Investigation of Gait Characteristics in Glaucoma Patients with a Shoe-Integrated Sensing System

Yuchao Ma[1], Sharon Henry[2], Alex Kierlanczyk[2], Majid Sarrafzadeh[3], Joseph Caprioli[2], Kouros Nouri-Mahdavi[2], Hassan Ghasemzadeh[1], Navid Amini[2]

[1]School of Electrical Engineering and Computer Science
Washington State University, Pullman, WA 99164
yuchao.ma@wsu.edu, hassan@eecs.wsu.edu

[2]UCLA Stein Eye Institute
University of California, Los Angeles, CA 90095
{henry,caprioli,nouri-mahdavi,amini}@jsei.ucla.edu, akierlanc@gmail.com

[3]UCLA Computer Science Department
University of California, Los Angeles, CA 90095
majid@cs.ucla.edu

Abstract—**Many studies have reported that older adults with glaucoma experience mobility issues due to gait difficulties. These include walking slowly and bumping into obstacles, which increase the risk of falls in glaucoma patients. In this paper, we design and develop a shoe-integrated sensing system as well as signal processing and machine learning algorithms to objectively quantify gait patterns in glaucoma patients. The sensor platform was utilized in a randomized clinical trial involving 9 glaucoma patients and 10 age-matched healthy participants performing a series of gait tests. Sensor signals are collected wirelessly and processed on a local computer. With the captured data, we develop data analysis techniques to make a comparison between gait characteristics in older adults with or without glaucoma. Our results demonstrate that the proposed system achieved an accuracy of more than 90% in distinguishing gait patterns of those with glaucoma from healthy individuals for various gait analysis tests.**

***Keywords*— Glaucoma; Accelerometer; Gait Analysis; Classification; Feature Selection**

I. Introduction

Glaucoma is the second leading cause of blindness, from which more than 2.7 million people suffer in the United States [1,2,3]. Approximately 2% of adults over the age of 40 suffer from this condition [2]. Several different types of glaucoma exist with the most common type being Primary Open-Angle Glaucoma (POAG), which has been diagnosed in about one percent of Americans. Patients with POAG often are not aware of the medical condition until the symptoms have advanced significantly that the condition turns into a serious irreversible vision impairment [1].

Due to the high prevalence of glaucoma in older adults, there are numerous studies seeking to gain understanding of the effect of glaucoma on quality of life. A number of studies report that glaucoma patients walk more slowly than age-matched non-glaucoma subjects [2], bump into objects more often, have increased postural sway [18], and they are more prone to falls [4]. However, there is still a lack of a quantitative gait study for glaucoma patients.

Gait analysis has already been adopted in the diagnosis of physical impairments and clinical research, since it can reflect one's mobility, which is affected by changes in health status [5]. A stable gait pattern depends on neuronal spinal and supraspinal pattern generators as well as sensory feedback from visual, vestibular, and proprioceptive systems. The system primarily responsible for dynamic stability in normal walking is the visual system [13]. Nowadays, gait evaluation based on wearable sensor systems avoids the subjective observational interpretations by clinicians or investigators [5]. To be best of our knowledge, this study is the first effort in designing, developing, and validating the utility of mobile wearable sensor technologies for gait analysis in people with glaucoma.

In this study, we establish a series of gait experiments to observe specific gait behaviours of two groups of individuals, healthy and glaucoma subjects, participating in a clinical study that uses our custom-designed wearable motion sensor system for data gathering. Participants in our study wore a shoe-integrated motion sensor system during the gait experiments to acquire temporal and spatial gait measures. We then extracted statistical features from the sensor data and fed these data to machine learning and subject classification. We applied various machine learning methods in order to find significant features or patterns, which distinguish glaucoma patients from healthy subjects.

The rest of this paper is organized as follows. In Section II, we discuss the related research studies in the area of wearable computing, mobility assessment and gait analysis. Section III covers our clinical study details. Section IV presents the procedure and approaches of data processing and data analysis. Section V discusses the result we obtained from our data analysis. We discuss our ongoing effort in the area of gait analysis for patients with visual impairment and introduce future research directions in Section VI. Finally, in the last section, we conclude our current study.

II. Related Work

Studies regarding gait patterns in the visually impaired and in particular, in glaucoma patients are scarce. Several studies reported on the kinematics of locomotion in case of low vision. Nakamura [13] compared step-time parameters of gait in normally sighted, late blind and blind from birth individuals. He concluded that blind individuals had a shorter stride length, slower walking speed, and a prolonged duration of stance.

Another study [15] has performed biomedical analysis of gait patterns for young adults with and without visual impairment, and demonstrated specific differences between these two groups in uncluttered environment.

To record gait information, early studies used clinician's observation, camera [17] or electric mat with pressure sensors [16]. However, such platforms fail in performing detailed measurements and devising kinematic trajectories. Moreover, the measurements are not real-time and they are limited to clinical settings. In light of the proliferation of wearable technologies and the development of various continuous monitoring body sensor networks, many studies adopted or explored sensor-based approaches, which can provide quantitative measurements of gait patterns. In one study [10], the authors developed sensor-based wearable device with integrated gait and balance analyzing algorithms, and conducted walking experiments on Alzheimer's disease patients to explore their gait patterns and postural sway characteristics. In another article [5], the investigators introduced a waist-mounted device with an embedded accelerometer for real-time gait cycle recognition. There are also specific software tools [14] developed to analyze the gait patterns extracted from accelerometer signals.

III. Wearable Sensor Platform and Clinical Study

A. Participants

This study was conducted at the University of California, Los Angeles with the goal of analysing gait patterns of glaucoma patients and investigating whether wearable motion sensors can distinguish gait patterns of such patients and that of healthy individuals. A total of 9 advanced glaucoma patients as well as 10 age-matched normal subjects were recruited and selected to participate in this study. All participants were required to sign an informed consent approved by the University of California, Los Angeles Institutional Review Board (IRB). In order to reduce the interference factors, participants were required to have no significant ocular disease other than glaucoma. Inclusion criteria were age above 40 years and the absence of gait affecting conditions such as fractures and broken bones, as well as neurological impairments (e.g., Parkinson's disease). Exclusion criteria were inability to walk without an assistive device as well as vision impairments that could not be corrected with contact lenses or regular eyeglasses.

Prior to data collection, all participants were informed by the study coordinator regarding the study aim, testing procedure, and testing methods. Subjects completed an eligibility questionnaire regarding physical condition, age, and gender. Normal subjects were recruited by advertising on the UCLA campus and soliciting spouses or friends of patients seen at the Stein Eye Institute's Glaucoma Clinic. All subjects underwent a thorough eye exam on the day of gait assessment and had visual acuity of 20/25 or better.

B. Wearable Shoe-Integrated Motion Sensor

Individual subject completed the gait assessment experiments while wearing the sensor-equipped shoes as shown in Fig. 1. The shoe base platform was appropriately modified to accommodate the two motion sensors. We used internal sensor integrated in the Shimmer (Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability) sensor platform, which is suitable for real-time and wireless motion sensing [8]. The sensor used in this study is a triaxial accelerometer (MMA7260Q) with an adjustable range of ± 1.5g to 6g and a sensitivity of 0.0025g at 4g [9].

Fig. 1 The sensor-equipped shoes with Shimmer® sensor devices

The Shimmer platform collects sensor signals with an integrated MSP430F1611 microcontroller (8MHz, 16bit). The data was captured synchronously from participants' feet through Bluetooth. The sampling rate for the output signals of accelerometer was 102.4Hz, while the sensitivity was set from -2g to +2g in this study. Our choice of Shimmer sensors was to enhance fast prototyping and algorithm development. Our algorithmic contributions and obtained results, however, are independent of the chosen motion sensor.

C. Procedures

The gait experiment included two standard tests, namely, the Timed Up and Go (TUG) test [6] and the 10-Meter-Walk Test [7], as well as an obstacle course test. Each test consisted of three repeated trials, and they were performed in a large and well-illuminated hallway in the Jules Stein building on UCLA campus.

1) Timed Up and Go Test: The TUG test requires both static and dynamic balance and is performed to assess a person's basic mobility skills [6]. To perform one complete trial of the TUG test, subjects were required to rise from an arm chair, walk at a comfortable speed to a line on the floor three meters away, make a pivot turn and walk back to the chair and sit down again. Fig 2 shows the experiment location and setup for the TUG test.

Fig. 2 Timed Up and Go (TUG) test

2) 10-Meter-Walk Test [7]*:* Subjects were asked to walk for 10 meters as straight as possible at their ordinary speed. This test is usually used to assess walking speed as well as to determine gait parameters. The 10-Meter-Walk Test is long enough for the gait behaviour to reach a steady state phase after an acceleration period and before deceleration.

3) Obstacle Course Test: The obstacle course test was built on the 10-Meter-Walk-Test and required subjects to step over and around obstacles. The purpose of the test is to observe how the subjects identify ground-level obstacles and react to them as they walk. The obstacles that need to be stepped over are foam blocks with different heights (2", 4", and 8") and the ones that subjects step around are cones of height 12". Normal subjects are able to walk around the cones safely without loss of balance and changing gait speed.

IV. Data analysis

Our data analysis includes pre-processing and calibration, signal segmentation, feature extraction, feature selection, and classification. Data collected by each accelerometer is required to undergo certain signal processing defined by the application. The purpose of signal processing is to reduce complexity of raw data and extract useful information specified by the application. An example of per-node signal processing for gait classification is shown in Fig. 3. During data collection, the Shimmer's processor samples the accelerometer signal. After calibration, the signal is fed into the segmentation block to split into same size of sample points for the feature extraction. Statistical attributes that are generated during feature extraction are used to train various classifiers to distinguish between glaucoma and healthy subjects.

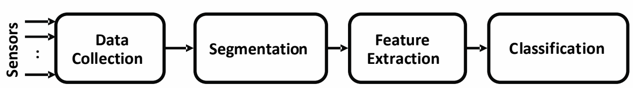

Fig. 3 Overview of data analysis procedure

A. Pre-Processing

The sensor signals captured by our wearable platform are first calibrated. The purpose of calibration is to reduce the drift error and offsets from the raw signals [10]. We then proceed with the following two steps to complete our pre-processing prior to extracting statistical features from the motion sensor signals.

Step 1: Calculation of the Signal Vector Magnitude (SVM) of acceleration signals obtained from the two shoe-integrated sensing systems. The SVMs reveal the degree of movement intensity in each gait test [10]. The calculation is based on the following equation:

$$SVM(t) = \sqrt{x^2(\mathrm{t}) + y^2(\mathrm{t}) + z^2(t)}. \qquad (1)$$

Here x(t), y(t) and z(t) indicate the acceleration along the x, y, and z axes at time t.

Step 2: Segmenting acceleration signals by means of sliding windows. The acceleration signals along the three directions and the corresponding SVM signal were all segmented and annotated for each trial of the three gait tests. The sliding windows were chosen to have 400 sample points (approximately 4s) with an overlap of 102 sample points (1s). This step yields smaller signal segments ready for obtaining statistical features.

B. Feature Extraction

The Statistical features were extracted from pre-processed data. We extract statistical features from the segmented overlapping signals. For the current study, ten types of features were extracted to distinguish between glaucoma patients and healthy subjects. These features are listed in Table I. All features were computed for both feet, three axes and the SVM signal. Hence, a total of 80 features were extracted for each trial of the three gait tests.

TABLE I
Ten Types of Statistical Features Extracted in This Study

No.	Feature	Description
1	Max	The maximum value among all the sample points in the window
2	Min	The minimum value among all the sample points in the window
3	Mean	The average value of all the sample points in the window
4	Median	The median value of all the sample points in the window
5	Range	The difference between the maximum and minimum values in the window
6	Amplitude	The difference between the maximum and mean values in the window
7	Variance	Measures the spreading range of sample points in the window
8	Standard Deviation	Measures the amount of variation from the average value of sample points in the window
9	RMS	Root Mean Square measures the average magnitude of all the sample points
10	Start-to-End	The difference between the value of the first sample point and the last sample point in the window

C. Feature Selection

Correlation-based Feature Selection [12] combined with Best-First Search strategy was used in the process of feature selection to choose the most prominent features from all the 80 available features.

We used the WEKA (Waikato Environment for Knowledge Analysis [11]) data mining package for feature analysis and classification. The feature selection algorithm reduced the number of features by considering each feature's individual predictive ability as well as the degree of redundancy between them [12].

For each gait test discussed in Section III-C, we combined the statistical feature samples of all the three trials, and then ran the Best-First Search feature selection algorithm. We then only used those selected features to train the classifier, and compared the classification accuracy with the result obtained via approaches described in next sub-section. As it will be discussed later, the feature selection algorithm improves the accuracy of the machine learning algorithm for all the gait tests.

D. Classification

Four different classifiers were trained in this study, namely, Decision Tree, Naïve Bayes, Logistic Regression, and Nearest Neighbour. The integrated machine learning algorithms in WEKA performed the training. Since we conducted three repeated trials for each gait test, the classification accuracy were assessed with two distinct approaches for each gait test, as described below.

1) *10-Fold Cross-Validation:* In this approach, we gathered the data from three repeated trials for each gait test, and then trained four different classifiers with this dataset. The number of statistical feature samples for each trial is listed in Table II. The overall size of statistical feature samples for each gait test is adequate for training the classifiers we chose. The accuracy of classification is evaluated through a 10-fold cross-validation method.

2) *Supplied Test Set:* In this approach, we first combined the data from first and second trials in each gait test, and then trained the classifier with this combined data set. Then, we used the statistical feature samples from the third trial as a supplied test set to evaluate the classification accuracy. This approach provided smaller training data than the 10-fold cross-validation method, however, it had a larger independent testing set, which could lead to a more accurate assessment of classifiers' performance. Since the subjects repeated the same movements in the three trials, the combination of these statistical feature samples will likely not affect their gait patterns.

TABLE II
SIZE OF STATISTICAL FEATURE SAMPLES FOR EACH TRIAL

Gait Test	Trial 1	Trial 2	Trial 3	Overall
Timed Up and Go	214	198	177	589
10-Meter-Walk	156	168	156	480
Obstacle Course	308	258	271	837

V. RESULTS

Table III below summarizes the demographics of our study participants.

TABLE III
CHARACTERISTICS OF STUDY PARTICIPANTS

Parameters	Glaucoma Subjects	Normal Subjects	p-value
Gender (M/F)	4/5	3/7	0.541
Age (years)	63.7 ± 8.57	60.7 ± 4.99	0.363
Height (cm)	168.73 ± 7.13	161.96 ± 8.43	0.078
Weight (kg)	71.08 ± 11.26	69.52 ± 15.48	0.807
BMI (kg/m^2)	24.84 ± 2.61	26.29 ± 4.20	0.385

We performed Analysis of Variance (ANOVA) test for each demographic features to compare the differences of the mean value between two groups. The common significant difference will be concluded, if the p-value resides between 0.05 and 0.01. However, the results listed in Table III revealed that the two groups of subjects have no significant difference in the means according to these demographic features.

A. *Classification Results with Original Features*

We first trained the four classifiers for each gait test based on all the statistical feature samples extracted from the acceleration signals. The classification accuracy was assessed for each gait test by 10-fold cross-validation. Fig. 4 illustrates the classification accuracy for this approach, while Table IV presents the detailed classification results of each classifier for each gait test.

In Table IV, TP Rate and FP Rate indicate the True Positive and False Positive rates for the glaucoma group. One can observe from the table that Decision Tree and Nearest Neighbour Classifiers deliver good performance in all the three gait tests.

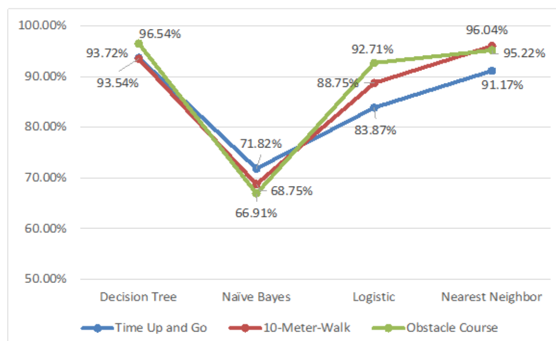

Fig. 4 Classification Accuracy with 10-Fold Cross-Validation

Table V shows the classification results when all classifiers were fed with the supplied test set for the three gait tests. Similar to the 10-fold cross-validation results, Decision Tree Classifier and Nearest Neighbour exhibit higher accuracy than Naïve Bayes and Logistic Regression classifiers. However, the overall accuracy is lower than the 10-fold cross-validation method, as a result of a smaller training set than 10-fold cross-validation.

TABLE IV
CLASSIFICATION RESULT USING 10-FOLD CROSS-VALIDATION

Gait Test		Decision Tree	Naïve Bayes	Logistic Regression	Nearest Neighbor
Timed Up and Go	Accuracy	93.72%	71.82%	83.87%	91.17%
	TP Rate	93%	51.4%	83.9%	88.5%
	FP Rate	5.6%	8.9%	16.2%	6.3%
10-Meter-Walk	Accuracy	93.54%	68.75%	88.75%	96.04%
	TP Rate	92.7%	90.1%	87.6%	97%
	FP Rate	5.7%	51.4%	10.1%	4.9%
Obstacle Course	Accuracy	96.54%	66.91%	92.71%	95.22%
	TP Rate	97%	45.8%	93.9%	95.6%
	FP Rate	3.9%	11%	8.6%	5.1%

TABLE V
CLASSIFICATION RESULT USING SUPPLIED TEST SET

Gait Test		Decision Tree	Naïve Bayes	Logistic Regression	Nearest Neighbor
Timed Up and Go	Accuracy	90.40%	71.75%	76.27%	88.14%
	TP Rate	89.4%	45.9%	72.9%	89.4%
	FP Rate	8.7%	4.3%	20.7%	13%
10-Meter-Walk	Accuracy	81.41%	64.10%	73.08%	92.31%
	TP Rate	77.3%	72%	74.7%	96%
	FP Rate	14.8%	43.2%	28.4%	11.1%
Obstacle Course	Accuracy	87.08%	63.84%	80.07%	88.56%
	TP Rate	94.1%	38.5%	81.5%	93.3%
	FP Rate	19.9%	11%	21.3%	16.2%

B. *Classification Results with Feature Selection*

In this step, the classifiers were trained only with the most relevant statistical features selected by the Best First Search algorithm [12]. There were 23 features selected for the Timed Up and Go test, including the maximum value, minimum value, mean value, median value, range and amplitude of the acceleration signals along x axis, y axis, z axis as well as the SVMs. 10 of the selected features were related to the signals from the accelerometer attached to participant's left shoe, while 13 were related to the signals from the accelerometer on the right shoe.

For 10-Meter-Walk test, we selected 11 highly correlated statistical features, which were mainly related to the minimum value, mean, median, and range of acceleration signals along x-, y-, and z- axes, as well as the maximum value of the SVM. There were 7 features extracted from the acceleration signals related to left foot, while 4 features were related to right foot.

For the obstacle course test, only 10 features were selected by the Best First Search algorithm. 7 of these features were associated with the left foot, namely, maximum, mean, and median of the acceleration signal along the x axis, median and range of the acceleration signal along the y axis, median of z axis acceleration signal, and the variance of the SVM. 3 features were related to the right foot. Those included the median and amplitude of the x axis acceleration signal and range of y axis acceleration signal.

We trained four classifiers for each gait test with the selected feature subset, and evaluated their performance via 10-fold cross-validation. The classifier with the highest accuracy for each gait test is listed in Table VI. As it can be observed, utilizing the optimal feature set will lead to an overall increase in accuracy.

TABLE VI
CLASSIFICATION RESULT TRAINED WITH SELECTED FEATURES

Gait Test	Features	Best Classifier	Accuracy	TP Rate	FP Rate	Precision
Timed Up and Go	L-Acc (max_x, $mean_x$, $median_x$, $range_x$, amp_x, $mean_y$, max_z, $range_z$, min_{SVM}, $mean_{SVM}$), R-Acc (min_x, $mean_x$, $median_x$, $range_x$, $median_y$, $range_y$, amp_y, max_z, $median_z$, $mean_z$, amp_z, max_{SVM}, min_{SVM})	Decision Tree	95.58%	95.8%	4.6%	95.1%
10-Meter-Walk	L-Acc ($mean_x$, min_x, $range_x$, max_y, $median_y$, $mean_z$, $median_z$), R-Acc (min_x, $median_y$, $median_z$, max_{SVM})	Nearest Neighbor	97.29%	97.4%	2.8%	97%
Obstacle Course	L-Acc (max_x, $mean_x$, $median_x$, $median_y$, $range_y$, $median_z$, var_{SVM}), R-Acc ($mean_x$, $range_x$, $median_y$)	Nearest Neighbor	98.57%	99.3%	2.2%	97.9%

VI. DISCUSSION AND FUTURE WORK

Active visual sensory feedback has an important role during locomotion in the maintenance of gait stability. Glaucoma-related visual field loss occurs more frequently in the upper hemifield, which is not the hemifield that intuitively would have a larger impact on legged locomotion. Nevertheless, the facts that patients with glaucoma walk more slowly [19], bump into objects more often [20], demonstrate increased postural sway [18], and fall two times as often as those without glaucoma [19] imply that gait disturbances are likely to occur as glaucoma progresses.

In this study, we showed that glaucoma-related visual field loss might have a direct effect on the structure of statistical features of the acceleration signal from walking, which provides us with a more clear view of which gait parameters could be affected by glaucoma-related visual field loss. One immediate implication of our preliminary results is that machine learning techniques may be used for assessing gait patterns in the visually impaired and in particular, glaucoma patients. Early detection of locomotion impairments via supervised pattern recognition techniques would provide the opportunity to identify at-risk gait and initiate corrective measures to, e.g., identify potential elderly fallers and develop fall prevention programs.

We are developing more advanced signal processing and machine learning techniques to measure various gait parameters from the accelerometer signals. We plan to segment dynamic interval and static interval for each gait cycle and further decompose the dynamic interval to acquire more detailed gait parameters corresponding to the pace, cadence, walking velocity, foot elevation, and other relevant measures. With thorough and in-depth gait analysis, we can design accurate classifiers to detect early glaucoma-related locomotion impairments. We have already employed a more advanced shoe-integrated sensing system equipped with pressure and optical proximity sensors in order to directly measure more complex gait parameters that are usually estimated in existing research studies. We are also investigating how upper body sway correlates with gait parameters in patients with visual impairment. Our goal is to examine feasibility of using pervasive mobile devices such as smartphones to continuously measure body sway and use that measure for fall risk reduction. Last but not least, we plan to incorporate angular eye and head movement measurements into our analysis.

One shortcoming of our study is the limited number of participants. We are actively recruiting subjects to acquire more data for our classifiers. A larger dataset would allow us to examine the statistical significance of the obtained results. Another criticism of our work is that glaucoma patients suffer from a wide range of visual field damage; however, we simply placed all of the glaucoma subjects in one group. It has been shown that primary open angle glaucoma and normal tension glaucoma, as two common types of glaucoma, exhibit different field loss patterns. With a larger cohort, we will be able to perform fine grain analysis and relate local visual field defects [21,22] as well as other visual performance measures, such as visual acuity, contrast sensitivity, light adaptation, color vision, and depth perception to gait disturbances.

VII. CONCLUSIONS

In this paper, we presented an inertial-sensor-based study to distinguish glaucoma patients with healthy controls using quantitative measurements of their gait patterns, and also to explore essential statistical features based on comparison of glaucoma patients and healthy individuals via machine learning approaches. We collected acceleration signals during a series of gait tests, and the steady-state gait features of individuals were used to train a learning algorithm to automatically recognize glaucoma and normal gait patterns. Our results demonstrated that two sensors mounted on subject's feet can be used to obtain more than 90% accuracy in distinguishing glaucoma patients from healthy subjects.

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