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 · 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.

2 Background

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/

2.1 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]

2.2 Tutorial

The three primary techniques leveraged in our model are Acceleration Vector Changes, K-Means Clustering, and Support Vector Machines. Each of these techniques, in ensemble, form the final state of our fall classification pipeline. This represents a synthesis of multiple previous efforts discussed in our Related Works, along with our own analysis of the data.

Acceleration Vector Changes are a signal processing method of calculating the per-trial acceleration vector.

K-means clustering is an unsupervised learning technique by which unlabelled input vectors are assigned squared Euclidean distances from centroids defined by the user-defined hyperparameters. Typically, the user defines the number of expected clusters in order to create labels for the data. K-means is rooted in signal processing and data mining, thus it is a strong choice for the problem at hand.

Specifically, we are using k-means to create labels for our dataset. Since we already know we want to define the input vectors into falls and ADLs from the various activities, k-means will group and label these vectors accordingly.

Support Vector Machines are a supervised machine learning technique wherein, given a 2D feature space, a hyperplane (also known as a decision boundary), is defined which separates one class from another. It requires labelled data to define these classes, and relies on kernels (mathematical functions to elevate the feature space) to define the hyperplane.

We will define an SVM to classify the centroid distances generated by k-means to predict falls vs ADLs. We will need to test a variety of kernels, since the k-means feature space may or may not be linear, quadratic, or possibly separable in a 3D feature space. We will use accuracy and precision as competitive measures to determine which kernel is best in our final model.

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).

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.

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

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 3 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 sensor data was pro-

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

vided 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 to reduce the data dimensions and identify potential sensor threshold values that can distinguish falls from ADLs through the following representation:

$$magnitude_a = a_x + a_y + a_z$$

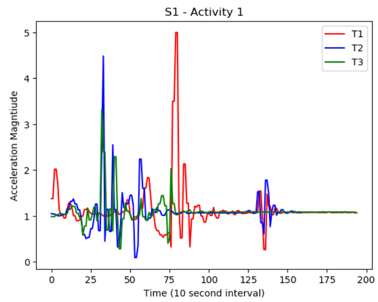
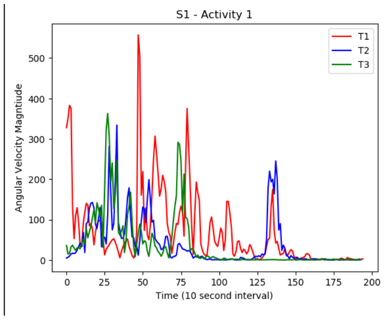
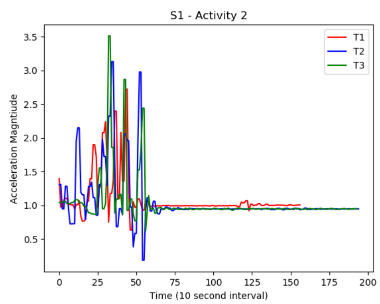
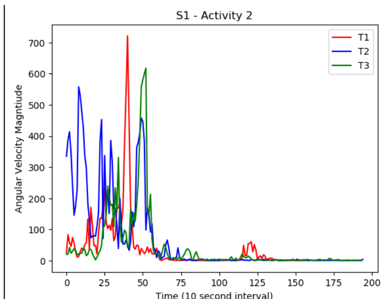
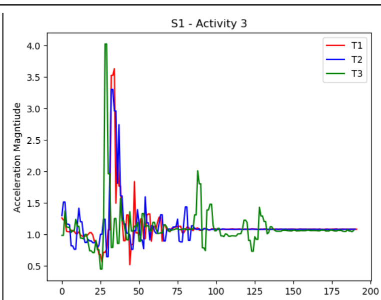
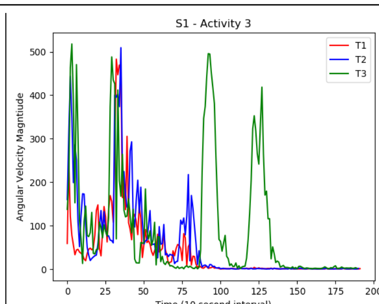
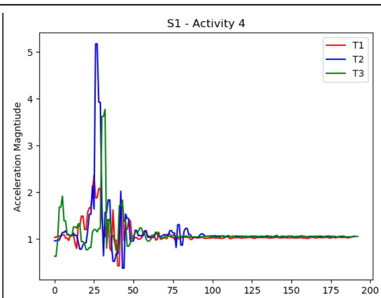
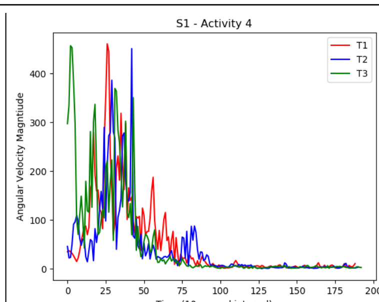
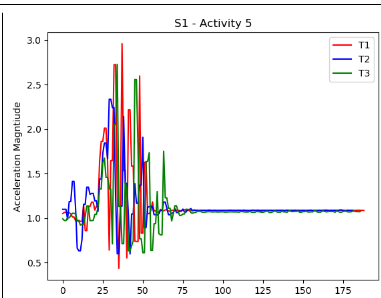
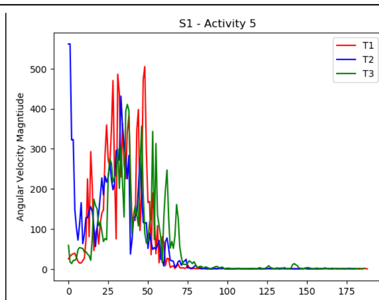
$$magnitude_w = w_x + w_y + w_z$$

The plots in Table three present the acceleration and angular velocity magnitude values as a time series for each simulated fall trial over the data collection interval. The peaks of these plot provide insight on potential threshold values that can 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. These values will be further evaluated and optimized in our fall detection algorithm, either generalized to a threshold value for all falls or designated to specific types of falls.

3.2 Methods

K-means clustering was employed to identify potential threshold values that can distinguish between different clusters of the experimental activities in the data. Since the data from each trial is a time series, it was further processed by taking the maximum magnitudes for acceleration and angular velocity in each trial. The

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

<table>
<tr><th>Activity ID</th><th>Acceleration (g)</th><th>Angular Velocity (deg/s)</th></tr>
<tr><td>1</td><td></td><td></td></tr>
<tr><td>2</td><td></td><td></td></tr>
<tr><td>3</td><td></td><td></td></tr>
<tr><td>4</td><td></td><td></td></tr>
<tr><td>5</td><td></td><td></td></tr>
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maximum value is the peak signal strength measured in a trial and represents a candidate threshold that must be attained to indicate that a certain activity is being performed. This processing step results in a total of 559 data points from three trials per eleven activities for each of the 17 subjects; two data points are missing because subject eight is missing sensor measurements for trials two and three in activity eleven.

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 1 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 threshold values from the fall cluster are 3.502 g or acceleration and 694.076 deg/s for angular velocity. The threshold values for the ADL cluster are 2.331 g for acceleration and 292.689 deg/s for angular velocity.

This analysis was repeated on individual axes of the sensor measurements to test if this additional precision provides better performance in our classification model that distinguishes falls from activities of daily living. The magnitudes of these triaxial measurements were also calculated and yielded lower threshold values compared to the maximum magnitudes. These two sets of values will provide competing models to examine if the classification model performs better with lower or higher thresholds to provide a competing model against the maximum magnitude thresholds. Table 4 provides a summary of the triaxial sensor measurements and Table five provides a summary of the magnitude threshold values to be tested in the classifier.

Table 4. Maximum Triaxial Threshold Measurements

Axis	Acceleration Threshold (g)	Angular Velocity Threshold (deg/s)
X	1.424 (Fall) 0.859 (ADL)	487.244 (Fall) 181.375 (ADL)
Y	1.359 (Fall) 0.621 (ADL)	289.069 (Fall) 135.140 (ADL)
Z	1.589 (Fall) 1.136 (ADL)	314.613 (Fall) 126.999 (ADL)

For the final step in the model, we created a binary classifier using support vector machines. In order to leverage the labelling we accomplished through clustering, we accepted the centroid distance vectors as input criteria for the SVC.

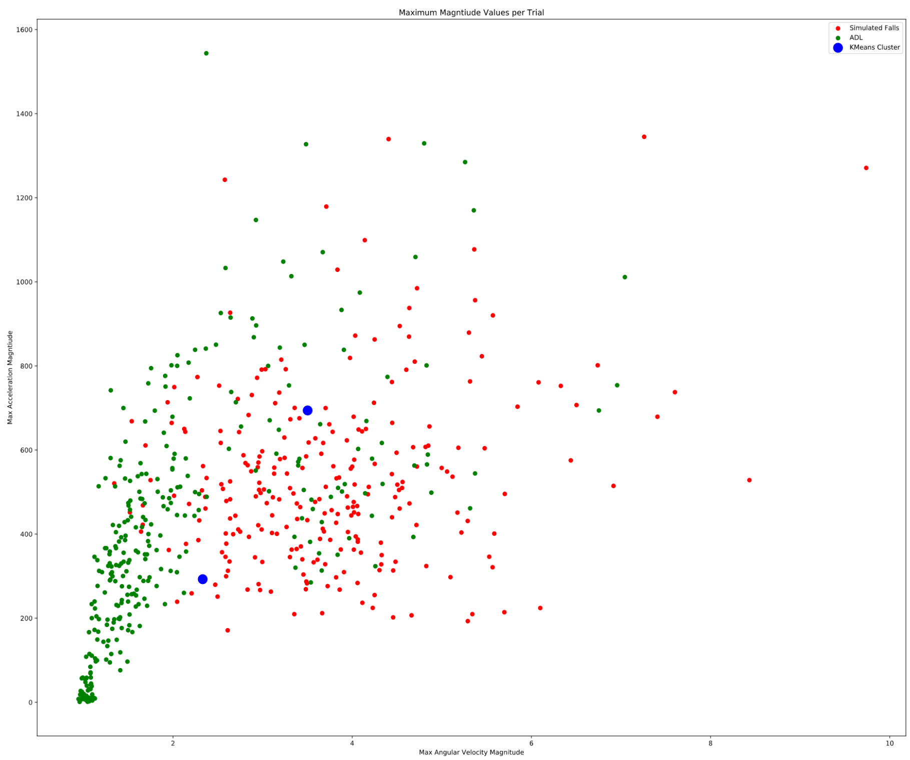

Fig. 1. : K-Means Centroids of Falls and ADLs on Max Acceleration and Angular Velocity Magnitudes

Table 5. Summary of Magnitude Threshold Values to be Tested in Classifier

Threshold Type	Acceleration Threshold (g)	Angular Velocity Threshold (deg/s)
Maximum Magnitude	3.502 (Fall) 2.331 (ADL)	694.076 (Fall) 292.689 (ADL)
Triaxial Magnitude	2.530 (Fall) 1.554 (ADL)	648.035 (Fall) 259.401 (ADL)

Since we used similar clustering methods for both the triaxial and magnitude models, we tested models of linear, polynomial, and sigmoid kernels on each cluster method, for a total of six classification tests.

4 Results

The triaxial provided two distance vectors per axis (since one cluster was provided for each), for a total of six vectors. To reduce dimensionality in the classification, we applied PCA with three components, representing each axis distance. These distance components were then input into an SVM classifier and tested with different kernels. The results are stored in the table below.

Table 6. SVM Classifier Accuracy for Triaxial Distance Components By Kernel

Kernel Type	Accuracy Percent
Linear Kernel	52.972
Polynomial Kernel	52.972
Gaussian Kernel	50.622

None of the models were very accurate, with each at less than 53 percent accuracy. When plotting a 3D decision boundary of the linear kernel, there were very few points clustered correctly on the boundary plane, such that the plane did not appear among the points. Given that the accuracy was around 50 percent, suggesting the model was incorrect as often as it was correct, this is to be expected.

Due to the inaccuracy of the trixial and magnitude models, we pivoted our input to use AVCs instead. A pre-processing step was added prior to clustering to create AVC's using the formula in the above section. These vectors were then passed into the kmeans algorithm and consequent SVM.

Similar to the triaxial model, the magnitude cluster model provided two distance vectors, but since we had created one cluster model using both magnitude thresholds, there was no need for dimensionality reduction. Therefore, the distance vectors were passed to the SVM classifier in their raw form. Again, we repeated these tests on linear, polynomial, and sigmoid kernels. Their accuracy measures are in the below table.

We observed significant improvement in using a linear kernel on these distances. Although still not very accurate, a roughly 66 percent accuracy performs much better than the other kernels and the triaxial component model. A plot of the decision boundary is below.

Many of the decision points appear to be clustered in an elbow shape around the origin, with most representing the majority class. This likely accounts for much of the accuracy. To account for some of the issues we saw in our first

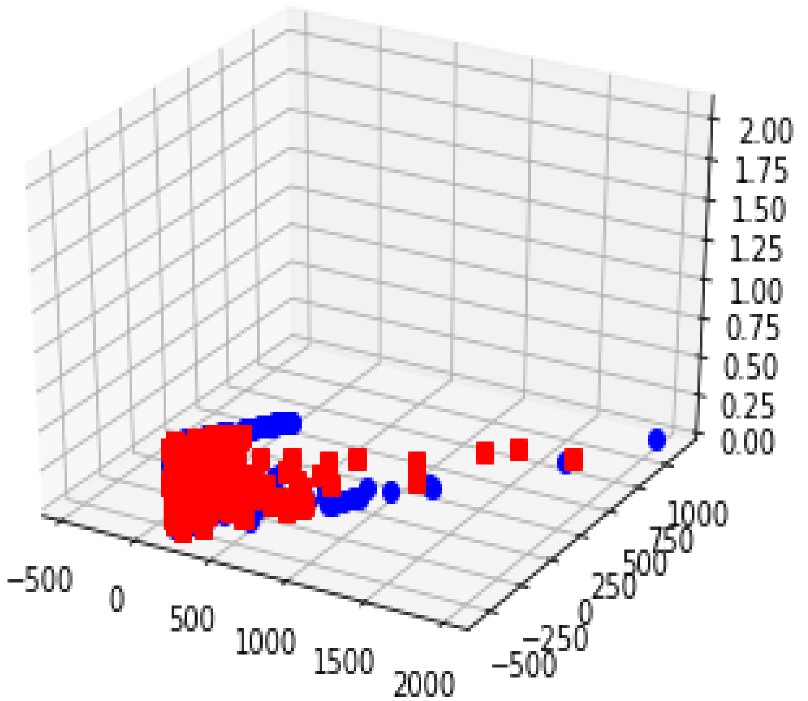

Fig. 2. : 3D PCA Decision Boundary of Triaxial Distance Components

Table 7. SVM Classifier Accuracy for Magnitude Distance By Kernel

Kernel Type	Accuracy Percent
Linear Kernel	65.945
Polynomial Kernel	51.891
Gaussian Kernel	52.972

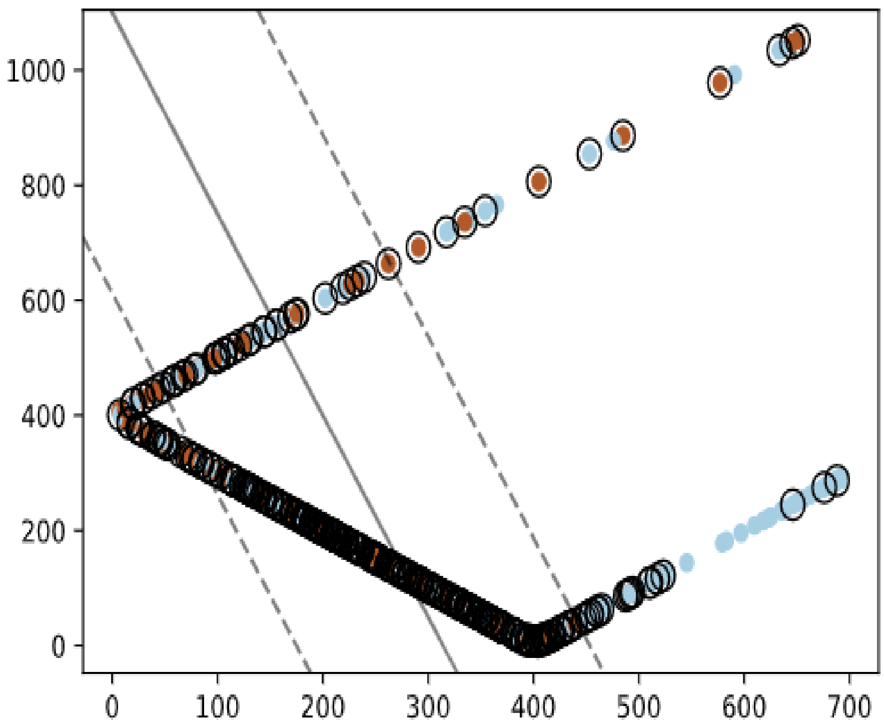

Fig. 3. : Linear SVM Classifier of Magnitude Thresholds

trials, we added a pre-processing step to the model: calculating Acceleration Vector Changes and using these as our threshold instead of the raw magnitude. After calculating these vectors we used the same k-means clustering as before to group and label the activities.

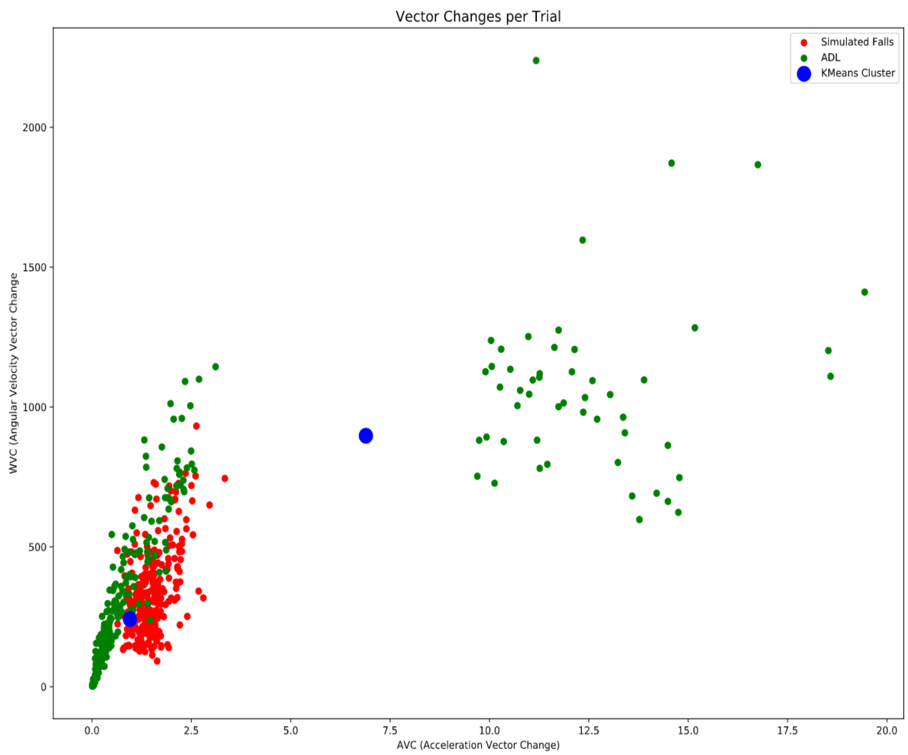

Fig. 4. : K-Means Centroids of Falls and ADLs on AVC and WVC

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.

Table 8. SVM Classifier Accuracy for Magnitude Distance By Kernel

Kernel Type	Accuracy Percent
Linear Kernel	77.300

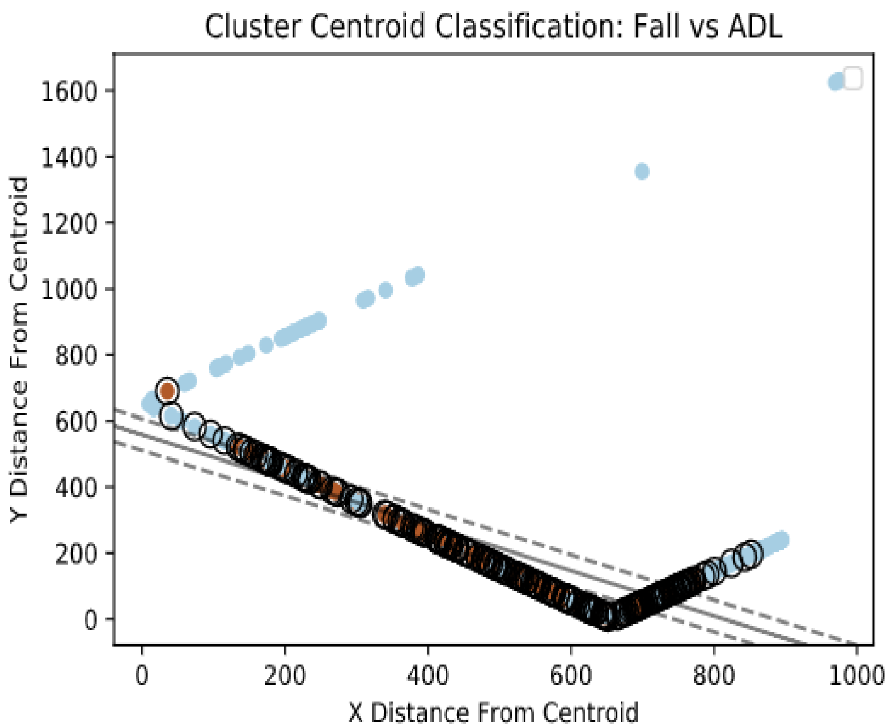

Fig. 5. : Linear SVM Classifier of AVC and WVC

With this model there was significantly improved accuracy: over 77 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.

5 Discussion

As mentioned in the results, our final model (AVC to K-Means to SVM) had an accuracy of about 77 percent, on par with many fall detection systems currently in production in products such as FitBit and the Apple Watch. However, unlike these products our model is much more precise. We would like to see our model adopted into wearables for comparison to existing products.

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 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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