Bayesian Classification of Falls Risk

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Abstract

Background: Prior research in falls risk prediction often relies on qualitative and/or clinical methods. There are two challenges with these methods. First, qualitative methods typically use falls history to determine falls risk. Second, clinical methods do not quantify the uncertainty in the classification decision. In this paper, we propose using Bayesian classification to predict falls risk using vectors of gait variables shown to contribute to falls risk.

Research Questions: 1) Using a vector of risk ratios for specific gait variables shown to contribute to falls risk, how can older adults be classified as low or high falls risk? and 2) how can the uncertainty in the classifier decision be quantified when using a vector of gait variables?

Methods: Using a pressure sensitive walkway, biomechanical measurements of gait were collected from 854 adults over the age of 65. In our method, we first determine low and high falls risk labels for vectors of risk ratios using the k-means algorithm. Next, the posterior probability of low or high falls risk class membership is obtained from a two component Gaussian Mixture Model (GMM) of gait vectors, which enables risk assessment directly from the underlying biomechanics. We classify the gait vectors using a threshold based on Youden's J statistic.

Results: Through a Monte Carlo simulation and an analysis of the receiver operating characteristic (ROC), we demonstrate that our Bayesian classifier, when compared to the k-means falls risk labels, achieves an accuracy greater than 96% at predicting low or high falls risk.

Significance: Our analysis indicates that our approach based on a Bayesian framework and an individual's underlying biomechanics can predict falls risk while quantifying uncertainty in the classification decision.

Keywords: Gait analysis, falls risk prediction, Bayesian classification, falls prevention

1. Introduction

Falls prevention efforts for older adults have become increasingly important and are now a significant health research effort. Unintentional falls are a leading cause of injury to those over 65 years of age and have significant societal and economic impacts [1]. One of the current trends in health informatics is the use of machine learning to predict adverse outcomes [2, 3]. Prior research has shown that machine learning can be used to analyze gait and classify older adults as a faller or non-faller, where a faller has a past history of falling [4, 5].

In supervised learning, a binary classifier maps an input vector to one of two labels, e.g. faller vs. non-faller. Labels for falls risk prediction are typically inferred from empirical data including the use of expert domain knowledge and are usually obtained using two methods. The first is through the use of questionnaires which assess, for example, an individual's history of falling, medication usage, and home environment all of which may increase an individual's risk [1]. The second method uses clinical mobility-based assessments to evaluate an individual's gait, strength, and balance which have also been shown to be indicators of falls risk. These assessments include but are not limited to the Timed Up and Go test [6], the 30-second Chair Stand [7], and the 4-Stage Balance Test [8].

There are two challenges with these methods for classifying falls risk. First, the questionnaires can be error prone due to their qualitative nature [4]. Additionally, they often use a threshold to place individuals into one of two categories, faller or non-faller. However, these labels are only indicative of the individual's falls history, fail to capture their level of risk [1], and do not account for biomechanical risk factors associated with a prospective fall. It has also been shown that mobility-based measures of falls risk are uncorrelated with falls risk assessments that use falls history, home environment, and medication to assess falls risk [1]. The second issue is that although clinical assessments have been shown to be successful at identifying older adults at risk of falling or those who have fallen in the

past [9, 10], to maintain simplicity they classify individuals as low or high falls risk using threshold-based methods. Additionally, they do not quantify the uncertainty in classifying an individual as either low or high falls risk or provide a probability of an adverse outcome [11].

In this paper, we propose using gait variables measured with a pressure sensitive walkway to classify older adults as low and high falls risk using a Bayesian framework. We first determine low and high falls risk labels using vectors of the relative increase in risk ratios using the k-means algorithm. These risk ratios quantify how an individual's falls risk increases with changes in each gait variable. Next, parameters of a two component Gaussian Mixture Model (GMM) [12] of gait vectors are estimated where each component models the low and high falls risk classes and posterior probabilities for low and high falls risk class membership are then computed. Unlike classifiers that identify individuals as faller or non-faller, the proposed Bayesian framework quantifies the uncertainty that an individual is classified as high falls risk. Using a Monte Carlo simulation and Receiver Operating Characteristic (ROC) curve analysis, we determine the decision threshold which maximizes Youden's J statistic [13] for the classifier.

The contributions of this paper are as follows.

1. Although prior research [14, 15, 16] has quantified how changes in specific gait variables increase falls risk, no definitive method is provided to identify individuals as low or high falls risk. We demonstrate that by using k-means clustering of vectors whose elements are risk ratio increases, defined in Section 3.2, we can effectively cluster the vectors into low and high falls risk classes.

2. Prior research [4, 5] and clinical methods, have been shown to be successful at classifying individuals who have fallen in the past or are at risk of falling. However, these methods do not provide an uncertainty associated with the classification. By using a Bayesian framework, we demonstrate that we can classify individuals as low and high falls risk while also providing uncertainty of the classifier's decision.

This paper is organized as follows. In Section 2, we provide a review of factors associated with falls risk. We then discuss our data set and a method for hard label assignment based on risk ratios in Section 3. In Section 4, we describe the use of a GMM in data modeling and the Bayesian framework. In Section 5, we give performance results of our classifier using the risk ratio labels and we provide conclusions in Section 6.

2. Falls Risk

Risk factors associated with falls in older adults are both extrinsic and intrinsic. Extrinsic factors include medications, home environment, and footwear. Medications associated with an increased risk of falls include psychotropics, diabetes medication, non-steroidal anti-inflammatory drugs, cardiovascular medications, and anti-epileptics [17, 1]. Home environment factors include poor lighting and loose rugs, and an increase in falls risk due to footwear is attributed to the use of slippers and walking barefoot in the home [17]. Intrinsic risk factors include demographics, bodily system functioning, and disease-associated symptoms. Demographics associated with an increase falls risk include age, sex, and race: adults over the age of 85 fall at rate of $4\times$ that of adults between the ages of 65 and 74; women are 58% more likely than men to suffer from a non-fatal fall, whereas, men are 46% more likely to experience a fatal fall; and White women are $2.5\times$ more likely to experience a fatal fall and have a higher incidence of fall related hip fractures than African American women [17]. Falls risk associated with system decline include gait and balance disorders, a decrease in strength, a decline in vision, and a decline in cognitive function [1, 17]. Additionally, disease-associated symptoms such as dizziness and vertigo, cardiovascular disease, dementia, and depression have been shown to contribute to an increased falls risk [14, 15, 17].

Although the above risk factors contribute to an increased risk of falling, gait and balance disorders are among the strongest indicators of falls risk [17]. This is a result of age-related degradation in the gait pattern, which is stiffer and less coordinated [17]. As a result of age-related physiological decline, older adults are less capable of self-correcting after experiencing a slip or trip. This is due to a decrease in muscle strength and tone, a decrease in step height and length, and reduced body orienting reflexes [17]. Additionally, older adults are unable to step rapidly after a loss of balance resulting in several erratic steps [17].

Five gait variables, identified in previous studies [14, 15, 16], have been shown to contribute to an increase in the risk of falls. These variables are gait speed, cadence, stride length, time spent in swing phase as a percentage of the gait cycle, and time spent in double support as a percentage of gait cycle. Using Principle Component Analysis (PCA) with varimax rotation, the authors in [15] group these five variables into two factors: pace (gait speed, cadence, and stride length) and rhythm (time spent in swing phase and double support as a percentage of the gait cycle). As well as identifying the components of gait responsible for increasing the risk of falls, the authors also attributed a risk ratio to each variable, where the risk ratio is reported as a per unit change from the median reported value. For all variables except double-support, the unit change is reported as a decrease. Table 1 summarizes the median value, unit change, and risk ratio for each variable. For each variable x in Table 1, the associated increase in risk is calculated as

$$\Delta_{\text{risk}} = \frac{x - \text{median}}{\text{unit change}} * (\text{risk ratio} - 1.0). \qquad (1)$$

These risk ratios quantify how an individual's falls risk in-

Table 1: Summary of median value, unit change, and risk ratio for each variable where the unit change for all variables except double-support are reported as decreases.

Gait Variable	Median	Unit Change	Risk Ratio
Gait Speed (cm/s)	95.1	−10	1.078
Cadence (steps/min)	101.8	−10	1.085
Stride Length (cm)	112.5	−10	1.095
Swing phase (%)	36.6	−10	1.503
Double-support (%)	26.6	10	1.207

Table 2: Anthropometrics and disease domain information for study participants.

Variable	Female (n=601)	Male (n=253)
Age, y (std dev)	78.9 (7.9)	78.5 (7.8)
Weight, kg (std dev)	70.8 (16.5)	85.3 (17.4)
Cardiovascular (%)	237 (38.4)	91 (36.0)
Arthritis (%)	323 (53.7)	109 (43.1)
Neurologic (%)	183 (30.4)	68 (26.9)
Metabolic (%)	213 (35.4)	83 (32.8)
More-Than-One (%)	248 (41.3)	89 (35.2)

creases with changes in each gait variable. However, these risk ratios do not provide an overall measure of risk or quantify the uncertainty of being at high risk for falling. They are instead a measure of the increase or decrease in risk [18].

3. Gait Data and Risk Labeling

3.1. Gait Data

In partnership with the Electronic Caregiver® (ECG) Company, biomechanical measurements of gait were collected using a TekScan® Walkway™ System, which utilizes piezoresistive sensors to measure plantar pressure and force. The measurements include gait, kinetic, and timing variables. The gait variables include step and gait time, distance, velocity, and cadence. The sensing dimensions are 85.8 inches × 14.5 inches and sufficient for participants to take approximately 3-4 steps. Walkway data was processed by calculating a mean value over the gait cycles for each of the gait variables in Table 1; swing time and double support time were converted to a percentage of the gait cycle.

Gait data was collected from 854 adults over the age of 65 from 50 sites in the Southwestern and Southern U.S. by ECG Co. Participants were recruited on site, were selected based on age, cognitive ability, ability to read and understand the liability waiver, and ability to ambulate for 30s with or without an assistive walking device. All participants completed a liability waiver informing them of all protocols, potential risks and benefits, rights as volunteers, and right to withdraw consent. The use of the walkway data for secondary analysis was approved by New Mexico State University Internal Review Board under reference number 15405.

The demographic composition of participants is as follows: 82.8% White (non-Hispanic), 5.6% African-American, 3.4% Hispanic, 1.1% Asian, 0.4% Native American, 1.2% other, and 5.6% did not provide information regarding ethnicity. Compared to U.S. Census Bureau data, all ethnicities are under-represented with exception of Whites [19]. In addition, the proportion of female participants in our data set (70.4%) is higher than the U.S. population [19]. However, we consider both sex-dependent and sex-independent models so consequences (if any) of this imbalance may be

accounted for. Finally, the anthropometric and health/medical history data in Table 2 indicates that our data set is considered healthier than the overall U.S. population over the age of 65 [20, 21, 22, 23].

3.2. Risk Ratio Based Labeling

While prior research [14, 15, 16] has quantified changes in gait variables to increases in falls risk (Table 1), there is no overall definitive measure of risk using these variables. We determine risk ratio based hard labels, which are used to evaluate our Bayesian classifier, as follows. For each participant, we construct a 5-D vector composed of the associated increase in risk for each variable using (1). If the increased risk for the variable is less than zero, we set that element to zero, indicating no increase in risk. We refer to this vector as the "risk vector". Next, the risk vectors are clustered into two classes using k-means [12] which is illustrated in Figure 1(a) where the risk vectors are projected onto 2-D space[1]. In addition, we color the markers by the magnitude of the risk vector in order to indicate how far from "no increase in risk" the participant is as illustrated in Figure 1(b). Thus as risk vectors increase in length, falls risk increases. Comparing Figures 1(a) with (b), we see that k-means effectively clusters the risk vectors into low falls risk (blue) and high falls risk (red) groups. With this approach 511 (59.8%), 343 (40.2%) of 854 participants were labeled as low falls risk and high falls risk, respectively.

4. Bayesian Classification

4.1. Gaussian Mixture Modeling

Using the expectation-maximization algorithm, we estimated parameters for a two component GMM where the components model low and high falls risk classes using vectors composed of the five gait variables in Table 1 obtained from walkway data. We refer to this vector, $\mathbf{x}$, as the "gait vector" and note that it is fundamentally different than the risk vector described in Section 3 and is directly constructed from biomechanical data. This is an important

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[1]Dimensionality reduction, from 5-D to 2-D, is accomplished using PCA [12].
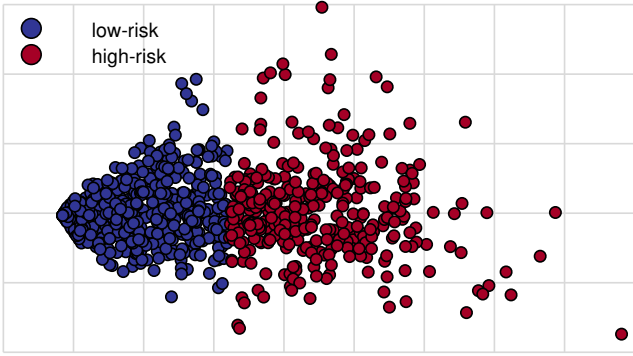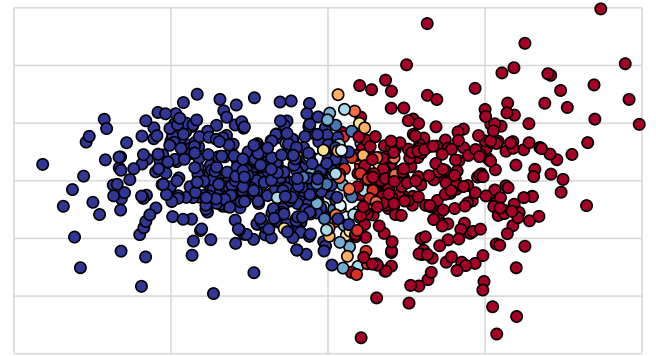
(a) Classification of risk vectors
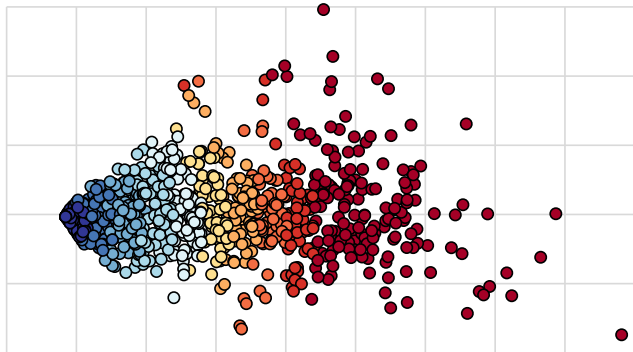
(b) Magnitude of normalized risk vector

Figure 1: Scatter plots of 5-D vectors of associated increase in risk for variables listed in Table 1 using (1); risk vectors are projected to 2-D for illustration purposes. (a) The 5-D risk vectors are clustered into two classes using k-means and (b) colored by the magnitude of the normalized risk vector in order to indicate overall risk. The k-means algorithm clusters the data into low falls risk (blue) and high falls risk (red) classes. With this method, we have 511 participants labeled as low falls risk and 343 labeled as high falls risk. These hard labels are used to evaluate the proposed Bayesian classifier.
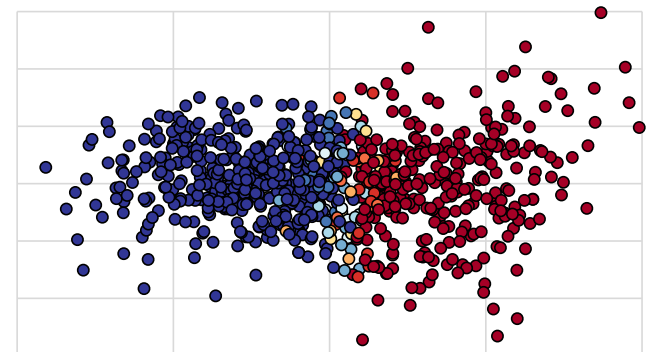
point because it enables risk assessment directly from underlying biomechanics. We consider both sex-independent and sex-dependent GMMs, the latter is motivated by well-known sex difference across gait variables [24]. The use of diagonal covariance matrices in the GMM, despite correlations in the gait variables [15], led to more accurate classification of the gait vectors from the posterior probabilities as described below.

For the vector comprised of the median values (lowest risk) in Table 1, from Bayes' theorem we computed the posterior probability or *responsibility* of each component, k as

$$
\begin{aligned}
p(k|\mathbf{x}) &= \frac{p(\mathbf{x}|k)p(k)}{p(\mathbf{x})} \\
&= \frac{\pi_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\displaystyle\sum_{j=1}^{2} \pi_j \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}
\end{aligned}
\tag{2}
$$

(a) Sex-independent model

$p(C_2|\mathbf{x})$

(b) Sex-dependent model

Figure 2: Scatter plots of the 5-D gait vectors consisting of the gait variables in Table 1 projected onto 2-D space. The markers are shaded according to the posterior probability that the gait vector will be assigned membership to the high falls risk class, C_2.

where $k = 1$ or 2, $p(\mathbf{x}|k)$ is the likelihood, $p(k)$ is the prior, and $\{\pi_j, \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j\}$ are the distributional parameters (weight, mean vector, and covariance matrix) of the jth component. Using the vector of median values (low risk), we associate the component with the higher of the two responsibilities as the low falls risk class, C_1; the other component is therefore associated with the high falls risk class, C_2. Figure 2 shows the 5-D gait vectors projected onto 2-D space for the sex-independent and sex-dependent models. The markers are shaded according to the posterior probability, i.e. uncertainty that a gait vector will be classified as high falls risk.

We use the responsibilities (2) from the GMM to construct a Bayesian classifier which predicts the probability that a gait vector belongs to the kth class, $p(C_k|\mathbf{x})$. The classification decision is then made according to the rule

$$
\begin{aligned}
&C_1, \quad p(C_1|\mathbf{x}) \geq \theta \\
&C_2, \qquad \text{otherwise}
\end{aligned}
\tag{3}
$$

where θ is the decision threshold.

4

Table 3: Classifier performance using a J statistic threshold for the sex-independent and sex-dependent models including AUROC, accuracy (ACC), specificity (SPEC), and sensitivity (SENS) for the given decision threshold, θ. Any improvements in performance from sex-dependent modeling are minor.

Model	AUROC	θ	ACC	SPEC	SENS
Sex-indep	99.1%	0.461	96.5%	95.4%	98.1%
Female	99.1%	0.464	96.8%	95.3%	98.7%
Male	99.1%	0.601	95.5%	95.6%	95.4%

4.2. Assessment Methodology

We evaluate the Bayesian classifier by applying a threshold to the posterior probabilities from the GMMs and compare the classification decision to the risk ratio based labels in Section 3. We compute this threshold by maximizing Youden's J statistic [13]

$$J = \text{sensitivity} + \text{specificity} - 1 \qquad (4)$$

where the sensitivity and specificity are obtained from the ROC curve. We assess the Bayesian classifier using a Monte Carlo simulation (100 trials) where for each iteration, 80% of the gait vectors are used for estimating the parameters of the GMM and the J statistic threshold. The remaining 20% of the gait vectors are used to validate the model. Each gait vector in the training set is selected using the risk vectors in a stratified resampling technique [13].

5. Results and Discussion

The results from this evaluation are provided in Table 3. For the sex-dependent modeling, we demonstrate an area under the receiver operating characteristic (AUROC) curve of 99.1% with an accuracy, specificity, and sensitivity of 96.8%/95.5%, 95.3%/95.6%, and 98.7%/95.4%, respectively for female/male models. For the sex-independent modeling we demonstrate an AUROC curve of 99.1% with an accuracy, specificity, and sensitivity of 96.5%, 95.4%, and 98.1%, respectively.

After model evaluation we trained the GMMs using all available data and set the J statistic threshold based on an average threshold resulting from the Monte Carlo trials. The final sex-independent model achieved an accuracy of 96.4% and the sex-dependent models achieved an accuracy of 97.0%, 96.8% for the female, male model, respectively. Any improvements in performance from sex-dependent modeling are minor thus there appears to be no benefit to sex-dependent modeling.

Figure 3 shows the 5-D gait vectors projected onto 2-D space for the sex-independent and sex-dependent models. Classification of participants as low falls risk (blue) and high falls risk (red) for each gait vector is determined using the average J statistic threshold.

Perfect agreement between the hard labels from the k-means model and the Bayesian classifier would achieve an AUROC of 100% [13]. Thus the AUROC values in

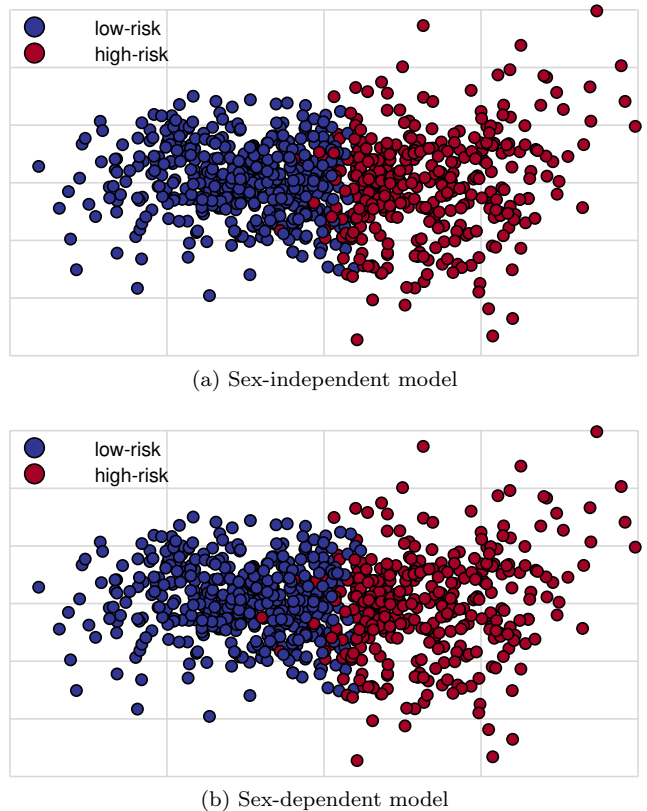(a) Sex-independent model

(b) Sex-dependent model

Figure 3: Scatter plots of the 5-D gait vectors consisting of the gait variables in Table 1 projected onto 2-D space for the sex-independent and sex-dependent models. The markers are assigned membership to the low falls risk (blue) and high falls risk (red) classes using (3) where the posterior probability threshold is given in Table 3. Classification results from the two models are similar with the exception of points near the transition from low to high risk.

Table 3 indicate a high agreement between the risk ratio based hard labels and the GMM based soft labels. Additionally, the AUROC results indicate that the Bayesian classifier effectively classifies the gait vectors according to risk level while the posterior probability provides a measure of uncertainty.

There are at least two limitations of this study. First, our data was collected in a laboratory like setting. Prior research has shown that spatial-temporal gait characteristics are dependent on setting [25] and variability is higher in free-living environments than in a laboratory [26]. Second, self-reported data was used to assess the health of the participants, which has been shown to influence a participant's psychological, cultural status, mood, false and/or forgotten memories, and the social desirability bias [27]. Mitigating strategies incorporated into data collection included the use of anonymity, biased statement avoidance, and the request for truthful responses.

6. Conclusion

In this paper, we have proposed a method for classifying older adults as low or high falls risk using a Bayesian

framework where the posterior probabilities are obtained from a two component GMM. Using gait data collected from a pressure sensitive walkway, we estimated parameters for both sex-independent and sex-dependent GMMs. The advantages of this approach is that low or high falls risk classification is based on an individual's underlying biomechanics while the Bayesian framework provides a measure of uncertainty of falls risk classification.

The proposed method demonstrated good agreement with hard labels based on risk ratios through a ROC curve analysis and a classification accuracy greater than 96% was achieved. The proposed Bayesian classifier could be used to assist clinicians with identifying older adults' falls risk using gait data. This in turn could improve a clinicians' recommendations for intervention for those at risk of falling.

Conflict of Interest Statement

The authors to best of our knowledge, have no conflict of interest, financial or otherwise.

Disclaimer

This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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