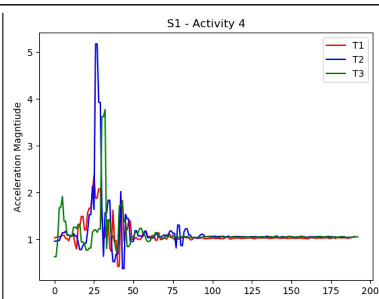
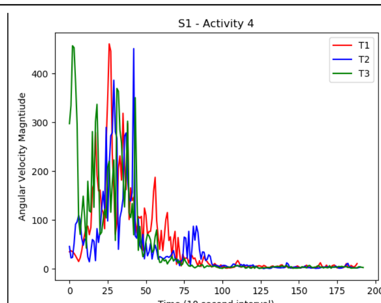
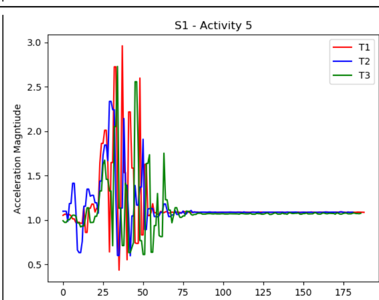
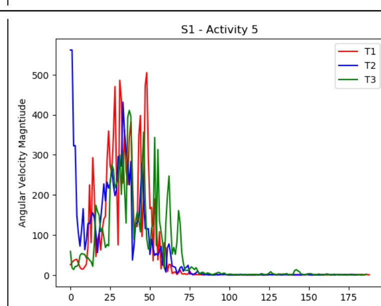
Activity ID	Description	Duration (s)
1	Falling forward on hands	10
2	Falling forward on knees	10
3	Falling backwards	10
4	Falling sidewards	10
5	Falling from seated position on chair	10
6	Walking	60
7	Standing	60
8	Sitting	60
9	Picking an object up	10
10	Jumping	30
11	Lying	60

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:

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

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

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

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

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

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

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

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.

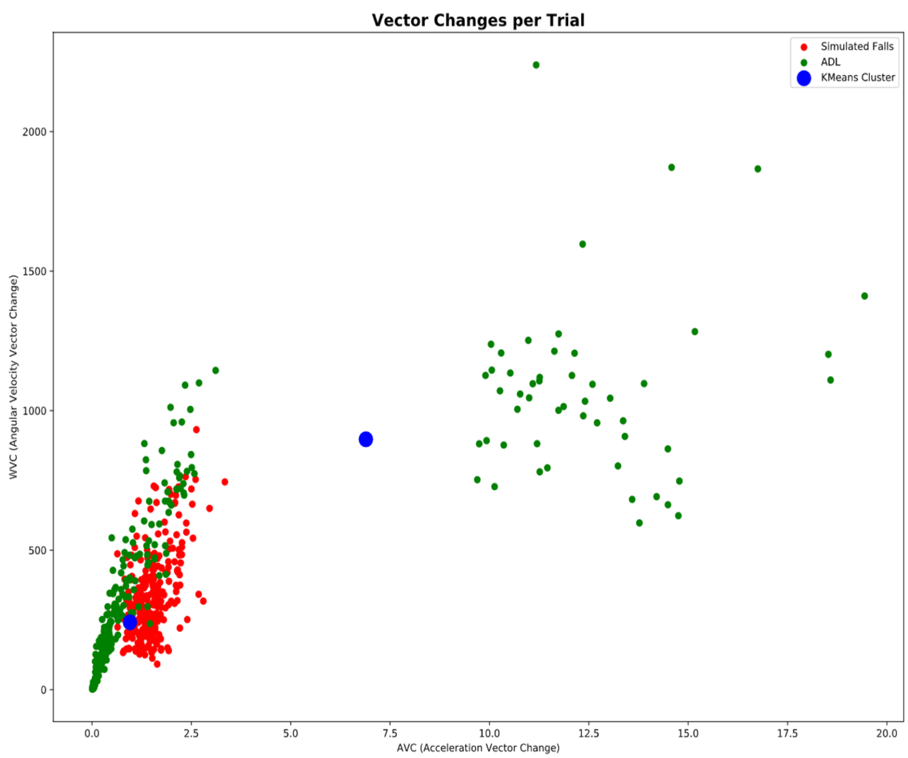


Fig. 1. : K-Means Fall and ADL Class Centroids for AVC & WVC thresholds

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 are a supervised machine learning technique wherein, given a 2D feature space, a decision line (hyperplane) is defined to separate one class from another. It requires labelled training data to define categorical classes. Once these are received, the vectors and implements transformation kernels to project the data onto higher-dimensional spaces so a separating hyperplane can be determined. The hyperplane is best defined as a decision boundary that maximizes the distance of the data points nearest the boundary line in each class label.

With non-linearly separable data, kernel tricks are employed to map the data into a different dimensionality space so that the SVM algorithm can better identify a decision boundary 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 f1-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 triaxial provided two distance vectors per axis (since one cluster was provided for each), 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 2:

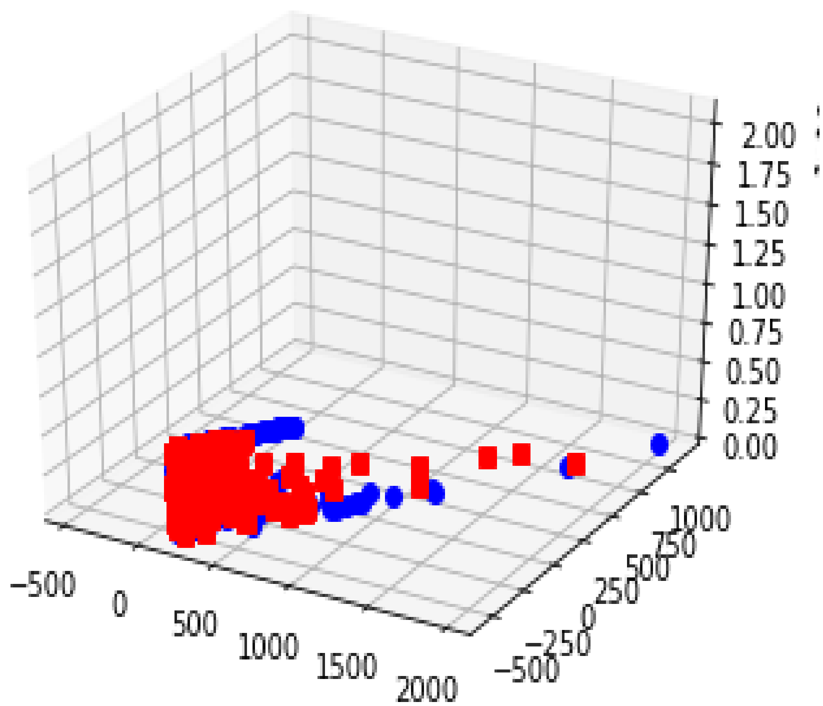


Fig. 2. : 3D PCA Decision Boundary of Triaxial Distance Components

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.

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.

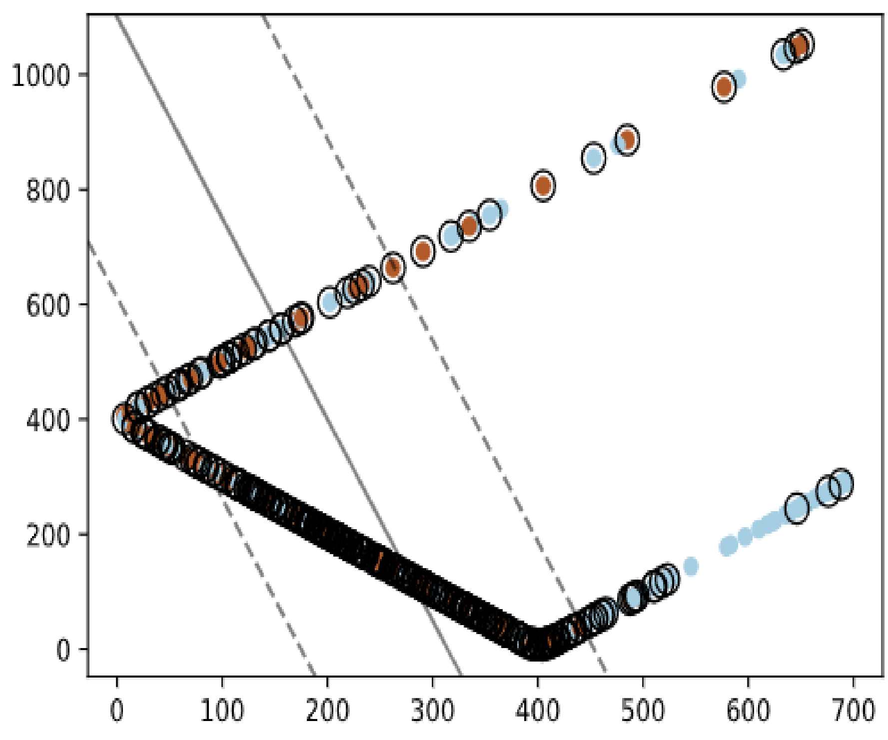


Fig. 3. : Linear SVM Classifier of Maximum Magnitude Thresholds

The AVC cluster classification produces a much more narrow hyperplane, along with the same elbow shape seen in previous classifiers. The vectors are much more closely clustered around the hyperplane as well. Unlike the previous classifier, the linear separation is clearer between the ADL vectors and the fall vectors. This will generate much higher accuracy, and more importantly, higher precision in classification. 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.

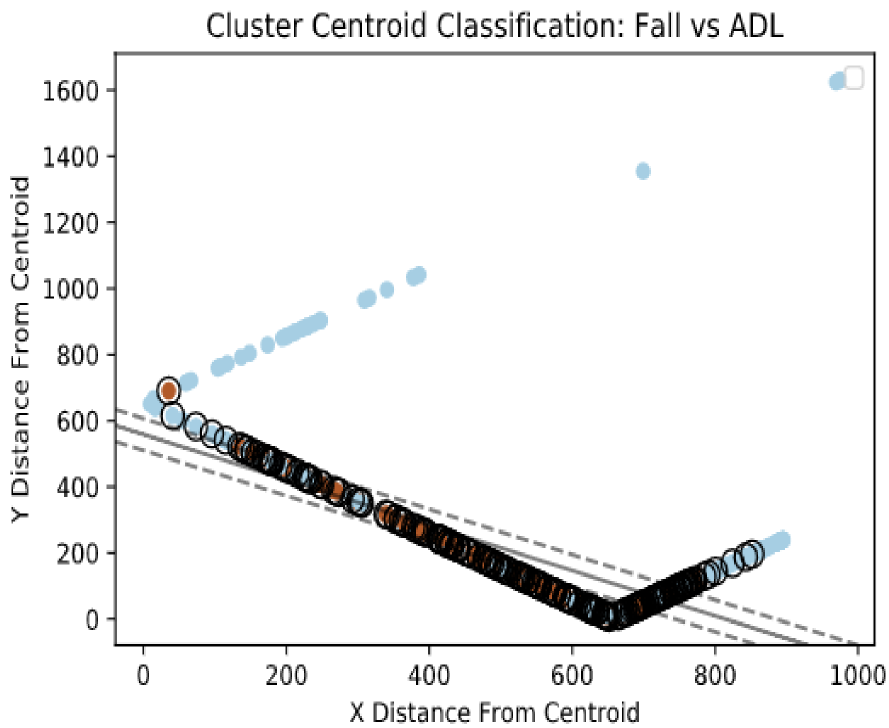


Fig. 4. : Linear SVM Classifier of AVC and WVC

There are a significant grouping of ADL outliers. For the time-being, we will ignore these and proceed with classification. Since we have had the greatest success with the SVM linear kernel, we will classify the centroid distances of the AVC model with this classifier as well.

With this model there was significantly improved accuracy: over 78 percent. The linear decision plot appears similar to the magnitude model, although more of the ADL values appear to be further from the 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 our best model results is below.

Table 5. SVM Classifier Accuracy for AVC Distance By Kernel

Pre-Processing	Kernel Type	Accuracy Percent	Precision Percent	Recall Percent	F1 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

Across the board the AVC pipeline model performed the best. As mentioned previously, the accuracy of the mode is above 78 percent. More importantly, our major objective of addressing precision issues with current fall detection algorithms has been addressed, with the AVC model producing 74 percent precision. This indicates a low rate of false positives given the rate of correct classifications. Revisiting the concern with the narrow hyperplane from this model, we observe a recall of over 82 percent. This indicates the model does well with selecting relevant items, assuaging fears of misclassification in the event our vectors are further away from the hyperplane. Finally, the F1 score is comparable to the overall accuracy, indicating a well-rounded model that is accurate, precise, and generalizes well.

5 Discussion

As mentioned in the results, our final model (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 percent) it is worth exploring some possible strategies to make the model more adaptable and resilient. Outliers were observed in the formed AVC and WVC 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 10 from the data collection process was jumping which consists of sudden acceleration changes. Given the nature of AVCs, it is expected that this activity would generate large vectors, which would then manifest as outliers in a cluster.

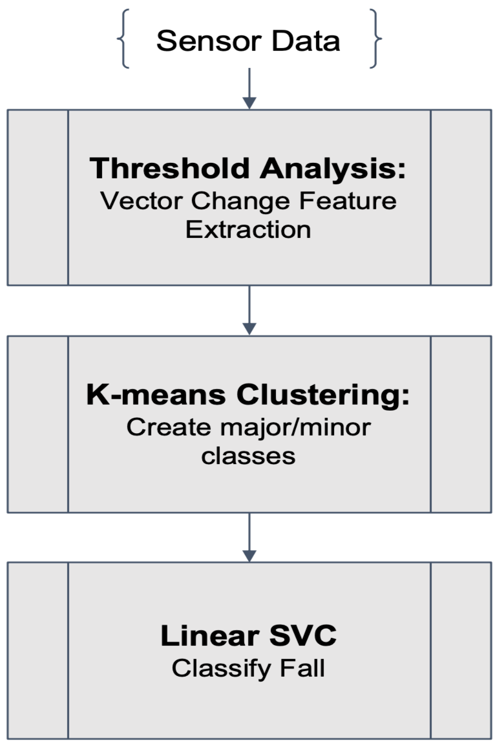


Fig. 5. : 3-Phased Model Approach

Two ways to address this in future models are capturing sudden changes and accounting for gravity. As observed in the outliers in the cluster model, which translated into the classifier, activities that involve sudden changes in acceleration, such as jumping, might skew the model. Two possible ways to address this would be to optimize the AVC window, ensuring that our signal processing time is consistent with the time of acceleration. The other is to adapt the AVC capture window into a multi-phase fall model: free fall, impact, and rest. This would contextualize each step and allow for more accurate comparisons between each phase between models and ADL.

Additionally, we will want to adjust our vectors for gravity to normalize the AVCs in future clustering. Signal processing techniques, such as band-pass and Butterworth filters remove constants and noise from data (such as gravity) to process deltas in a more effective manner. Incorporating such techniques will enable the model to classify between falls and ADLs by examining acceleration changes in as sterile an environment as possible.

For a next step, we would like to see our model adopted into wearables for comparison to existing products, for the eventual purpose of building an autonomous call system to summon emergency medical services, in the event a fall results in incapacitation. 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.[9] 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.[12] 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

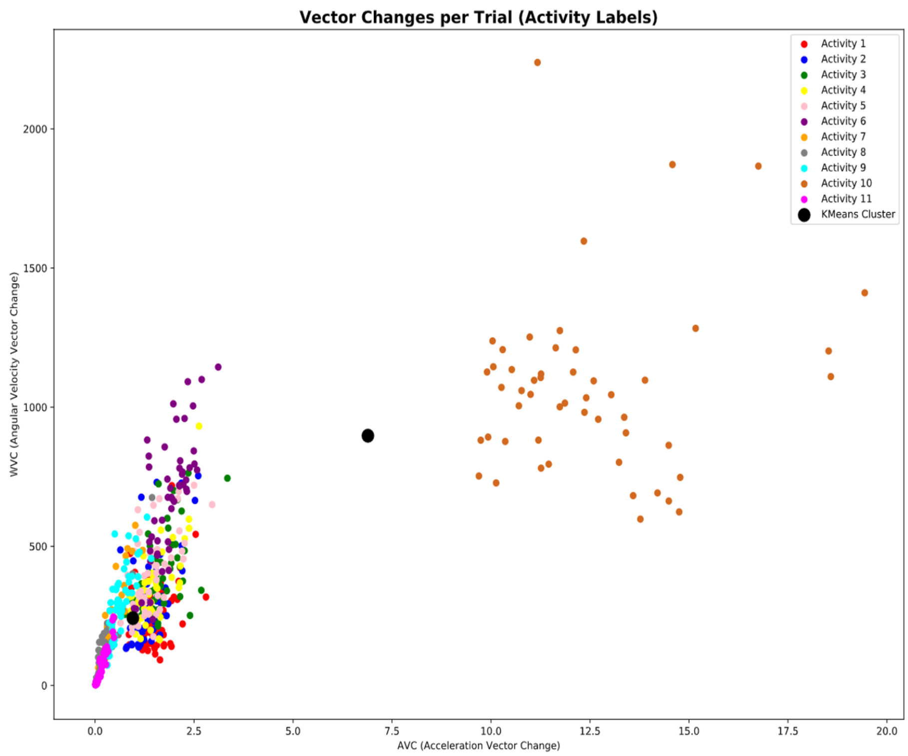


Fig. 6. : AVC % WVC highlighted by activity

concerns over whether user information is properly removed or anonymized in the event of data breaches.

6 Conclusion

The overall accuracy of the SVM classifier was low, until the AVC pre-processing step was added. The final, most accurate classifier was a linear kernel on AVC cluster, at about 77 percent. As mentioned above, there are many points clustered near the origin, suggesting a high rate of true negatives contributing to the overall accuracy. Additionally, another possible method could be Gaussian mixture model, which would essentially create both components (labelling plus classification) in a single process, although we would need to indicate or compute a threshold of probability for this to work practically.

The high number of outliers in the cluster analysis is also worth mentioning. Interestingly, most of these outliers corresponded with Activity ten, or the jumping ADL. Although removing this does not improve accuracy by much, it does present an interesting observation: clusters of AVCs are more linearly separable for fall-like acceleration versus other activities.

To further our analysis and the performance of our fall detection algorithm, better signal processing techniques should be employed to represent the time series data in each trial. In this analysis, taking the maximum values of the magnitude of the sensor signal caused all other measurements in each trial besides the peak signal to be discarded. Combinations of high-pass filters on the time series and regression analysis to extract a singular representative value for each trial are recommended as improvements over the current signal processing technique of taking the maximum value.

We propose a novel autonomous fall-detection system using algorithms trained on data extracted from wireless accelerometer and gyroscope wrist sensors as a potential solution to address these concerns. When our algorithm detects a fall and the user is unable to confirm consciousness through the wrist device, it could trigger an alert to dispatch local paramedics to the device's exact GPS location for an emergency evaluation and immediate medical intervention.

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