Survey on Gait Pattern Assessment in Glaucoma Patients Using Body Worn Sensors

Shara T Idicula¹ & Sharon Thomas²
¹ M.Tech Student, Computer Science and Engineering, RIT College of Engineering, Kottayam, Kerala, India
² M.Tech Student, Computer Science and Engineering, RIT College of Engineering, Kottayam, Kerala, India

Abstract: Many studies have reported that glaucoma patients experience mobility issues, such as walking slowly and bumping into obstacles frequently. However, little is known to date about how a person’s gait is impacted due to glaucoma. Design and development of a gait analysis approach using a shoe-integrated sensing system and accompanying machine learning techniques to quantitatively examine gait patterns in glaucoma patients was recently introduced. The customized sensor platform is utilized in a clinical trial conducted with nine glaucoma patients and ten age-matched healthy participants. The signal processing and machine learning algorithms automatically detect effective gait cycles and extract both steady-state and spatiotemporal gait features from the signal segments. Machine learning algorithms are performed to distinguish glaucoma patients from healthy controls, and identify several prominent features with high discriminability between the two groups. The results demonstrate that classification algorithms can be used to identify the gait patterns of glaucoma patients. The results suggest that emerging solutions, such as wearable sensing technologies, can be used for continuous and real-time assessment of gait and mobility problems in individuals with low vision, and may open new avenues for using changes in gait patterns for preventing life threatening situations such as falls.

Keywords: Gait analysis, glaucoma, wearable sensors, machine learning.

1. Introduction

Glaucoma is the second leading cause of blindness, and approximately 2% of adults over the age of 40 suffer from this condition [2]–[4]. It is estimated that the prevalence of glaucoma in the world will increase to 79.6 million by 2020 [4].

Unlike most causes of low vision and blindness, glaucoma is a chronic lifelong disorder that does not manifest any symptom until advanced stages of the disease when extensive peripheral visual loss becomes apparent. Such peripheral visual field loss results in a low self-reported quality of life, due to its major role in facilitating postural control based on its sensitivity to motion [5]. As a result, a number of studies report that glaucoma patients walk more slowly [3], bump into objects more often, have increased postural sway [6], and are more prone to fall [7] compared to non-glaucoma subjects.

Vision system plays multiple roles such as gait cycle modulation, navigation, and obstacle avoidance during locomotion [8]. The effect of vision system on gait patterns has been well-studied in several research studies [9]–[11]. Because visual system is primarily responsible for dynamic stability in normal walking, visual impairment has inevitable effects on individual’s gait behavior.

Gait analysis as a systematic study of human locomotion, has already been adopted in the diagnosis of physical impairments and monitoring of patient healing progress [12]. With rapid development and popularization of wireless sensor technologies, a number of studies explored wearable sensing systems to provide an objective and real-time gait and balance measurement that can serve as an assistive indicator of diagnosis in several diseases such as Alzheimer’s disease [13] and Parkinson’s disease [14].

Although the relationship between glaucoma and quality of life including the abnormality of walking has been established in prior research, the community still lacks a quantitative and pervasive approach for gait analysis in glaucoma patients. Therefore, a clinical study in glaucoma patients using customized wearable sensing system, to quantitatively estimate the difference in gait patterns between elderly with and without glaucoma disease was conducted.

This paper presents a survey of gait analysis techniques in glaucoma patients. Here we discuss five different method used for gait analysis. The first method describes Gait Pattern Assessment Using Body-Worn Sensors [1]. A gait analysis approach for gait pattern examination with foot mounted accelerometers, which is suggested to be effective for gait monitoring [15]–[17] was introduced. An information lossless algorithm to segment gait cycles...
for effective feature extraction was developed. To examine gait patterns in glaucoma patients, gait-related sensor data in a series of clinical gait experiments were collected. The collected data through customized shoe-integrated motion sensor system with wireless data transmission capability during the experiments [18] in the clinical trials are used to develop machine learning algorithms and perform statistical analysis to examine gait differences in glaucoma patients and healthy individuals.

Second method is Gait Analysis Using a Shoe-Integrated Wireless Sensor System[21], a wireless wearable system that was developed to provide quantitative gait analysis outside the confines of the traditional motion laboratory. The sensor suite includes three orthogonal accelerometers, three orthogonal gyroscopes, four force sensors, two bidirectional bend sensors, two dynamic pressure sensors, as well as electric field height sensors. The “GaitShoe” was built to be worn in any shoe, without interfering with gait and was designed to collect data unobtrusively, in any environment, and over long periods. Clinical gait analysis is the investigation of the pattern of walking.

In the third method a new sensing technology to healthcare maybe part of a solution to the financial and demographic crisis facing global healthcare systems. Researchers applying new approaches to noninvasive patient monitoring and diagnostics are assisted by the features of Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability (SHIMMER™)[23], a flexible sensing platform. Integrated peripherals, open software, modular expansion, specific power management hardware, and a library of applications supported with platform validation provide SHIMMER with advantages over many other medical research platforms.

In next method a Timed-Up-and-Go (TUG)[22] test is described which is a simple, easy to administer, and frequently used test for assessing balance and mobility in elderly and people with Parkinson’s disease. An instrumented version of the test (iTUG) has been recently introduced to better quantify subject’s movements during the test. The subject is typically instrumented by a dedicated device designed to capture signals from inertial sensors that are later analyzed by healthcare professionals.

The last method is a framework called foot mounted accelerometer[15] to detect changes in gait patterns. This method investigate how data from a foot mounted accelerometer can be used to detect motor pattern healthy subjects performed walking trails under two different conditions; normal and stiff ankle walking.

2. Gait Analysis Techniques


2.1. Gait Pattern Assessment Using Body Worn Sensors

The goal of this system is to provide physicians with quantitative and objective information about gait behaviors. These gait features can be used for discriminating between glaucoma patients and healthy people, and hence serve as assistive indicators for diagnosis and health assessment. There are two major procedures for information acquisition in this framework, namely signal processing (including signal pre-processing and segmentation) and data analysis (including feature extraction & analysis and classification) . The former automatically detects gait cycles and partitions raw sensor signal into gait segments. The latter extracts both statistical and spatio-temporal gait features from the segments. The data processing flow, consists of all the four phases, namely signal pre-processing, gait cycle segmentation, feature extraction & analysis, and classification.

Signal pre-processing aims to reduce the complexity of raw signal and acquire a simplified signal with clear cyclic patterns ready for segmentation. The 3-axis accelerometer signal are first calibrated in real-time as a result of which the vertical acceleration represents ±g and the horizontal acceleration refers to 0g when the sensor is stationary. The signal vector magnitude (SVM) is then calculated using equation given below. The advantage of using SVM signal for gait cycle detection is that (I) it reflects the overall intensity of the movement during ambulation; and (II) it neutralizes random noise in each signal axis and highlights the repeated cycles in the signal.

The data processing flow for gait cycle detection and filtering can be completed, along within the stepwise signal output and the process for filtering irregular gait cycles and mapping the cutting points back to original acceleration signal. The cyclic nature of human gait is due to the periodic leg movement. Human gait is composed of several phases. In this algorithm, gait cycles are detected by finding the start and the end points of dynamic intervals with high amplitude in SVM signal. As the smoothed SVM passes through the processing chain, the algorithm first detects the dynamic fragment of the first gait cycle by searching for its start sample point.
This start point is determined as the first sample point in a signal sequence with continuously increasing amplitude that can reach an experimental threshold.

The algorithm then recursively seeks for the start point of dynamic fragment. Based on prior clinical researches, the average cadence (steps/min) in normal gait is 100, which indicates that no more than two gait cycles would happen within 0.6s (the average duration of one step), since one gait cycle contains two steps. After all start points in the SVM are determined, detecting the end point of a dynamic fragment in the gait cycle is a reversed searching within two consecutive start points. An end point is determined as the last sample point of a continuously decreasing signal sequence with the largest drop-off in the corresponding signal segment. In the end, every two consecutive starting points mark off a candidate gait cycle, and the ending point in between separates the gait cycle into dynamic and at fragments.

Two conditions can be applied on the SVM signal to filter noisy cycles caused by irregular movement during a walk, such as stagger or turning. These conditions are (I) the temporal distance for the dynamic fragment is larger than the at fragment in each gait cycle; (II) the temporal distance for the at fragment is at least 20% of a general gait cycle. Noisy cycle filtering approach yields precedence to the quality of extracted gait cycles, instead of the quantity, to ensure the accuracy of feature extraction.

Knowing the start and the end points of dynamic fragments in gait cycles, the algorithm maps these points back to the original unsmoothed SVM signal. After determining the cutting points, both unsmoothed SVM signal and the tri-axial acceleration signal are segmented correspondingly. Therefore, the obtained gait cycle segments are information lossless.

Two types of gait feature are extracted including statistical features and spatio-temporal features. Statistical features are directly extracted from individual gait cycle segments. With extracted features, three widely used classifiers are trained to distinguish glaucoma patients from normal participants. These algorithms include Decision Tree, Nearest Neighbor and Logistic Regression. The integrated machine learning algorithms in WEKA (Waikato Environment for Knowledge Analysis) perform the supervised training. For validation purpose, both 10-fold cross validation and supplied testing set methods are used in this study. The 10-fold cross validation is efficient for small dataset due to its high utilization of data instances. The former approach randomly selects 10 percent of the instances as test case in each iteration without repetition, and then averages the results over all iterations. However, supplied testing set validation is a better fit in a real scenario that, with some labeled instances collected from an individual previously, and some newly collected observations, a classifier is trained using the labeled dataset and directly applied on unlabeled data for event detection.

2.2 Gait Analysis Using a Shoe-Integrated Wireless Sensor System

This paper describes a wireless wearable system that was developed to provide quantitative gait analysis outside the confines of the traditional motion laboratory. The sensor suite includes three orthogonal accelerometers, three orthogonal gyroscopes, four force sensors, two bidirectional bend sensors, two dynamic pressure sensors, as well as electric field height sensors. The “GaitShoe” was built to be worn in any shoe, without interfering with gait and was designed to collect data unobtrusively, in any environment, and over long periods.

Clinical gait analysis is the investigation of the pattern of walking. At present, gait analysis is primarily carried out in one of two ways: in a motion laboratory, with full analysis of the motion of body segments using highly accurate computer based force and optical tracking sensors, or in an office with the clinician making visual observations. The first method is expensive, requires the maintenance of a dedicated motion laboratory, and uses cumbersome equipment attached to the patient, but produces well-quantified and accurate results for short-distance ambulation. The second method is inexpensive and does not require special equipment, but requires additional time from the clinician, and the results are qualitative, unreliable, and difficult to compare across multiple visits. There is a need for an alternative analysis method that is capable of providing quantitative and repeatable results over extended time periods. A system that can quantitatively analyze gait for patients offers clinicians and patients new opportunities for diagnosis and treatment of chronic walking problems. There has been considerable previous work in both research and commercial spheres focused on the development of more mobile methods of analyzing gait. The advantage of directly measuring the pressure distribution beneath the foot drove many early shoe-based systems. The shrinking size of data storage has further encouraged the development of untethered systems.

The “GaitShoe.” system has the potential to be highly informative by allowing data collection throughout the day in a variety of environments, thus providing a vast quantity of long-term data not obtainable with current gait analysis systems. The “GaitShoe” system has been designed with components configured to minimally affect gait, and is readily fixed on typical athletic shoes. These initial results demonstrate that the GaitShoe promises to be an important research tool, capable of enabling the
analysis of gait in untraditional ways, such as over long time periods and in the home environment or through the use of multisensory pattern recognition. Fast processing of the data stream can provide real-time feedback for use in applications such as sports medicine, electro stimulation, or physical therapy. Additional research with the GaitShoe sensor outputs has involved the application of standard pattern recognition techniques to discriminate between healthy gait and Parkinsonian gait, as well as to discriminate between individuals and real-time analysis of the data to provide therapeutic musical feedback to investigate interactive applications in physical therapy.

2.3 SHIMMER™ – A Wireless Sensor Platform for Noninvasive Biomedical Research

This study deals with applying new sensing technology to healthcare maybe part of a solution to the financial and demographic crisis facing global healthcare systems. Researchers applying new approaches to noninvasive patient monitoring and diagnostics are assisted by the features of Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability (SHIMMER™), a flexible sensing platform. Integrated peripherals, open software, modular expansion, specific power management hardware, and a library of applications supported with platform validation provide SHIMMER with advantages over many other medical research platforms.

Wireless sensors applications utilize wireless sensing capabilities in the form of either body worn or ambient sensing devices. Sensed data is transmitted in real time or opportunistically through a web of local devices and often wide area networks resulting in rich data sets that underpin new options for analysis and intervention. Wireless sensor applications have demonstrated the ability to monitor a variety of multiple parameters including physiological, kinematics, ambient, and environment measurements. Combining sensor readings increases the overall quality of information generated beyond the sum of the parts. A platform approach where the sensing capability can be modified via physical and software device configuration addresses the need for heterogeneous sensing capabilities while minimizing the complexity of the hardware and software development, validation and support. This engineering approach predates modern electronics and has been proven in many domains. In recent sensing systems, the transducer, associated signal conditioning and support subsystems are functionally encapsulated in a daughterboard which connects to a common baseboard providing the computational and communications capabilities. SHIMMER is an extremely flexible sensor platform. Above all, its ability to seamlessly expand to meet the various biomedical research project requirements has proven to TRIL researchers that the small sensor platform has massive research potential. In this study, it is reported on the motivation and scope of the capabilities of the SHIMMER platform.

SHIMMER has been actively used for kinematic, physiological and ambient sensing applications within the TRIL Centre and due to its extensibility and ease of integration into other healthcare systems; the TRIL center plans will include Shimmer in many future projects. SHIMMER’s ability to work in connected or disconnected settings allows biomedical research trials that have previously been run in laboratories to now be run in wherever participants call home. From a TRIL perspective, an exciting potential for SHIMMER is the introduction and application of new technologies supporting older people living independently.

2.4 Quantifying Timed-Up-and-Go Test: A Smartphone Implementation

Timed-Up-and-Go (TUG) is a simple, easy to administer, and frequently used test for assessing balance and mobility in elderly and people with Parkinson’s disease. An instrumented version of the test (iTUG) has been recently introduced to better quantify subject’s movements during the test. The subject is typically instrumented by a dedicated device designed to capture signals from inertial sensors that are later analyzed by healthcare professionals.

In this study it introduce a smartphone application called sTUG that completely automates the iTUG test so it can be performed at home. sTUG captures the subject’s movements utilizing smartphone’s built-in accelerometer and gyroscope sensors, determines the beginning and the end of the test and quantifies its individual phases, and optionally uploads test descriptors into a medical database. TUG is simple and easy to administer in an office, and thus can be used in screening protocols. The test measures the time a person takes to perform the following tasks: rise from a chair, walk three meters, turn around, walk back to the chair, and sit down. Longer TUG times have been associated with mobility impairments and increased fall risks. Adults without balance problems can perform this test in less than 10 seconds. Alternatively, adults with mobility difficulty may require more than 30 seconds. TUG duration is also sensitive to therapeutic interventions.

An instrumented Timed-Up-and-Go (iTUG) test has been recently introduced. In this test, the subject is instrumented by a dedicated device specially designed for gait and movement analysis. A number of additional parameters can be derived that can better indicate gait and balance impairments,
including Sit-to-Stand duration, Stand-to-Sit duration, the amplitude range of anterior-posterior acceleration. The prior TUG studies utilized either specialized devices for movement analysis or custom inertial sensors that were mounted on the subject’s lower back. Such devices typically include a 3 dimensional accelerometer and can record x, y, and z acceleration components during the TUG test. The data are later analyzed off-line to parameterize the TUG test. Recognition and quantification of human activities using small wearable sensors during activities of daily living has been increasingly used in many applications. Automatic activity recognition and quantification systems that utilize inertial sensors are proposed for long-term health and fitness monitoring, assessment of mobility in elderly and people with Parkinson’s disease, automatic fall detection, and rehabilitation.

Approaches for automatic activity recognition used by researchers vary in number, type, and placement of utilized sensors, as well as in processing of recorded signals. While some researchers used multiple sensors for automatic activity recognition increasing number of projects use a single inertial sensor usually placed on the subject’s chest. Modern smartphones integrate a growing number of inertial and location sensors, such as an accelerometer, magnetometer (digital compass), gyroscope, and GPS. In this paper they introduce a smartphone iTUG application called sTUG. A subject mounts the smartphone on his/her chest or belt and starts the application. The application records and processes the signals from the smartphone’s gyroscope and accelerometer sensors to extract the following parameters that quantify individual phases of the TUG test: (a) the total duration of the TUG test, (b) the total duration of the sit-to-stand transition, and (c) the total duration of the stand-to-sit transition. In addition, we extract parameters that further quantify body movements during the sit-to-stand and stand-to-sit transitions, including the duration of sub phases, maximum angular velocities and upper trunk angles. These parameters are recorded on the smartphone and optionally uploaded to an mHealth server. sTUG could be of great interest for older individuals and Parkinson’s disease patients as well as for healthcare professionals. The procedure requires minimum setup and inexpensive instrumentation. The feedback is provided instantaneously to the user in a form of a report with the values of all significant parameters that characterize the TUG test. It is easy to use and users can take multiple tests in a single day at home.

2.5 Using a foot mounted accelerometer to detect changes in gait patterns

The purpose of this study is to investigate how data from a foot mounted accelerometer can be used to detect motor pattern healthy subjects performed walking trials under two different conditions; normal and stiff ankle walking. Lower body kinematic data were collected as well as accelerometer data from both feet. An algorithm is presented which quantifies relevant swing phase characteristics from the foot accelerometer. Peak total acceleration during initial swing was significantly higher in the stiff ankle condition than in the normal walking condition. There was a large effect size. Time between peak acceleration during initial swing to foot strike was significantly shorter in the stiff ankle condition than in the normal condition. There was a large effect size. Simple to process metrics from tri-axial accelerometer data on the foot show potential to detect changes in ankle kinematic patterns.

Traditional gait analysis tools are expensive and take a significant amount of time to obtain data from. These factors severely limit how often gait analyses can be performed on a patient and also limit the number of patients gait analysis can be performed on. The complexity and cost associated with traditional gait analysis techniques it is important for research to address issues concerning the use of wearable sensor technology which may allow gait analysis to be accessible to more patients in easier to use and deployable applications outside the laboratory. A significant body of work in the ambulatory monitoring field has gone into using inertial measurement units to determine kinematic data during various movements. This approach provides useful data in an easier to use set-up than traditional measurement techniques. However, the fact that sensors are required on each body segment limits such an approach from being applied to deployable, every-day monitoring applications. Long-term patient monitoring has traditionally obtained metrics such as activity recognition, calorie counting or step-counting. While these metrics are very useful for many clinicians, there is an opportunity to obtain more detailed quality of movement data from the sensors that are used to obtain these gross metrics.

Previous work has shown the potential for shoe mounted accelerometers to predict lower body kinematic patterns during gait in a long-term monitoring scenario. This approach only worked well when a complex calibration was performed on each patient. Perhaps, replicating traditional measurement tools is not necessary. Perhaps, the inertial data from the foot on its own could be used to determine if an abnormal gait pattern exists. Capturing gait metrics with inexpensive sensors in an unobtrusive manner, while people go about their daily lives would allow for more patients to have their gait analyzed on a regular basis. This may allow more people to live healthier lives and decrease health-care costs by allowing for earlier intervention in disease and injury development. The aim of this
investigation is to determine if data from a foot mounted accelerometer can be used to identify change in a person’s gait patterns.

3. Conclusion

In this paper we have discussed several methods used for gait analysis. A data analysis framework for gait pattern examination using a wearable system and machine learning techniques in glaucoma patients was discussed. To this end, also discussed about the design and development of algorithms to obtain effective gait cycle segments in acceleration signal from the foot. Both the steady-state and the spatio-temporal gait features of individuals were extracted, and used to train learning algorithms to automatically recognize glaucoma and normal gait patterns. Furthermore, the discriminability of individual feature selected by correlation-based feature selection algorithm was examined. The goal of this study is to provide physicians with quantitative and objective information about gait behaviors. These gait features can be used for discriminating between glaucoma patients and healthy people, and hence serve as assistive indicators for diagnosis and health assessment.

4. References

[1]. Glaucoma-Specific Gait Pattern Assessment Using Body-Worn Sensors Yuchao Ma, Student Member, IEEE, Ramin Fallahzadeh, Student Member, IEEE, and Hassan Ghasemzadeh, Senior Member, IEEE


