# NOVELTY DETECTION FOR PREDICTING FALLS RISK USING SMARTPHONE GAIT DATA


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## ABSTRACT

In this paper, we consider the problem of falls risk prediction in elderly adults using smartphone-based inertial gait measurements. We begin by collecting a parallel data set from a pressure sensitive walkway and smartphones. The walkway data is used to calculate the falls risk ground truth using well-established biomechanical norms. The smartphone data and falls risk labels are then used to train and evaluate both the one-class support vector machine (OC-SVM) and the support vector data description (SVDD) novelty detectors. In our evaluation we find the SVDD has an average $F_1$ score, used as a measure of classifier performance by equally weighting precision and recall, of 76% for females and 79% for males compared to 79% for a universal model. These results demonstrate the potential for predicting falls risk from smartphone data using novelty detection.



***Index Terms***— Falls Risk, smartphone, novelty detection, one-class svm, support vector data description.


## 1. INTRODUCTION

As the elderly population increases, the prediction of falls risk has become an important research area since falling is one of the leading causes of injury and death among people over the age of 65 [1]. An individual's risk factor is determined by external and age-related factors, including but not limited to home safety, medications, muscle weakness, and gait deficits. External risk factors can be measured using a variety of assessments [1] that account for fall and medical history, prescription/non-prescription medications, and home safety. Physiological risk factors, such as gait deficits, can be measured using foot pressure sensors, motion capture systems, and inertial sensors. Measurements from these sensors can be incorporated into biomechanical models, and machine learning systems can be used to predict falls risk [2]. Micro Electro-Mechanical Systems (MEMS) based Inertial Measurement Units (IMUs) are attractive for measuring gait because of their low cost and demonstrated effectiveness in falls prediction [2]. MEMs based IMUs can be found in most smartphones, making them compelling research device.

Previous studies using inertial gait data and supervised learning techniques have relied on labeled training data based on an individual's falls history [2], i.e. "faller" and "non-faller." Three problems arise with the faller/non-faller classifier approach. First, a large number of examples, equally representing both classes, is needed to train and evaluate the classifier. Balanced data sets can be costly and time-consuming to collect, especially for the faller class. Second, if an individual has fallen, their gait pattern may reflect injuries related to the fall, but not necessarily changes leading up to the fall. Furthermore, if an individual has fallen and undergone rehabilitation, their gait may not reveal patterns indicative of falls risk. Finally, we do not believe a smooth trajectory in feature space exists between high-risk non-fallers and general fallers. The lack of a smooth trajectory implies a classifier trained on faller/non-faller data may not accurately *predict* a falls risk.

On the other hand, novelty detection can be used to construct predictive models using data from a single class. This approach has three advantages. First, a novelty detector does not require a balanced dataset. Therefore, a reduction in data collection costs can be achieved since low falls risk individuals are more accessible. Second, as opposed to a binary classifier, we do not have to extensively monitor an individual's gait before and after a falls event, which would be required to understand the trajectory in feature space. Third, novelty detection is more practical for the ultimate goal of continuous monitoring of gait using smartphones since abnormal patterns indicating a risk of falling can be detected and flagged.

Novelty detectors can be categorized as probabilistic-, distance-, or domain-based [3]. Probabilistic methods use parametric/non-parametric methods to estimate a probability density function (pdf), which is then used to define the threshold between normal/anomalous data points. Distance methods measure the similarity between two data points. Both probabilistic and distance methods, work well on large training sets of low-dimension [3]. Domain methods construct a decision boundary following the data distribution.

These methods work well on high-dimensional data and do not rely on the training data distribution [3]. Domain methods include the one class support vector machine (OC-SVM) and support vector data description (SVDD).

Previous studies have applied novelty detection to the analysis of gait pathology [4, 5]. In [4], Principal Component Analysis (PCA) was used as a measure of how close a given gait pattern was to normal. The technique was applied to measurements from 71 individuals with cerebral palsy. Twenty-four individuals did not exhibit gait pathology and were used to build a model representing normal gait. Using the PCA technique, the authors were able to demonstrate their method for clinical applications. In [5], the authors collected spatial and temporal measurements from 596 healthy subjects using a pressure sensitive platform. Multiple linear regression was then used to determine the deviation from normality.

In this work, we investigate the application of novelty detection for predicting falls risk from smartphone based inertial data. We describe the collection of a parallel dataset using both smartphones and a pressure sensitivity walkway. The data from the walkway is used to provide a "ground-truth" label for falls risk using biomechanical-based norms [6–8]. Using features extracted from the inertial data and the falls risk labels, we train and evaluate the OC-SVM and SVDD novelty detectors. This paper is organized as follows. In Section 2, we review the OC-SVM and SVDD. In Section 3, we discuss the collection of gait data, calculation of falls risk, data processing and feature extraction. In Section 4, we describe model training, hyperparameter optimization, and the $F_1$ score. and in Section 5 we provide simulation results. Finally, in Section 6 we give our conclusions.

## 2. SVM-BASED NOVELTY DETECTION

Both one-class (novelty) and two-class (binary) classification problems assign previously unseen data points to one of two predefined classes. Training data is represented as an $n$-dimensional feature vector, $\mathbf{x} = [x_0, x_1, \ldots, x_{n-1}]^T$ and appropriately labeled as $y = +1$ for the positive class or $y = -1$ for the negative class. In the two-class problem, labeled training data is first used to construct a decision boundary in feature space for the SVM [9]. Then depending on which side of the decision boundary the unseen data point lies on, the class is estimated. In the one-class problem, when the classifier is used for novelty detection, only data points from one class are used in training. When used for anomaly detection, unlabeled data points from both classes are used and examples from the positive, negative class correspond to the anomalous, normal data points, respectively.

As described in [10], the OC-SVM uses a hyperplane to separate data points from the feature space's origin according to a maximum margin constraint. The method returns a binary decision function, $f(\mathbf{x}) \in \{+1, -1\}$, which captures regions containing the majority of data points. A decision, $\hat{y} = -1$ corresponds to the region containing a majority of data points and $\hat{y} = +1$ corresponds to other region(s).

Construction of $f$ is achieved by solving the constrained, quadratic programming problem

$$\begin{aligned} \underset{w,\zeta_i,\rho}{\text{minimize}} \quad & \|w\|^2 + \frac{1}{\nu n}\sum_i \zeta_i - \rho \\ \text{subject to} \quad & w \cdot \Phi(\mathbf{x}_i) \geq \rho - \zeta_i \end{aligned} \tag{1}$$

where the parameter $0 < \nu \leq 1$ establishes a lower bound on the number of training samples used as support vectors and an upper bound on the fraction of training examples considered outliers, $\zeta_i \geq 0$ are the slack variables, $\mathbf{x}_i$ are the support vectors, $\Phi$ is a non-linear mapping from feature space to a higher dimension space, and $w$ and $\rho$ characterize the hyperplane.

The decision function is then

$$f(\mathbf{x}') = \operatorname{sgn}\left[\sum_i \alpha_i K(\mathbf{x}_i, \mathbf{x}') - \rho\right] \tag{2}$$

where $\mathbf{x}'$ is the test example, $\alpha_i$ are Lagrange multipliers, and $K$ is the kernel function defined as $K(\mathbf{x}, \mathbf{x}') = \Phi(\mathbf{x})^T\Phi(\mathbf{x}')$.

As described in [11], the SVDD uses a hypersphere to form a boundary around data points in the feature space. The hypersphere is described by its center point, $\mathbf{a}$ and radius, $R > 0$. The volume of the hypersphere is minimized such that all training data, $\mathbf{x}_i$, are contained within the hypersphere. To allow for outliers in the data, slack variables allow the distance from $\mathbf{x}_i$ to $\mathbf{a}$ to be greater than $R$. The hypersphere parameters are obtained by solving a constrained, quadratic programming problem

$$\begin{aligned} \underset{R,\mathbf{a}}{\text{minimize}} \quad & R^2 + C\sum_i \zeta_i \\ \text{subject to} \quad & \|\mathbf{x}_i - \mathbf{a}\|^2 \leq R^2 \end{aligned} \tag{3}$$

where $C$ is a penalty parameter, $\mathbf{x}_i$ are support vectors, and $\|\cdot\|$ is the Euclidian distance measure. A new datapoint, $\mathbf{x}'$ is evaluated as anomalous (outside the target class) if it lies outside the hypersphere, $\|\mathbf{a} - \mathbf{x}'\| > R$.

## 3. GAIT DATA

### 3.1. Data Collection

Gait data was collected by The Electronic Caregiver Co. (ECG), Mobile Fall-Risk Assessment Unit from two sensor platforms: a pressure sensitive walkway and two Apple® iPhone® 6 devices. The walkway measured planter force and pressure while both smartphones, using the ECG GaitLogger app [12], made inertial gait measurements. The two smartphones were attached to the left and right hip using a gait belt and holster clip and oriented such that the long edge of the device was oriented vertically. During each trial, a participant walked down the walkway (outbound), turned around, and returned.

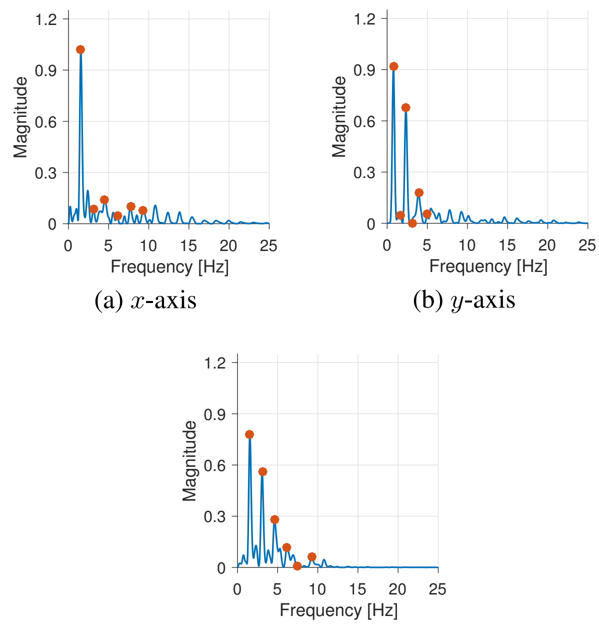
For the outbound pass, both platforms collected data in parallel and only the smartphones collected data for the return pass. In total, smartphone data was collected for 54 participants. Thirty-five of the participants were female and 19 of the participants were male. Due to a technical issue, one smartphone for three participants was unusable. In total, we collected smartphone-based inertial gait measurements from 190 walking segments. We also collected 54 sets of walkway biomechanical measurements.

### 3.2. Falls Risk Ground Truth from Walkway Data

The walkway measurements were used to calculate a falls risk ratio for each participant. An initial assessment was used to determine a measure of gait stability (central tendency) and instability (variance). A two step process was used to classify individuals with increased falls risk. First, the gait data was analyzed using factor analysis to ensure the variables were consistent with previous reports [6, 7], i.e. gait velocity, cadence and stride length load on the "pace factor" (Factor 1) and both percent time in double leg support and in swing load on a "rhythm factor" (Factor 2). Second, a falls risk ratio [8] was calculated using the percentage of change in both Factor 1 (cadence, stride length and gait velocity) and Factor 2 (percent time in double leg support and percent time in swing). Due to cross-correlations in the gait variables, a participant was considered to have an elevated risk, i.e. $y = +1$ if the risk ratio was greater than 8% on two of the three variables loading on Factor 1 and greater than 8% on both variables loading on Factor 2. Of the 54 participants, 19 were labeled as having a falls risk and 35 labeled as having a low falls risk. Thirteen female participants were labeled as having a falls risk and 22 were labeled as having a low falls risk. Of the 19 male participants, 13 were labeled as having a low falls risk and 6 were labeled as having a falls risk. Overall our dataset contains 120 gait segment examples labeled low falls risk and 70 gait examples labeled as falls risk.

### 3.3. Feature Extraction

An extensive analysis of features used in falls risk classification can be found in [2]. From this study, the authors determined that the most discriminating features are computed using the spectrum of the acceleration signals. In our research, we use features 11-13 and 19-33 from Table I in [13]. Prior to feature extration, all signals were manually segmented using a semi-automated MATLAB® program, additional details can be found in [12]. Feature extraction is performed for the $x$-, $y$-, and $z$-axis acceleration signals. For each signal, the magnitude spectrum, $|F(\omega)|$, is calculated using a 2048-point Fast Fourier Transform (FFT). After the transformation, the fundamental frequency $\omega_0$, is estimated as the frequency whose six harmonics maximize the cost function, $J(\omega_0) = \sum_{k=1}^{6} |F(jk\omega_0)|$ [13]. Since human gait is quasi-periodic, it is not expected that the harmonics are exact multiples of the fundamental thus true harmonics falling close to a peak are replaced by the frequency of the closest peaks. Harmonics which fall in a valley are not replaced. Figure 1 shows the magnitude spectra for the $x$-, $y$-, and $z$-axis acceleration signals. The circular markers denote the six harmonics.




(a) $x$-axis

(b) $y$-axis

(c) $z$-axis

**Fig. 1**. Magnitude spectrum for (a) $x$-, (b) $y$-, and (c) $z$-axis acceleration signals. Circular markers denote the six harmonics. Features are extracted from the acceleration harmonics according to [13].

Once the spectral peaks corresponding to the fundamental and its harmonics are found, features for each acceleration signal are extracted according to [2, 12, 13]. In total, seven features are extracted for each accelerometer axis and concatenated together to form a 21-D feature vector. Features 1, 8, and 15 are the fundamental frequencies for the $x$-, $y$-, and $z$-acceleration signals, respectively. Features 2-5, 9-12, 16-19 are the ratios of the area under the first harmonic (fundamental, second, third, and fourth) to the sum of the area under the first six harmonics for the $x$-, $y$-, $z$-axis, respectively. Features 6, 13, 20 are based on the ratio of the sum of the area under the first six harmonics to the sum of the remaining area under the spectrum for the $x$-, $y$-, $z$-axis, respectively. Features 7, 14, 21 are based on the ratio of the sum of the area under the even harmonics to the sum of the area under the odd harmonics for the $x$-, $y$-, and $z$-acceleration signals, respectively. The area under the harmonics is calculated by integrating the magnitude spectrum in a window of $\pm 0.15$ Hz around the frequencey of interest [13].

## 4. MODEL BUILDING

### 4.1. Training and Hyperparameter Optimization

The OC-SVM and SVDD novelty detectors were trained using only examples labeled as having a falls risk. Training with the falls risk class was motivated by [14] where it is suggested that classification results can be improved by learning only the minority class. The training set was constructed by randomly selecting 80% of the falls risk examples. The model was tested using examples from both classes, where the remaining 20% of the falls risk examples were used to construct part of the testing set. The remaining part was constructed such that the same percentage of examples with low falls risk was the same as the complete dataset. The low falls risk examples were also selected at random.

The OC-SVM and SVDD methods each have one hyperparameter, $\nu$ and $C$, which can be optimized. Depending on the SVM kernel, additional hyperparameters may also need to be optimized, i.e. Radial Basis Function (RBF) kernel's $\gamma$ parameter which controls the width of the kernel. Hyperparameter optimization was performed using a grid search over the hyperparameter space. To improve robustness and avoid over-fitting, Monte-Carlo cross-validation was used. [15]. The cross-validation procedure employed the same training and testing technique described above.

### 4.2. Evaluation Metric

Novelty detection problems use unbalanced datasets, where the number of negative examples can far exceed the number of positive examples. For this reason, the use of classifier accuracy can be misleading, since the classifier can easily achieve a high level of accuracy by classifying all observations as the dominant class. Instead, a more appropriate evaluation metric is the $F_1$ score [16] defined as

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

where

$$\text{Precision} = \frac{t_p}{t_p + f_p} \text{ and Recall} = \frac{t_p}{t_p + f_n} \tag{5}$$

and $t_p$, $f_p$, and $f_n$ are the number of true positives, false positives, and false negatives, respectively. Since both Precision and Recall are equally weighted, a good novelty detector should maximize both measures. A detector that performs moderately well on both measures is preferred over one that performs well on only a single measure; a novelty detector which classifies randomly has $F_1 = 0.5$.

## 5. SIMULATION RESULTS

Simulations were performed using MATLAB® and the LIBSVM library [17] which includes OC-SVM and SVDD implementations. For this study, both gender-dependent (male/female) and independent (universal) models were considered. The use of gender-dependent models was motivated by the work reported in [5], which noted differences in body mass and ratios between the body length segments can greatly effect models of normal gait. The model building process described in Section 4.1 was performed independently for each model; each SVM type was evaluated using the RBF and linear kernels.

Results for the OC-SVM and SVDD after hyperparameter optimization are presented in Table 1. For all models we found that the performance was similar. The SVDD with a linear kernel has an $F_1$ scores of 79.27% for males and the SVDD with a RBF kernel has an $F_1$ score of 76.23% for females. Whereas the best universal model obtains a score of 79.07% for the SVDD with a RBF kernel. These results suggest a novelty detector can be used to predict falls risk from smartphone-based inertial gait measurements. The smartphone's ease of use, data collection costs, and ubiquity offers the potential for continuous falls risk prediction and monitoring which is not possible with other sensor platforms.

**Table 1**. Best $F_1$ scores. SVDD out performs the OC-SVM for all models

| Model | SVM | Kernel | $\bar{F}_1$ |
|---|---|---|---|
| Universal | OC-SVM | Linear | 0.7705 |
| Universal | OC-SVM | RBF | 0.7705 |
| Universal | SVDD | Linear | 0.7734 |
| **Universal** | **SVDD** | **RBF** | **0.7907** |
| Female | OC-SVM | Linear | 0.7619 |
| Female | OC-SVM | RBF | 0.7619 |
| Female | SVDD | Linear | 0.7540 |
| **Female** | **SVDD** | **RBF** | **0.7623** |
| Male | OC-SVM | Linear | 0.7907 |
| Male | OC-SVM | RBF | 0.7907 |
| **Male** | **SVDD** | **Linear** | **0.7927** |
| Male | SVDD | RBF | 0.7911 |

## 6. CONCLUSION

Using a limited dataset, this research has successfully demonstrated the prediction of falls risk from smartphone inertial gait measurements using novelty detection. In this study, spatial-temporal gait measurements from a pressure sensitive walkway provided ground truth labels for a participants' falls risk. Using these labels we were able to asses the performance of the OC-SVM and the SVDD novelty detectors. The results indicate that for all models the SVDD provides the best $F_1$ scores for all models. As the number of participates in the dataset increases, it is expected that the results presented in this paper will improve.

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