

PAGAS: Portable and Accurate Gait Analysis System

Rojay Wagner and Aura Ganz, IEEE Fellow
Electrical and Computer Engineering Department
University of Massachusetts
Amherst, MA 01003

Abstract— Gait analysis systems are powerful tools in the monitoring and rehabilitation of many health conditions which result in an altered gait (such as Parkinson’s disease and rheumatoid arthritis), along with the injury of lower limbs. However, current systems that provide accurate gait monitoring and analysis are large and expensive, and therefore are available only in professional settings. The goal of this research is to develop and test a Portable and Accurate Gait Analysis System, denoted PAGAS, which enables patients to monitor their own gait and track their progress and improvement over time. Moreover, PAGAS will enable therapists to follow the progress of their patients over time without the need for multiple visits required at a rehabilitation facility, thus saving significant healthcare costs. PAGAS includes footswitches and a micro-controller, which connects to an Android Smart-phone using Bluetooth communication. An application on the Smartphone analyzes the raw data to produce temporal gait parameters that are displayed to the user on a graphical user interface.

I. INTRODUCTION

Gait analysis is a powerful tool in the rehabilitation of many injuries and disorders that result in an altered gait pattern. It has been used heavily in the treatment of neurological and musculoskeletal conditions, and has been proven useful to monitor therapy progress after leg injuries [1]. Many of these conditions, such as Parkinson’s disease and spinal cord injury along with many types of injury to the lower limbs, often result in an altered gait [2]. It should be noted that diagnosis of conditions such as Parkinson’s disease is traditionally left to the expertise of the clinician. However, recent studies have been able to reliably detect the disease using gait analysis alone [3]. A critical part of the rehabilitation process following an altered gait is the ability to document and monitor the mobility of patients over time [4]. In order to objectively track changes in gait, various spatial and temporal parameters are used. These parameters can be compared to expected values and monitored over time to assess the progress of rehabilitation.

There are many technologies used for gait analysis. Five common traditional systems are ground reaction force analyzers, metabolic energy expenditure, goniometers,

optical sensors, and footswitch stride analyzers. Ground reaction force analyzers consist of force plates on the ground which subjects walk on. They are able to detect the force exerted by the patient’s feet and collect both spatial and temporal data [1]. Metabolic energy expenditure involves calculating the energy needed for a subject to perform certain movements related to walking [5]. Goniometers are tools that allow clinicians to measure the degree of freedom of a joint. For example, they may want to measure the degree that a patient can bend their knee and monitor this mark over time [6]. Optical systems use cameras to capture gait metrics, however, it has been shown that these metrics can change significantly based on unrelated factors such as the subject’s clothes, the lighting, or the camera angles. Optical systems are also expensive and almost exclusively used in a professional setting [3].

Recent works use accelerometer-based systems in smartphones [7,8]. However, accelerometer-based systems are not the standard method of measuring gait, and are not as accurate in recording gait metrics as footswitch based systems [4].

The goal of this paper is to develop and test a Portable and Accurate Gait Analysis System, denoted PAGAS, which enables patients to monitor their own gait and track their progress and improvement over time. PAGAS combines the accuracy of footswitches with the portability of smartphones used for communication and analysis. PAGAS consists of two insoles (with embedded footswitches), each of which is connected to a microcontroller. The microcontroller monitors the footswitch data and transmits the desired information using Bluetooth to the subject’s Android smartphone. Finally, an application on the phone analyzes the data to provide accurate results in a short amount of time, which is displayed to the user through a graphical user interface.

This paper is organized as follows. In the next section we introduce the temporal gait parameters, in Section III we provide the system overview, and data analysis is summarized in Section IV. Section V describes the graphical user interface and Section VI concludes the paper.

II. TEMPORAL GAIT PARAMETERS

We plan to calculate five temporal gait parameters: stride time, swing time, stance time, step time balance, and stride

Acknowledgement: This project was supported in part by DUE- 1003743 from the National Science Foundation. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Science Foundation.

time variability. Figure 1 for a description of these parameters.

- **Stride time** is the equivalent of one full gait cycle, and is measured from the heel-down (the moment the heel strikes the ground) of one foot to the subsequent heel-down of that same foot. A stride is made up of two steps, which begin with heel-down of one foot and end with heel-down of the opposite foot. In a normal gait, step times starting with the left foot are nearly symmetric to step times starting with the right [9].
- **Swing time** is the duration of time from one foot's toe-off (the moment the toe of a foot leaves the ground) to its successive heel-down.
- **Stance time** is from one foot's heel-down to its successive toe-off. Swing time should account for around 40% of stride time, while stance time should represent the remaining 60% [9].
- **Stride time variability** (STV) has been proven to be extremely valuable. This is a measure of how much stride times vary over the course of walking. It is computed by dividing the standard deviation of stride times by the mean of stride times [8]. Previous studies have shown that normality of gait is strongly correlated to stride time variability [8,10]. In addition, increased stride time variability has been linked to increased fall risk and other mobility limitations [1].
- **Step time balance** (STB) compares the duration of steps starting with the right foot to those starting with the left. In normal gaits, these times are roughly symmetric, but certain leg injuries that impair only one limb will benefit from monitoring this parameter [9].

The five gait parameters are calculated using heel-down/toe-off times from each foot. We define RH_i as the i 'th time the right heel hit the floor, LH_i as the i 'th time the left heel hit the floor, RT_i as the i 'th time the right toe hit the floor, and LT_i as the i 'th time the left toe hit the floor. ST denotes stride time, LSt_i and RSt_i are left and right stance times, respectively. LSw_i and RSw_i are left and right swing times, respectively. LSp_i and RSp_i are left and right step times, respectively. We have measured N gait cycles.

Using these definitions, the gait parameters are computed as follows (see Figure 1):

For $i = 0 \dots N-1$

$$ST_i = RH_{i+1} - RH_i$$

$$LSt_i = LT_{i+1} - LH_i$$

$$RSt_i = RT_i - RH_i$$

$$LSw_i = LH_i - LT_i$$

$$RSw_i = RH_{i+1} - RT_i$$

$$LSp_i = RH_{i+1} - LH_i$$

$$RSp_i = LH_i - RH_i$$

$$Avg. LSt = \frac{\sum_{i=0}^{N-1} LSt_i}{N-1}$$

$$Avg. RSt = \frac{\sum_{i=0}^{N-1} RSt_i}{N-1}$$

$$Avg. LSw = \frac{\sum_{i=0}^{N-1} LSw_i}{N-1}$$

$$Avg. RSw = \frac{\sum_{i=0}^{N-1} RSw_i}{N-1}$$

$$Avg. LSp = \frac{\sum_{i=0}^{N-1} LSp_i}{N-1}$$

$$Avg. RSp = \frac{\sum_{i=0}^{N-1} RSp_i}{N-1}$$

$$STB = \frac{Avg. LSp}{Avg. RSp}$$

$$STV = \frac{Std.Dev.ST}{Avg.ST}$$

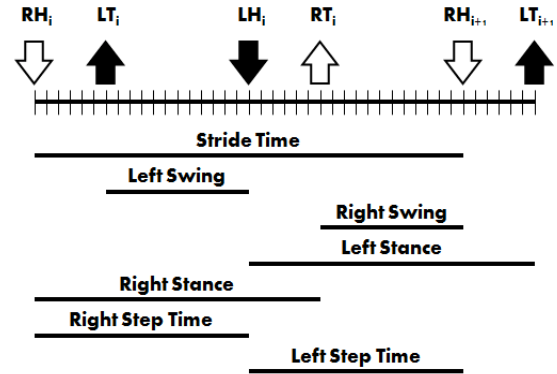


Figure 1. Graphical representation of gait parameters based on heel-downs and toe-offs.

III. SYSTEM OVERVIEW

The goal of our work is to develop a system that allows subjects to monitor their own gait and track progress and improvement over time. It consists of footwear (insoles and a microcontroller board attached to each shoe) and interacts with the user's Android smartphone. Our system includes two parts: data acquisition and data analysis.

Figure 2 displays a high-level data flow diagram. Data acquisition includes footswitches embedded in the shoe insoles and a microcontroller (Arduino BT with ATmega328) which captures that input from the footswitches and relays it to the Android Smartphone through Bluetooth. An application running on the phone receives and processes these data to determine the temporal gait parameters described above.

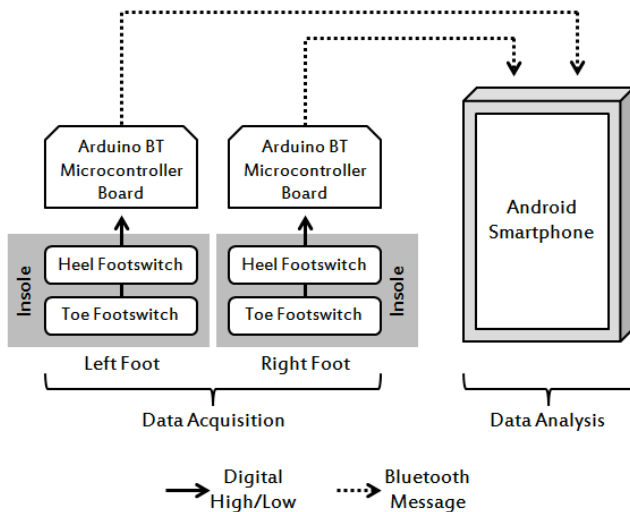


Figure 2. Block diagram of the dataflow

Since all temporal gait parameters we are interested in are calculated from heel-down and toe-off times, only four footswitches were needed, two in each foot. As shown in Figure 3, they are placed under the heel and first metatarsal of each foot [4]. They are embedded in the shoe insole by removing a portion of the foam insole from the bottom and placing the switch such that it lays flush with the bottom of the insole. This assures that the patient will not feel two large bumps where the switches lie.



Figure 3. Footswitches in the right shoe insole.

The switches used (Philmore Tactile Switch # 30-14416) are momentary, meaning they only remain depressed while pressure is asserted on them. This allows us to measure toe-off times. These switches are then wired to a microcontroller board that is attached to the shoe, as shown in Figure 4. When pushed, each switch will result in a high voltage reading on its wire. These wires are connected to digital inputs on the board which are pulled down to ground by 10KΩ resistors. The microcontroller runs a loop function that constantly reads the value of the two input wires. Because the voltage will sometimes jump and give false heel-down or toe-off values, the microcontroller will only accept alternate heel and toe entries, starting with heel. If a value is somehow missed, algorithms on the smartphone will ignore the outlying data. Once it has been determined that a heel-down or toe-off has taken place, the microcontroller sends a Bluetooth message, with the type of event along with the current time in milliseconds, to the smartphone. This process takes place on both the left and right foot.



Figure 4. PAGAS System Prototype

IV. DATA ANALYSIS

The software that we developed on the Android phone computes the five temporal gait parameters using footswitch data (see Section II). The job of the microcontroller is to detect a heel-down or toe-off. A heel-down occurs when the heel footswitch changes from a state of unpressed to pressed. Similarly, a toe-off is detected when the toe footswitch changes from pressed to unpressed. When either of these events occur, the microcontroller will send a Bluetooth message to the phone.

When calculating the gait parameters, the smartphone application is supplied with a list of events and times that these events occurred. The first step is to normalize the data by removing any outlying entries. Given a list of times that should be approximately equal (i.e. stride times, step times), the mean and standard deviation are calculated for the set and any values lying more than one half of the standard deviation from the mean are discarded. This is done because the microcontroller board may sometimes read false values or miss the reading of a value. Over a long enough walking period, these mistakes can be ignored and the remaining data can be analyzed.

Once the data have been normalized, the five temporal gait parameters are calculated using the equations presented in Section II and shown in Figure 1.

V. GRAPHICAL USER INTERFACE

The Android application allows the user to interact with their gait data through a graphical user interface (GUI). As shown in Figure 5, the GUI contains two main sections: monitor and history. The monitor section allows the user to operate the system and observe their current gait. Once the system is properly connected to the phone through Bluetooth, the user can push a button and start walking. This triggers the system to begin. Once a “ramp-up” period has passed, the system will automatically start recording data. Once the parameters are calculated, they are displayed to the user on the screen.

Two of the five parameters calculated, step time balance (STB) and stride time variability (STV), are also displayed graphically to the user. Steps originating from the right and left feet should be roughly symmetric in normal gaits. Step time balance parameter is useful for detecting differences between the two feet, such as a walk (limp) favoring one leg [9]. A sliding bar will display this parameter to the user as shown in Figure 5. If the bar is to the left of center, the user favors their left foot more than their right, as would be expected with an injured right leg. A bar to the right signifies a favoring of the right leg. Similarly, stride time variability has been very closely linked to the normality of gait and gait stability [8,10]. A larger stride time variability corresponds to a more abnormal gait, which is also relayed to the user through a sliding bar interface.

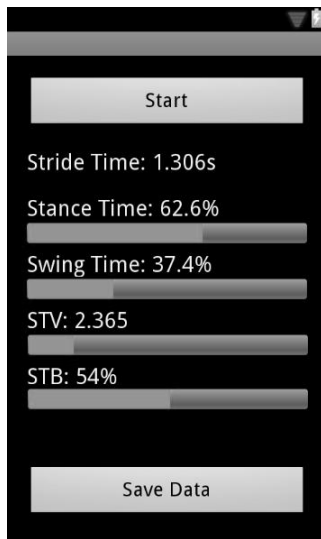


Figure 5. Screenshot of Android application

Now that the user has their gait results, they have an option to save them. Saved results are stored in the history section of the application, and can be viewed at any time. This provides the user with a simple method for tracking their progress over time.

VI. CONCLUSION

We introduced a portable gait analysis system which enables patients to monitor their own gait and track their progress and improvement over time. Moreover, PAGAS will enable therapists to follow the progress of their patients over time without the need for multiple visits required at a rehabilitation facility, thus saving significant healthcare costs.

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