Microprocessors and Microsystems 46 (2016) 67–74

Contents lists available at ScienceDirect

Microprocessors and Microsystems

journal homepage: www.elsevier.com/locate/micpro

Wearable sensors for gait pattern examination in glaucoma patients

Yuchao Ma[a,*], Navid Amini[b], Hassan Ghasemzadeh[a]

[a] School of Electrical Engineering and Computer Science, Washington State University, Pullman, WA 99164, USA
[b] UCLA Stein Eye Institute, University of California, Los Angeles, CA 90095, USA

ARTICLE INFO

Article history:
Received 14 December 2015
Revised 15 June 2016
Accepted 7 July 2016
Available online 9 July 2016

Keywords:
Glaucoma
Gait analysis
Wearable sensor
Machine learning

ABSTRACT

This paper presents a wearable wireless sensor system designed for real-time gait pattern analysis in glaucoma patients. Many clinical studies have reported that glaucoma patients experienced mobility issues such as walking slowly and bumping into obstacles frequently. The gait attributes of glaucoma patients, however, have not been studied in the literature. We design and develop a shoe-integrated sensing system for objective bio-information collection, utilize signal processing algorithms for feature estimation and leverage machine learning as well as statistical analysis approaches for gait pattern examination. The developed sensor platform is utilized in a randomized clinical trial conducted at UCLA Stein Eye Institute with 19 participants. Our trial involved both glaucoma patients and age-matched healthy participants performing a series of gait tests. With the captured sensor data, we develop signal processing and machine learning algorithms to provide a quantitative comparison between gait characteristics in older adults with and without glaucoma. Our results demonstrate that machine learning algorithms achieve an accuracy of over 80% in distinguishing extracted gait features of those with glaucoma from healthy individuals. Our results also demonstrate significant difference between two groups based on extracted gait features. In particular, several features are highly discriminative with a p-value of less than1×10^{-10}.

1. Introduction

Glaucoma is the second leading cause of blindness, and approximately 2% of adults over the age of 40 suffer from this condition [5–7]. The estimation shows that the prevalence of glaucoma in the world will increase to 79.6 million by 2020 [7]. 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 where the condition turns into a serious irreversible vision impairment [5].

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 reported that glaucoma patients walk more slowly than non-glaucoma subjects [6], bump into objects more often, have increased postural sway [8], and they are prone to fall [9].

Logan et al. [4] have reported that vision plays multiple roles during locomotion, such as gait cycle modulation, navigation, and obstacle avoidance, which are reflected in the dynamics of trunk control. Moreover, a number of studies proved that vision has various effects on gait patterns [3,14]. Therefore, visual impairment has inevitable effects on individual's gait behavior. Although the relationship between glaucoma and quality of life has been established in many papers, there is still a lack of a quantitative gait analysis for glaucoma patients.

Gait analysis is the systematic study of human locomotion [1]. It has already been adopted in the diagnosis of physical impairments as well as monitoring the rehabilitation progress, since it can reflect one's mobility [[1], [2]]. A stable gait pattern depends on neuronal spinal and supra spinal 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 [3].

Several studies reported on the kinematics of locomotion in case of low vision. Nakamura [14] 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 [11] 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.

In this study, we collected quantitative gait information in real-time and carried out gait analysis for subjects with glaucoma

* Corresponding author.
E-mail addresses: yuchao.ma@wsu.edu (Y. Ma), amini@jsei.ucla.edu (N. Amini), hassan@eecs.wsu.edu (H. Ghasemzadeh).

http://dx.doi.org/10.1016/j.micpro.2016.07.001
0141-9331/

disease. We established a series of gait experiments to observe specific gait patterns of two groups of individuals, namely healthy and glaucoma subjects, participating in our clinical study [32]. Participants were required to wear a custom-designed shoe-integrated motion sensor system during the gait experiments to acquire temporal and spatial gait measures.

We then extracted statistical features from automatically segmented sensor signals and trained several machine learning models with these features for the purpose of classification. Machine learning algorithms have already been adopted in the area of smart health as an assistive indicator in detection and diagnosis of many conditions [35]. Leveraging machine learning algorithms to identify glaucoma patients based on gait patterns offers an objective and practical method to automatically assess one's eye condition through simple tasks, such as normal walking, which can be carried out by non-specialist in daily life.

We further applied feature selection algorithm to identify predictable features, and performed statistical analysis over the selected features to further compare the difference in gait patterns between glaucoma patients and healthy controls.

The main contributions of this paper are (1) we design and develop an approach for glaucoma identification through gait analysis using wearable sensors, and evaluate its effectiveness via clinical experiments on glaucoma patients; (2) we demonstrate the potential of machine learning techniques to distinguish glaucoma patients from healthy controls according to their gait behaviors; (3) we perform statistical analysis to highlight highly discriminative gait features between people with and without glaucoma.

The rest of this paper is organized as follow. In Section 2, we discuss the related research studies in the area of wearable computing, mobility assessment and gait analysis. Section 3 introduces our system architecture and data analysis approaches. Section 4 covers clinical experimental design as well as participants' demographics. Section 5 presents and discusses the results of applying machine learning algorithms and statistical analysis on extracted features. Section 6 discusses the potential of our study and introduces our ongoing effort in the area of gait analysis for patients with visual impairment and the future research directions. Finally, we conclude our current study in Section 7.

2. Related work

Machine learning techniques have already been adopted in glaucoma type classification [21] as well as glaucoma detection at latter stage [22–24]. However, the studies regarding gait information in visually impaired individuals and particularly, in glaucoma patients are scarce.

To record gait information, early studies used clinician's observation, reflective markers and camera [11,12,14] or electric mat with pressure sensors [13]. Nakamura and colleagues [14] have placed reflective markers over eight distinct places on the body of visually impaired subjects during the 10-Meter-Walk experiment, and a motion analyzer system was used to record the trajectories of the markers. In another study [11], automated infrared camera and reflective markers were also used in a gait pattern analysis of 10 young adults with a visual impairment and 20 age-matched controls. The results demonstrated the difference between the young adults with and without vision impairment for locomotion control in uncluttered environment.

Even though these approaches could digitally record gait patterns precisely with low noise, they require a controlled laboratory environment and usually expensive to set up.

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

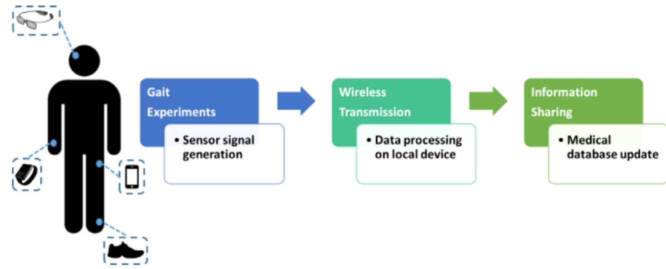

Fig. 1. Gait study using wearable sensing systems.

for human movement monitoring, which can provide flexible and quantitative measurements of gait patterns.

In one study [16], authors developed a 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 study [2], two accelerometers were used to measure the acceleration patterns of the head and pelvis during the walk for the elderly. Their results showed the difference in the movement of head, hip and leg during the walk, as well as variability in steps between older people who fell frequently and who did not. In [17], authors developed a smartphone application, which captures the subject's movements through built-in motion sensors, determines the time interval of a standard gait test and quantifies its individual phases. The test descriptors can be optionally uploaded into a medical database.

In addition to accelerometers and gyroscopes, many other types of wearable wireless sensors were involved in the studies for human movement analysis. Bamberg and etc. [18] introduced a shoe-integrated sensor system providing a quantitative gait analysis approach. Besides motion sensors, their system also included force sensors, bend sensors, dynamic pressure sensors, and electric field height sensors. Another study [19] utilized the signals generated from force sensing resistor and accelerometer during a 6-Meter-Walk experiment performed in a laboratory condition. The signals were taken as input and then trained a neural network classifier to determine the gait phases of stance and swing. In another study [20], the authors designed and developed a real-time gait phase detection system with three force sensitive resistors taped on the shoe insole, and one gyroscope attached to the posterior aspect of the shoe. Their experiment result demonstrated the system's high capability of gait phase detection with an accuracy of over 99%.

3. System architecture and data processing

Fig. 1 shows the general architecture of gait analysis using wearable sensing systems. The biophysical information is collected using various sensor-embedded equipment during gait experiments, then wirelessly transmitted to a local computer or smartphone for signal processing and data analysis, and the result is automatically sent to the physician for future examination, or uploaded to private medical database.

For this experimental study, we use shoe-based wearable system for motion monitoring and gait analysis. The signals collected using wireless sensors are transmitted, in real-time, to a local computer via Bluetooth. We then perform data analysis off-line. The following text in this section introduces our motion sensor platform and data analysis approach in detail.

3.1. Motion sensor platform

We designed a shoe-based wearable sensor platform for real-time gait monitoring, as shown in Fig. 2. This platform consists of a

Fig. 2. The sensor-equipped shoes with Shimmer® sensor devices.

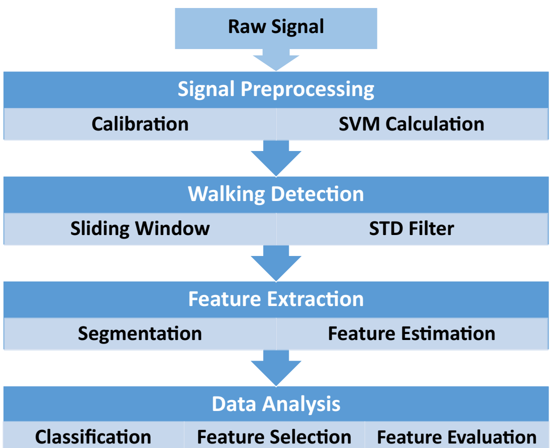

Fig. 3. Data processing workflow.

motion sensor integrated in the Shimmer (Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability) sensor device, which is suitable for real-time and wireless motion sensing [25]. The motion sensor used in this study is a triaxial accelerometer (MMA7260Q) with an adjustable range of $\pm$ 1.5 g–6 g and a sensitivity of 0.0025 g at 4 g.

This motion sensor platform collects acceleration signals with an integrated MSP430F1611 microcontroller (8 MHz, 16bit) in the Shimmer device. In the experiments, the data is captured synchronously from participants' feet through Bluetooth using a custom MATLAB interface. The sampling rate is programmable. In this study, we used a sampling rate of 102.4 Hz for the output signals, and the sensitivity range was set to $\pm$ 2 g. One should note that our algorithmic contributions and the obtained results are independent of the chosen motion sensor.

3.2. Data processing

Our data processing approach includes four major procedures, namely signal pre-processing, walking detection, feature extraction and data analysis, as it is shown in Fig. 3.

During data collection, the Shimmer's processor samples the accelerometer signals. After pre-processing, the signal segment approximately referring to walking activity is detected using a sliding window and standard deviation (STD) filter [34]. This walking segment is then fed into the segmentation block to split into same size of sample points for feature extraction. Statistical attributes that are generated during feature estimation are used to train various classifiers to distinguish between glaucoma and healthy subjects. The discriminability of these features is further analyzed to seek for possible impact of glaucoma disease on individual's gait patterns.

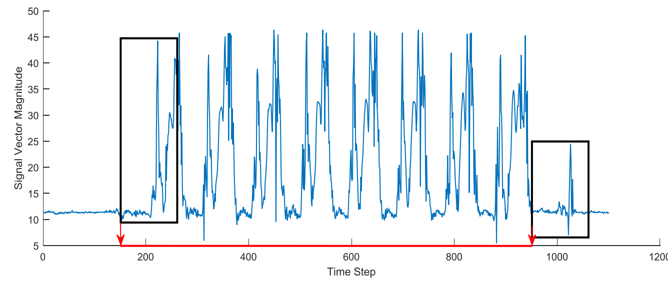

Fig. 4. Walking detection on SVM signal for one trial in 10-Meter-Walk test. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2.1. Signal 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]. It then calculates the signal vector magnitude (SVM) from the three axial accelerometer readouts following the equation below:

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

Here x(t), y(t) and z(t) indicate the acceleration along the x, y, and z axes at time t. The SVMs reveal the degree of movement intensity in each gait test [10]. The plot in Fig. 4 shows the SVM of left foot acceleration in a 10-Meter-Walk test.

3.2.2. Walking detection

This procedure first approximately determines the start and the end sample point of a continuous gait behavior using a size-fixed window sliding from the beginning of the signal sequence to the end [36]. According to previous study [33], human stride frequency is minimal 1 Hz, which indicates that at least one gait cycle is recorded in the signal samples for every second during the walk. Therefore, the size of the sliding window is set as 110 samples (roughly 1 s) with an overlap of 50 samples.

The standard deviation (STD) is calculated over all the samples for each window. In one SVM signal sequence, the first window with STD value larger than a given threshold is considered as the start window of walking activity; and hence, the first sample point in this window is selected as the start point. In this study, we used an empirical value as the threshold to determine the significant change of acceleration signals inside the window, which implied the start of walking behavior.

After the start window been settled, the first window with STD value dropping below the same threshold is considered as the ending window of that walking activity; and the first sample point in this window is selected as the ending point.

The two rectangles in Fig. 4 indicate the automatically selected start window and ending window, and the red segment defined by the first sample points of those two windows is the output of walking detection procedure, which covers the sample points regarding to the continuous gait behavior in the sensor signal.

3.2.3. Feature extraction

With the start and the end sample points of walking activity detected in SVM signal, the time step of these two sample points are utilized to find the continuous gait signal in the original three axial accelerometer readouts. Then, two steps are proceeded to extract useful features from tri-axial acceleration signals.

Table 1
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

Step 1: Segmentation. Acceleration signal regarding to walking activity is divided into segments with size 110 samples (1 s) without overlapping. This step yields smaller signal segments ready for obtaining statistical features.

Step 2: Feature estimation. The statistical features are estimated based on samples in each segment obtained from previous step. In this study, ten types of steady-state feature are extracted to study the differences in gait pattern between glaucoma patients and healthy subjects. These features are listed in Table 1. All features are computed for three axes, which results in a total number of 30 features for signal foot in each trial of a gait test.

3.2.4. Data analysis

To provide a comprehensive investigation in extracted features for glaucoma patients, the data analysis procedure consists of three major approaches, namely classification, feature selection and feature evaluation.

Classification: In order to seek for a learning algorithm that can distinguish glaucoma patients from normal individuals in an accurate manner, we first trained four commonly used classifiers, namely, Decision Tree, Nearest Neighbor, Logistic Regression and Naïve Bayes. The integrated machine learning algorithms in WEKA (Waikato Environment for Knowledge Analysis [28]) performed the training.

According to the empirical analysis and experimental results, we chose 10-fold cross validation to assess the classification accuracy. As it will be introduced in Section 4.2, each gait test contained three repeated trials. We first gathered statistical feature samples extracted from all three trials for each gait test. Then, we used 10-fold cross-validation to evaluate the classification accuracy. This approach provided adequate training samples for supervised learning as well as enough test cases to effectively reflect the accuracy of classification results.

Feature selection: Correlation-based feature selection algorithm [29] combined with Best-First Search strategy was used in the process of feature selection to choose the most prominent features from all the 30 available features. We used the WEKA 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 [29].

Table 2
Characteristics of study participants.

Parameters	Glaucoma subjects	Healthy 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

Feature evaluation: To quantitatively investigate the difference in gait patterns between people with and without glaucoma, we used analysis of variance (ANOVA) test on individual features selected in previous step. As the common criteria, a p-value less than 0.05 indicates there is significant difference in the feature instances between two groups. We further compared the average value and standard derivation for those distinguished features to depict the abnormality of gait behavior for glaucoma patients.

4. Experimental design

4.1. Participants

This study was conducted at Stein Eye Institute of University of California, Los Angeles with the goal of analyzing gait patterns of glaucoma patients and investigating whether wearable motion sensors can distinguish between gait patterns of such patients and those of healthy individuals. A total of 9 advanced glaucoma patients as well as 10 age-matched healthy subjects were recruited 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).

To reduce the interference factors, participants were required to have no significant ocular disease other than glaucoma. Inclusion criteria were age above 40 years, visual acuity of 20/25 or better, 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 co-existing vision impairments (e.g., macular degeneration) that could not be corrected with contact lenses or regular eyeglasses. In current study, recruited glaucoma patients were on the advanced stage.

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. Healthy 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.

Table 2 summarizes the demographics of the study participants. We performed ANOVA test for each demographic characteristic to compare the differences of the mean value between two groups. The common significant difference was concluded if the p-value resided between 0.05 and 0. However, the results listed in Table 2 revealed that there was no significant difference between the means of the two groups.

4.2. Procedures

The gait experiment included two standard tests, namely, the Timed Up and Go (TUG) test [26] and the 10-Meter-Walk test [27], as well as a designed obstacle course test [15]. The effectiveness of the first two standard tests on gait analysis has already been established in earlier studies [26,27]. Each test consisted of three repeated trials, and they were performed in a large

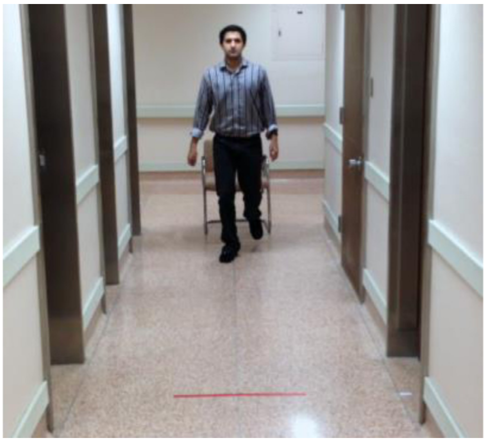

Fig. 5. Timed Up and Go (TUG) test.

and well-illuminated hallway in the Jules Stein building on UCLA campus.

4.2.1. Timed Up and Go (TUG) test

The TUG test [26] requires both static and dynamic balance and is performed to assess a person's basic mobility skills. In one complete trial of the TUG test, subjects are 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. 5 shows the experiment environment and process for the TUG test.

4.2.2. 10-Meter-Walk test

In this test, subjects are asked to walk for 10 m 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 behavior to reach a steady state phase after an acceleration period and before deceleration [3].

4.2.3. Obstacle course test

The obstacle course test is built on the 10-Meter-Walk test and requires subjects to step over and around ground-level obstacles. In addition to observe subject's normal gait pattern as the major function of 10-Meter-Walk test, obstacle course also provides an assessment of subject's capability for obstacle identification and avoidance during the walk, in which activity that visual feedback plays an important role. The design idea of this test is from the indoor test [15] for mobility performance assessment, which is used to observe individual's walking behavior while avoiding obstacles.

In this study, 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.

It is worth mentioning that 10-Meter-Walk test contains only normal gait behavior, while the other two tests involve multiple movements, such as pivot turn or moving across ground obstacles, which occur in daily living movements. Although the data collected in the former test is expected to be more accurate for gait pattern estimation, in natural scenario, people may have slight pause, veer, or stagger during the walk without awareness, which can introduce extra noise in sensor data. Therefore, we are interested in comparing the performance of machine learning algorithms in distinguishing glaucoma patients with healthy subjects under several scenarios.

Table 3
Definition of classification evaluation measures.

Measures	Definition
Accuracy	The percentage of correct labeled instances
Recall	The ratio of number of correctly classified glaucoma samples to the total number of real glaucoma samples
Precision	The ratio of number of correctly classified glaucoma samples to number of all the classified glaucoma samples
ROC area	Shows the relationship between false positive rate and true positive rate

Table 4
Size of statistical feature instances for each experiment.

Gait test	Left foot	Right foot
Timed Up and Go	403	420
10-meter-walk	535	532
Obstacle course	778	765

5. Results

5.1. Classification results

Except for classification accuracy, we took account of another three evaluation measures to provide a more thorough comparison of each classifier's performance, as well as the robustness of the statistical samples extracted from different gait tests. These measures included recall, precision and area under the receiver operating characteristic (ROC) curve, as it listed in Table 3.

We first gathered the statistical feature instances for all three trials of each gait test, then we trained four classifiers to distinguish glaucoma patients from healthy controls based on these feature instances. The classification accuracy was assessed by 10-fold cross-validation method for each gait test.

Table 4 summarizes the number of feature instances for different gait tests. Since all the subjects were required to repeat the same trial for three times, the combination of these feature instances will likely not affect their gait patterns.

Table 5 presents the detailed performance of each classifier according to the acceleration of different feet in three different gait tests. One can observe from Table 5 that Decision Tree achieved the best performance overall with an average accuracy of over 80% for 10-Meter-Walk test and obstacle course test. The possible reasons for a relatively low accuracy of TUG test will be discussed shortly in this section.

Although the other three classifiers did not identify glaucoma patients accurately, it is not sufficient to consider the feature instances between these two groups are indiscriminative, because the signal segmentation was proceeded in an approximate manner that could introduce gait irrelevant noise to the extracted features. What's more, different learning algorithms have distinct mechanisms. For example, Naïve Bayes classifier assumes independency among all the features over the instances. Nevertheless, this assumption does not hold in this dataset, since some statistical features, such as maximum, minimum and range, have direct interrelations that leads to overestimated weight parameters. Therefore, the accuracy of Naïve Bayes is the lowest compare with another three classifiers.

In addition to the comparison across different learning algorithms, we were also concerned about the effectiveness of biophysical gait data collected during different experiments. Fig. 6 shows the classification results of three gait tests using Decision Tree and Nearest Neighbor algorithms. The accuracy based on the data collected in 10-Meter-Walk test was the highest overall. The average accuracy of both feet was 80.33% using Decision Tree algorithm

Table 5
Classification results trained by thirty statistical feature.

Gait test	Measures	Decision Tree		Nearest Neighbor		Logistic Regression		Naïve Bayes	
		Left	Right	Left	Right	Left	Right	Left	Right
Timed Up and Go	Accuracy	73.20%	66.43%	64.27%	65.48%	60.55%	57.86%	61.04%	53.57%
	Recall	67.10%	63.80%	61.50%	64.50%	57.80%	57.60%	56.20%	54.50%
	Precision	83.50%	72.80%	62.80%	66.00%	57.40%	53.40%	74.50%	32.50%
	ROC area	73.20%	73.30%	64.20%	65.50%	64.50%	64.90%	62.40%	59.20%
10-Meter-Walk	Accuracy	79.63%	81.02%	79.81%	76.88%	69.53%	59.96%	53.27%	54.14%
	Recall	78.10%	80.80%	79.10%	74.10%	67.90%	58.50%	53.20%	52.60%
	Precision	80.20%	79.20%	79.10%	79.60%	69.80%	56.90%	26.00%	43.50%
	ROC area	82.20%	82.10%	79.80%	77.00%	75.00%	65.20%	59.40%	56.20%
Obstacle course	Accuracy	80.33%	81.18%	70.18%	67.32%	68.00%	67.32%	64.52%	56.34%
	Recall	79.20%	79.40%	69.80%	66.90%	67.10%	67.00%	59.40%	56.90%
	Precision	82.20%	82.40%	70.90%	64.10%	70.40%	63.80%	91.00%	40.00%
	ROC area	81.80%	83.80%	70.20%	67.20%	76.40%	74.00%	72.30%	63.80%

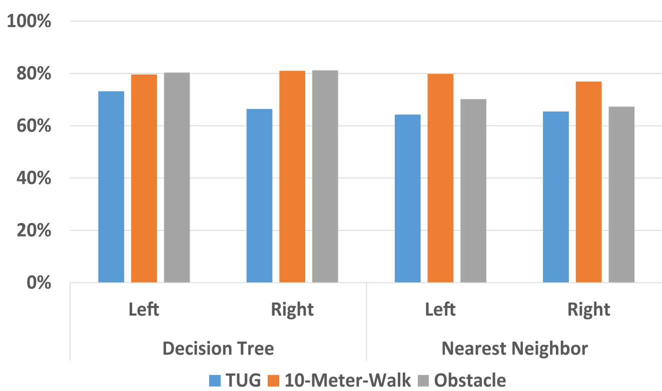

Fig. 6. Classification results comparison among three gait tests.

and 78.35% using Nearest Neighbor algorithm. One possible reason is 10-Meter-Walk test only contained normal walking activity, and hence the extracted features had relatively pure and consistent values.

However, TUG test included the movements other than normal walking, such as pivot turn, which could introduce irregular data in the signal sequence. Therefore, the average accuracy of both feet based on the data collected in TUG test was less than 70% using Decision Tree algorithm and less than 65% using Nearest Neighbor algorithm.

Obstacle course test also required extra movement, like stepping across the ground obstacles, during the normal walk. But because the obstacles used in our clinical study were not sufficiently tall for safety considerations, the difference in foot acceleration between lifting one foot to across the obstacle and lifting to make a step is not dramatic. As a result, gait features extracted from the data collected in obstacle course test had a higher classification accuracy than it collected in TUG test.

5.2. Feature selection results

For each gait test discussed in Section 4.2, we combined the statistical feature instances of all the trials and ran the correlation-based feature selection algorithm. Among 30 original features, a total number of 13 distinct features were selected. 6 features were selected according to the data collected in TUG test; 11 were selected according to the data collected in 10-Meter-Walk test; and 11 features were selected according to the data collected in obstacle course test.

Table 6 lists all the selected features based on three acceleration directions. It indicates that maximum, minimum, median and amplitude are the highly predictable features, which represent the

Table 6
Selected features for individual signal directions.

Signal direction	Selected features
Anterior-posterior (x-axis)	Maximum, minimum, median, mean, range, amplitude
Medio-lateral (y-axis)	Maximum, minimum, median, amplitude
Vertical (z-axis)	Maximum, median, root-mean-square

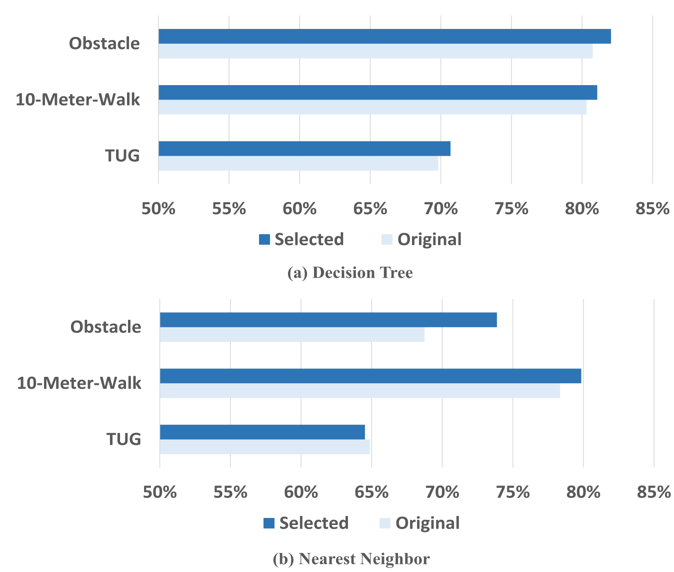

Fig. 7. Classification accuracy comparison between original and selected feature sets using (a) Decision Tree algorithm (b) Nearest Neighbor algorithm.

distribution of acceleration signal samples in approximately 1 s of walking activity. We then only used these 13 features to train Decision Tree and Nearest Neighbor algorithms to classify two groups with and without glaucoma.

Fig. 7 shows classification accuracy of using the original feature set comparing to the selected feature set. The result demonstrated that utilizing the optimal feature set leaded to an overall increase in classification accuracy. For Decision Tree algorithm, the average accuracy of three gait tests increased 1.26% using selected feature set, and for Nearest Neighbor algorithm, the average accuracy increased 2.96%.

5.3. Feature evaluation results

To further understand the difference in gait patterns between two groups, we performed statistical test on 13 features selected

Table 7
Statistical analysis for discriminative features.

Test		Features	p-value	Glaucoma	Healthy
TUG	Left	mean_x	0.016	4.25 ± 2.25	3.60 ± 3.00
		median_x	0.003	4.26 ± 1.77	3.63 ± 2.39
		median_y	0.008	5.17 ± 1.23	5.52 ± 1.37
		median_z	0.015	9.00 ± 0.90	8.78 ± 0.87
	Right	mean_x	0.043	0.90 ± 3.91	0.22 ± 2.91
		median_x	0.033	0.71 ± 3.07	0.15 ± 2.22
		median_y	1.11×10^{-6}	4.23 ± 1.99	5.13 ± 1.76
10-Meter-Walk	Left	mean_x	4.43×10^{-9}	4.86 ± 1.89	3.64 ± 2.74
		median_x	2.25×10^{-9}	4.55 ± 1.80	3.50 ± 2.16
		median_y	0.4×10^{-3}	5.26 ± 1.32	5.62 ± 1.07
	Right	median_x	0.008	0.26 ± 2.85	-0.29 ± 1.8
		median_y	7.7×10^{-9}	4.26 ± 1.71	4.90 ± 0.64
Obstacle course	Left	max_x	0.005	26 ± 2.84	25.2 ± 4.59
		mean_x	1.51×10^{-19}	4.64 ± 1.73	3.08 ± 2.81
		median_x	1.42×10^{-24}	4.47 ± 1.44	3.13 ± 2.06
		amplitude_x	0.010	21.36 ± 3.23	22.15 ± 5.1
		median_y	1.03×10^{-14}	5.20 ± 1.00	5.858 ± 1.3
		amplitude_y	2.38×10^{-5}	18.55 ± 2.87	17.56 ± 3.6
		median_z	0.011	8.95 ± 1.00	8.85 ± 0.51
	Right	min_x	0.016	-23.69 ± 5.5	-24.6 ± 4.8
		mean_x	1.35×10^{-10}	0.51 ± 3.70	-1.05 ± 2.9
		median_x	1.09×10^{-8}	0.63 ± 2.98	-0.44 ± 2.1
		amplitude_x	0.003	24.06 ± 5.9	25.37 ± 6.0
		median_y	1.11×10^{-6}	4.47 ± 2.14	5.06 ± 0.99
		amplitude_y	0.2×10	19.20 ± 3.4	18.28 ± 3.4
		rms_z	0.025	12.00 ± 1.62	12.28 ± 1.8

previously based on the data collected from signal foot in three gait tests. Table 7 below lists all the features been observed of significant difference between two groups by a p-value less than 0.05, where rms_z stands for the root-mean-square of z-axis signal.

Among these features, the mean of x-axial acceleration and the median of x- and y- axial acceleration appeared to be highly discriminative in all gait tests. As Table 7 shows below, the p-value of mean_x and median_x for left foot acceleration was 1.51×10^{-19} and 1.42×10^{-24} respectively, and for right foot was 1.35×10^{-10} and 1.09×10^{-8} respectively, according to the data collected in obstacle course test. The average value of these features revealed some consistent phenomenon for all three gait tests. For example, glaucoma patients tend to have higher mean and median foot acceleration along anterior-posterior direction (x-axis), but lower foot acceleration along medio-lateral direction (y-axis).

6. 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 [30], bump into objects more often [31], demonstrate increased postural sway [8], and fall two times as often as those without glaucoma [30] 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 can 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.

The features we extracted and analyzed in this study are steady-state features based on sensor-derived metrics. To gain an insight into individual's gait behavior, many studies look into spatio-temporal features, such as cadence and stride length, to better estimate personalized gait patterns in consideration of time and displacement. Therefore, we are now developing more advanced signal processing techniques to measure spatio-temporal gait parameters from the accelerometer signals.

In this paper we focuses on developing and validating signal processing and machine learning algorithms in the context of gait and mobility assessment. The feasibility of utilizing these algorithms for continuous gait monitoring and mobility assessment is out of scope of this study. To validate the usability of our wearable sensing system for adoption by end users, we are working on shoe-based platforms with significantly enhanced reliability and robustness under various dynamical and noisy scenarios. Specifically, we are currently working on developing highly power-efficient and durable sensing systems for continuous gait monitoring.

One shortcoming of this study is that glaucoma patients suffer from a wide range of visual field damage; however, we only had participants on the advanced stage. We are now actively recruiting glaucoma patients on different stages. With a larger cohort, we will be able to perform fine grain analysis and design more accurate classifiers to detect glaucoma-related locomotion impairments.

7. Conclusion

In this paper, we presented a wearable sensor system along with signal processing and data analysis approaches to examine the difference in gait patterns between glaucoma patients and healthy people. To this end, we designed a shoe-integrated sensing system to objectively quantify gait patterns. We collected motion sensor data during a series of gait tests. The steady-state gait features of individuals were used to train machine learning algorithms to automatically recognize glaucoma and normal gait patterns. Our result demonstrated that the steady-state features collected from two foot-mounted sensors can be used to distinguish glaucoma patients from healthy controls with an accuracy of 80%. We also identified highly discriminative features using correlation-based feature selection algorithm and statistical analysis techniques. These observations provide insights into studying the impact of glaucoma on individual's gait behavior.

References

[1] Tao Weijun, Tao Liu, Rencheng Zheng, Hutian Feng, Gait analysis using wearable sensors, Sensors 12 (2012) 2255–2283, doi:10.3390/s120202255.
[2] HyltonB. Menz, StephenR. Lord, RichardC. Fitzpatrick, Acceleration patterns of the head and pelvis when walking are associated with risk of falling in community-dwelling older people, J. Gerontol. 58A (5) (2003) 446–452.
[3] Marco Iosa, Augusto Fusco, Giovanni Morone, Stefano Paolucci, Effects of visual deprivation on gait dynamic stability, Sci. World J. 2012 (2012) Article ID 974560, 7 pages doi:10.1100/2012/974560.
[4] David Logan, Tim Kiemel, Nadia Dominici, Germana Cappellini, Yuri Ivanenko, Francesco Lacquaniti, JohnJ. Jeka, The many roles of vision during walking, Exp. Brain Res. 206 (2010) 337–350, doi:10.1007/s00221-010-2414-0.
[5] The Glaucoma Foundation, http://www.glaucomafoundation.org.
[6] Georgios Labiris, Athanassios Giarmoukakis and Vassilios P. Kozobolis (2011). Quality of Life (QoL) in Glaucoma Patients, Glaucoma - Basic and Clinical Concepts, ISBN: 978-953-307- 591-4.
[7] H.A. Quigley, A.T. Broman, The number of people with glaucoma worldwide in 2010 and 2020, British J. Ophthalmol. 90 (3) (2006).
[8] A. Black, J. Wood, Vision and falls, Clin. Exp. Optom. 88 (2005) 212–222.
[9] Ramulu, Pradeep. Glaucoma and Disability: Which Tasks are Affected, and At What Stage of Disease? Current Opinion in Ophthalmology, 2009.
[10] M. Iosa, et al., Effects of visual deprivation on gait dynamic stability, Sci. World J. (2012) 974560.
[11] Ann Hallemans, Els Ortibus, Francoise Meire, Peter Aerts, Low vision affects dynamic stability of gait, Gait Posture 32 (2010) 547–551.

[12] T. Nakamura, K. Meguro, H. Sasaki, Relationship between falls and stride length variability in senile dementia of the Alzheimer type, Gerontology 42 (2) (1996) 108–113.
[13] K.E. Webster, J.R. Merory, J.E. Wittwer, Gait variability in community dwelling adults with Alzheimer disease, Alzheimer Dis. Assoc. Disord. 20 (1) (2006) 37–40.
[14] Takashi Nakamura, Quantitative analysis of gait in the visually impaired, Disabil. Rehabil. 19 (5) (1997) 194–197.
[15] D.R. Geruschat, K.S. Turano, Connecting research on retinitis pigmentosa to the practice of orientation and mobility, J. Vis. Impair. Blindness 96 (2002) 69–85.
[16] Yu-Liang Hsu, et al., Gait and balance analysis for patients with Alzheimer's disease using an inertial-sensor-based wearable instrument, IEEE J. Biomed. Health Inform. 18 (6) (November 2014).
[17] Mladen Milosevic, Emil Jovanov, Aleksandar Milenkoviü, Quantifying Timed-Up-and-Go Test: A Smartphone Implementation, IEEE, 2013 978-1-4799-0330-6/13.
[18] StacyJ. Morris Bamberg, AriY. Benbasat, DonnaMoxley Scarborough, DavidE. Krebs, JosephA. Paradiso, Gait analysis using a shoe-integrated wireless sensor system, IEEE Trans. Inf. Technol. Biomed. 12 (4) (July 2008).
[19] Mijailoviü Nikola, Marijana Gavriloviü, Stefan Rafajloviü, Gait phases recognition from accelerations and ground reaction forces: application of neural networks, Telfor J. 1 (1) (2009).
[20] IonP.I. Pappas, MilosR. Popovic, Thierry Keller, Volker Dietz, A. Manfred Morari, Reliable gait phase detection system, IEEE Trans. Neural Syst. Rehabil. 9 (2) (June 2001).
[21] T. Khalil, S. Khalid, A.M. Syed, Review of machine learning techniques for glaucoma detection and prediction, in: IEEE Science and Information Conference, Aug. 2014, pp. 27–29. 438-442, ISBN 978-0-9893-1933-1.
[22] K. Chauhan, P. Chauhan, R. Gulati, Diagnosis system using data mining approach for glaucoma (a social threat), in: IEEE Conference on Technology and Society in Asia (T&SA), 2012, pp. 27–29. Oct, 1-4, ISBN: 978-1-4673-2069-6.
[23] U.R. Acharya, S. Dua, Du Xian, S.V. Sree, Automated diagnosis of glaucoma using texture and higher order spectra features, IEEE Trans. Inf. Technol. Biomed. 15 (3) (May 2011) 449–455 ISSN: 1089-7771.
[24] H. Ahmad, A. Yamin, A. Shakeel, S.O. Gillani, Detection of glaucoma using retinal fundus images, in: International Conference on Robotics and Emerging Allied Technologies in Engineering (iCREATE), 2014, pp. 321–324. ISBN: 978-1-4799-5131-4.
[25] Shimmer. (27.08). Wireless Sensor Platform for Wearable Applications [Website]. Available: http://www.shimmerresearch.com/.
[26] "Timed Up and Go (TUG)". Minnesota Falls Prevention, http://www.mnfallsprevention.org/professional/assessmenttools.html (accessed 16.02.10).
[27] S. Amatachaya, et al., Concurrent validity of the 10-meter walk test as compared with the 6-minute walk test in patients with spinal cord injury at various levels of ability, Spinal Cord. 52 (4) (2014 Apr) 333–336.
[28] WEKA, http://www.cs.waikato.ac.nz/ml/weka/
[29] M.A. Hall (1998). Correlation-Based Feature Subset Selection for Machine Learning. Hamilton, New Zealand.
[30] P.Y. Ramulu, E. Maul, C. Hochberg, et al., Real-world assessment of physical activity in glaucoma using an accelerometer, Ophthalmology 119 (2012) 1159–1166.
[31] K. Yuki, S. Tanabe, K. Kouyama, et al., The association between visual field defect severity and fear of falling in primary open-angle glaucoma, Invest. Ophthalmol. Vis. Sci. 54 (2013) 7739–7745.
[32] Yuchao Ma, Sharon Henry et al, Investigation of Gait Characteristics in Glaucoma Patients with a Shoe-Integrated Sensing System, accepted by IEEE PerMoby 2015
[33] F. Danion, E. Varraine, M. Bonnard, J. Pailhous, Stride variability in human gait: the effect of stride frequency and stride length, Gait Posture 18 (1) (2003 Aug) 69–77.
[34] Brajdic Agata, Robert Harle, Walk detection and step counting on unconstrained smartphones, UbiComp'13, September 8–12, 2013.
[35] Paul Sajda, Machine learning for detection and diagnosis of disease, Annu. Rev. Biomed. Eng. 8 (8) (2006) 1–8.29.
[36] P.C. Chung, Y.L. Hsu, C.Y. Wang, C.W. Lin, J.S. Wang, M.C. Pai, Gait analysis for patients with Alzheimer's disease using a triaxial accelerometer, Circuits and Systems (ISCAS), 2012 IEEE International Symposium on., IEEE, 2012.