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Anomaly Detection for Predicting Falls Risk using Smartphone Gait Data

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***Abstract*— In this paper, we consider the problem of predicting falls risk in elderly adults using smartphone based inertial gait measurements. We begin by collecting a parallel dataset from a pressure sensitive walkway and smartphones. The walkway data provides a falls risk ground truth using well-established biomechanical norms. Using the smartphone data and falls risk labels, we train and evaluate both the one-class support vector machine (OC-SVM) and the support vector data description (SVDD) anomaly detectors. In our evaluation, we find that OC-SVM has an F_1 scores of 80.0% for males and 82.8% for females compared to 73.3% for a universal model. These results indicate the potential for predicting falls risk using smartphone data.**

I. Introduction

As the elderly population sharply 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 can be used in machine learning systems to predict an individual's risk of falling [2]. Micro Electro-Mechanical Systems (MEMS) based Inertial Measurement Units (IMUs) are an attractive choice for measuring gait because of their low cost and demonstrated effectiveness in falls prediction [2]. Such IMUs can be found in most smartphones, making them compelling devices for falls research.

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 datasets 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 the changes leading up to the fall event. 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 that a classifier trained on faller/non-faller data may not accurately *predict* a falls risk.

On the other hand, anomaly detection can be used to construct predictive models using measurements from low-risk fallers and the limited amount of data from the high-risk class can be used for evaluation. This approach has three advantages. First an anomaly 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 fall event, which would be required to understand the trajectory in feature space. Third, anomaly detection is more practical for the ultimate goal of continuous monitoring of gait using smartphones since anomalous patterns indicating a risk of falling can be detected and flagged.

Anomaly detection techniques have been previously applied to the analysis of gait pathology [3], [4]. In [3], a Principle Component Analysis (PCA) technique was developed to measure of how close a given gait pattern is to normal. The technique was applied to measurements obtained from 71 individuals who all had cerebral palsy. Twenty-four of these 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 [4], the authors collected spatial and temporal biomechanical mechanical measurements from 596 healthy subjects using a pressure sensitive platform. The authors then built a model using multiple linear regression to calculate the deviation from normality.

In this work, we investigate the application of anomaly detection for predicting falls risk using inertial data collected with a smartphone. We describe the collection of a parallel dataset using both smartphones and a pressure sensitivity walkway. The data from the walkway is than used to provide a "ground-truth" for an individual's falls risk using well-established, biomechanical-based norms [5]–[7]. Using features extracted from the inertial data and corresponding falls risk values, we train and evaluate the anomaly detector; we consider both the OC-SVM and the SVDD. This paper is organized as follows. In Section II, we review the OC-SVM and the SVDD. In Section III, we discuss the collection of gait data, calculation of falls risk, data processing and feature extraction. In Section IV, we describe the model building process and evaluation metric based on the F_1 score and in Section V we provide simulation results. Finally, in Section VI we give our conclusions.

II. Support Vector Machine Based Anomaly Detection

Both one-class (anomaly) and two-class (binary) classification problems assign a previously unseen data point 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 from both classes is first used to construct a decision boundary in feature space for the SVM [8]. Then depending on which side of the decision boundary the unseen data point lies on, the class is estimated. In the one-class problem, the classifier is trained using data from only one class. When used for novelty detection, only data points from the normal class, $y = -1$ 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 [9], 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 of the input space 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 that are considered outliers, $\zeta_i \geq 0$ are the slack variables, $\mathbf{x}_i$ are the support vectors, Φ is a non-linear mapping from feature space to a higher dimension space, and w and ρ are parameters characterizing the hyperplane.

The decision function is then

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

where $\mathbf{x}'$ is the test example, α_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 [10], 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 hypershere 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, $\|\mathbf{a} - \mathbf{x}'\| > R$.

III. Gait Data

A. Data Collection

For this study, gait data was collected from two sensor platforms: a pressure sensitive walkway and two Apple® iPhone® 6. The walkway performed measurements of planter force and pressure while both smartphones measured gait. 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, data was collected for 24 participants. Fourteen of the participants were female and ten were male. Due to a technical issue, one smartphone on one participant was unusable. In addition, only nine participants completed both outbound and return passes. In total, we collected smartphone-based inertial gait measurements from 66 walking segments (outbound or return). We also collected 24 sets of biomechanical measurement from the walkway.

B. Determining Falls Risk Ground Truth from Walkway Data

The walkway measurements were used to calculate a falls risk ratio for each participant. The initial assessment of the individual's gait was used to determine a measure of stability (central tendency) and instability (variance). Following the initial assessment, classification of individuals with increased falls risk was performed using a two-step process. First, the gait data was analyzed using factor analysis to ensure the variables were consistent with previous reports [5], [6], i.e. gait velocity, cadence and stride length load on the "pace factor" (Factor 1) and both percent time in double leg support and percent time in swing load on a "rhythm factor" (Factor 2). Second, a falls risk ratio [7] 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. From this, 14 participants were considered as high risk for falling and 10 as not.

C. Post-Processing Smartphone Data

Post processing occurred in two stages. First, the acceleration signals were trimmed to remove any segments not corresponding to active walking. This includes the signal segment prior to the participant walking down the walkway, the turn around, and any segment after the participant finishes both passes. A semi-automated MATLAB® program was developed to assist in this process and additional details can be found in [11]. Second, a Savitsky-Golay (SG) filter, with a third order polynomial and 51 sample frame length, was applied to the acceleration signals to remove short-term fluctuations caused by the accelerometers [12]. SG filtering is preferred over a moving-average filter due to its ability to smooth the signal without distorting the peaks.

D. 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]. Feature extraction is performed for the x-, y-, and z-axis acceleration signals. For each signal, a Power Spectral Density (PSD) estimate is computed using Welch's Method using default settings in MATLAB® (Hamming window, 50% overlap, eight segments). The fundamental frequency is selected as the spectral peak with the greatest power appearing in the PSD. The remaining spectral peaks are assumed to be harmonic. Since human gait is quasi-periodic, it is not expected that the harmonics are exact multiples of the fundamental thus the peaks are sorted in order of occurrence and grouped into even and odd harmonics. Once grouped, features for each acceleration signal are extracted according to [2], [11], [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 a harmonic (fundamental, second, third, and fourth) to the sum of 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 first six harmonics to the sum of the remaining harmonics for the x-, y-, z-axis, respectively. Features 7, 14, 21 are based on the ratio of the sum of the even harmonics to the sum of the odd harmonics for the x-, y-, and z-acceleration signals, respectively.

IV. Model Building

A. Model Selection

The model building process used in this study is a two step process. In the first step, a sequential forward selection (SFS) algorithm [14] is used to find the most relevant features that best predicts the target class. Features are sequentially added until no further improvement in the prediction can be made. One of the disadvantages to the SFS algorithm is that once a feature is selected it will not be removed after additional features have been added. In the second step, hyperparameter optimization is performed using a grid search. The OC-SVM and SVDD methods each have one hyperparameter, ν and C. Depending on the SVM kernel, additional hyperparameters may need to be optimized, i.e. Radial Basis Function (RBF) kernel's γ parameter which controls the width of the kernel. To improve robustness and avoid over-fitting, both feature selection and hyperparameter optimization were performed using leave-one-out cross-validation [14].

B. Evaluation Metric

Anomaly detection problems use unbalanced data sets, 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 negative ($y = -1$) class. Instead, a more appropriate evaluation metric is the F_1 score [15] defined as

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

where

$$\text{Precision} = \frac{t_p}{t_p + f_p} \text{ and Recall} = \frac{t_p}{t_p + f_n} \quad (5)$$

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, than a good anomaly 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; an anomaly detector which classifies randomly has $F_1 = 0.5$.

V. Simulation Results

Simulations were performed using MATLAB® and the LIBSVM library [16] 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 work reported in [4], 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 IV-A was performed independently for each model; each SVM type was evaluated using the RBF and linear kernels.

Feature selection was performed recursively for an increasing number of feature set lengths, i.e. $1-21$, to determine the optimal number of features for each model. For the feature selection process the default LIBSVM parameters were used. The results of the feature selection process are listed in Table I where we find that universal models, in general, require fewer features than gender-dependent models. In particular Features 1, 3, 5, 8, 10, 12, 15, and 17 are the most discriminating. We find that for the universal models, eight features were selected. For female gait models, either eight

TABLE I

FEATURES IN [13] AFTER SEQUENTIAL FORWARD SELECTION. GENDER DEPENDENT MODELS REQUIRE FEWER FEATURES.

Model	SVM	Kernel	N	Features
Universal	OC-SVM	Linear	10	1, 3, 5, 8, 10, 12, 13, 15, 17, 21
Universal	OC-SVM	RBF	8	1, 3, 5, 8, 10, 12, 15, 17
Universal	SVDD	Linear	8	1, 3, 5, 8, 10, 12, 15, 17
Universal	SVDD	RBF	8	1, 3, 5, 8, 10, 12, 15, 17
Female	OC-SVM	Linear	10	1, 5, 6, 7, 8, 12, 15, 17, 18, 20
Female	OC-SVM	RBF	8	1, 5, 7, 8, 12, 15, 17, 18
Female	SVDD	Linear	8	1, 5, 7, 8, 12, 15, 17, 18
Female	SVDD	RBF	10	1, 5, 6, 7, 8, 12, 15, 17, 18, 19
Male	OC-SVM	Linear	21	1-21
Male	OC-SVM	RBF	21	1-21
Male	SVDD	Linear	11	5, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20
Male	SVDD	RBF	21	1-21

or ten features were selected while for male gait models, in general all 21 features were selected.

Results for the OC-SVM and SVDD after feature selection and hyperparameter optimization are presented in Table II. The gender dependent models obtain the highest F_1 scores. The OC-SVM with a RBF kernel has an F_1 scores of 80.0% for males and 82.8% for females. Where as the universal model obtains score of 73.3%. When using just biomechanical measurements from the walkway, an F_1 score of 72.0% was achieved for the universal model using the OC-SVM and an RBF kernel. The gender based models using biomechanical walkway measurements were not assessed due to the limited sample size. These results suggest an anomaly detector is useful in predicting 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.

VI. CONCLUSION

This research has successfully demonstrated prediction of falls risk using smartphone inertial gait measurements and anomaly detection. In this study, we used spatial-temporal gait measurements from a pressure sensitive walkway to provide 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 anomaly detectors when used with inertial gait measurements. The results indicate that the OC-SVM with an RBF kernel has the best F_1 score. In addition, gender based models have better predictive performance than a universal model for falls risk.

TABLE II

BEST F_1 SCORES. GENDER DEPENDENT MODELS OUT PERFORM CORRESPONDING UNIVERSAL MODELS

Model	SVM	Kernel	F_1
Universal	OC-SVM	Linear	0.5714
Universal	**OC-SVM**	**RBF**	**0.7333**
Universal	SVDD	Linear	0.7000
Universal	SVDD	RBF	0.7333
Female	OC-SVM	Linear	0.4706
Female	**OC-SVM**	**RBF**	**0.8276**
Female	SVDD	Linear	0.7500
Female	SVDD	RBF	0.8148
Male	OC-SVM	Linear	0.7272
Male	**OC-SVM**	**RBF**	**0.8000**
Male	SVDD	Linear	0.7895
Male	SVDD	RBF	0.8000

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