Chapter 16
GaitTracker: A Digital Platform for Measuring, Detecting and Analyzing Gait Changes

Aniruddh Jayant Muley, Kalyan Sasidhar, and Ronak Dhokai

Abstract Gait is an essential bio-marker for long-term health. Traditionally, Gait analysis depends on vision-based or expensive pressure mats where patients are instructed to walk or perform standard limb movements. Early monitoring and detection of gait changes could prevent severe conditions. However, such tests happen late in the onset of the problem. Despite a plethora of wearable devices, such as fitness bands and health trackers, no single device monitors gait and provides an early diagnosis. This work presents a proof-of-concept of our in-house developed wearable inertial measurement unit (IMU) for extracting gait patterns. In addition, the results presented in this work detect changes in gait patterns. The device was tested with ten volunteers (six males and four females, 25 +/− 1.8 years, 163 +/− 8.8 cm) who provided data for both normal and abnormal walking resulting in around 700 gait samples. The results show that sudden changes in gait can be detected with an affordable and portable wearable device.

Keywords Wearable device · Accelerometer · Gait analysis

Introduction

Gait refers to a walking pattern and is unique to every individual (Gafurov et al. 2007). A typical gait pattern consists of multiple events occurring with alternate movement of the limbs. Gait of a person can change due to various reasons including body weight, injuries, age-related cognitive impairments and neurological dysfunctions (Cimolinn et al. 2011). Moreover, gait could change suddenly and if left unnoticed/ignored for a prolonged time, can lead to abnormal gait such as antalgic gait (limping

A. J. Muley · K. Sasidhar (✉) · R. Dhokai
Dhirubhai Ambani Institute of Information and Communication Technology Gandhinagar, Gujarat 382007, India
e-mail: kalyan_sasidhar@daiict.ac.in

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on one leg leading to a bend on one side of the body).[1] Various attempts have been made to detect this form of abnormal gait (Kozlow et al. 2018). However, as revealed by orthopedics, in most cases, individuals realize their abnormalities very late in their lives due to the lack of early assessment or diagnostic facilities and hence resort to kneecaps, medications, and exercises. Still, the gait patterns remain unchanged and abnormal gaits are becoming one of the contributors to knee problems (Gait and Knee Problems 2023) and lower back pains (da Fonseca et al. 2009). The sudden gait changes, if unnoticed, could persist for a longer time, resulting in abnormal gait.

With the evolution of wearable sensing systems, portable fitness bands and smartwatches have already proliferated in the consumer market. However, none of these gadgets is capable of monitoring one's walking and detecting changes or abnormalities in gait patterns. In other words, these devices do not record or extract gait patterns and detect gait changes. This highlights the necessity to encourage regular gait measurement periodically, similar to measuring blood pressure, sugar levels and even oxygen saturation levels at regular intervals. Various survey articles have been published discussing the use of wearable sensing systems for gait analysis (Yang and Hsu 2010; Bhosale et al. 2015). The gap in the literature includes a dedicated device for long-term gait monitoring. To accomplish continuous monitoring and detection, an individual's gait must be stored in a database for which a digital platform is required.

To analyze the importance of the problem, this work conducted a survey across a pool of 30 doctors and physiotherapists. The responses were the following:

- 80% believe that preventive health care is the need of the hour.
- 83.34% believe that a portable device measuring gait parameters with analysis can be useful.
- 86.67% denied when asked if there is any similar device in the market.
- 90% would test and recommend such a device to their patients, if given to them.

Backed by survey responses, we designed and developed a wearable device that can detect gait changes in an individual and store the data in a database. In a natural world setting, analyzing gait abnormalities is limited to a handful of hospitals. The patients have to visit the hospitals for a facility like a Motion Capture system (Estévez-García et al. 2015). This is often an expensive affair and beyond the reach of a majority of the population. With digital health on the rise, there is a pressing need to create a digital repository of individual health data. In a country like India, having a vast population base, there is a need to have arrangements for a huge healthcare database. This is where our affordable device can contribute. Our proposed device can be used to create a gait database that can provide a historical perspective for various stakeholders, including orthopedics, and physiotherapists, who can analyze the data through our algorithms and provide early diagnoses to patients about gait changes.

[1] Auerbach N, Tadi P. Antalgic Gait in Adults. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2022 January. Available from: https://www.ncbi.nlm.nih.gov/books/NBK559243.

These changes could be subtle, but, if they persist for a long time, could lead to potentially serious medical conditions.

The following are our contributions:

- The wearable device is in itself a novel attempt to provide personalized healthcare diagnostics.
- For the first time in India, the abnormal gait detection system paired with a smartphone application is implemented. Till now, no such work has been observed.
- The differences in gait parameters between normal and abnormal walking within a user are identified.
- We show how changes in walking are identified, detected and presented to the concerned personnel.

Related Work

Analysis of gait is commonly performed by measuring speed, length of rhythm and pitch while moving. The most common approaches are using camera-based systems to extract the gait parameters during locomotion. However, this approach requires a complex set up which is bulky, and incurs infrastructure cost. Such facilities in India are available only in multi-specialty hospitals which are beyond the reach of the general population.

Gait analysis using external sensors has been conducted by placing an accelerometer sensor on the hip, ankles and foot. A wearable body-worn sensing system for analyzing gait and classifying between normal and abnormal has been proposed by Sant'Anna et al. (2012). The gait of subjects with lower back pains is measured and it explores the correlation between improper gait and back pain in Chan et al. (2013). In Cheng et al. (2013), researchers developed GaitTrack, a smartphone app that computes the walking or gait speed of patients and provides a correlation between gait speed and patients with Chronic Obstructive Pulmonary Disease (COPD). Activity recognition, i.e., recognizing walking, running, taking the stairs or sitting still, is an application which has used inertial sensors such as the accelerometer to a great extent. Various research works have proposed unique algorithms for activity recognition (Kwapisz et al. 2011; Sun et al. 2010; Yang 2009; Zhong et al. 2010).

A personalized wearable system that enables the movement of persons with Parkinson's disease is developed by Mazilu et al. (2014). The system detected freezing episodes or abrupt stops in walking using ankle-mounted motion sensors and responded by playing a rhythmic auditory sound that adapted to the patient's regular gait speed, alerting the person to move, and used a smartphone as a Processing Unit. Godfrey et al. validated a low-cost body sensor unit to quantify gait characteristics in a large group of young and older adults (Godfrey 2015). Authors in (Pepa et al. 2015) extract step length using the data collected from a smartphone accelerometer to assess gait of an individual. Perez performed a gait analysis to assess the balance and risk of patients falling with walking difficulties (Perez and Labrador 2016). Miniature-sized accelerometers and gyroscope sensors (Roy et al. 2016) embedded in smartphones have tremendous application usage.

Works specific to gait analysis through smartphones have been attempted in Chan et al. (2013), Zhong et al. (2010), Pepa et al. (2015), Nishiguchi et al. (2012), Sasidhar and Satyajeet (2017).

We conclude that most of the existing work consists of

- Validating the use of accelerometers in sensing gait parameters.
- Performing kinetic analysis using wearable sensors and understanding gait.
- Identifying the correlation between gait patterns and walking speeds with symptoms of various diseases that have been shown to affect gait.
- Performing classification of different sets of gait samples into multiple classes.

In contrast to the existing work, we propose a system that aims to do the following: a) monitor gait, b) store periodic gait data for identifying and detecting gait changes, c) calculate the extent of the change in gait and d) provide diagnostic information to stakeholders such as physiotherapists and orthopedics.

Methodology

Data Collection

Ten participants, all graduate students residing on the campus of our institute, volunteered to wear the device and provide data. The demographics of the subjects is presented in Table 16.1.

The instruction is given to each user to walk a 10 m path. Users walked with their body posture and pace similar for each walk. However, to induce sudden changes in their walk pattern, a video of antalgic gait has been shown to the users. Under the

Table 16.1 Participating users in experiment

User	Gender	Height (cm)	Age
User 1	Male	171.2	29
User 2	Male	173	24
User 3	Female	154	25
User 4	Male	160	25
User 5	Female	150	24
User 6	Female	155.5	24
User 7	Female	160	26
User 8	Male	170	25
User 9	Male	165	25
User 10	Male	176	23

supervision of the physiotherapist, each user mimicked the action to bring a change in the walking pattern. We obtained a total of 70 gait data sets (50 normal walking and 20 abnormal walking data sets) per user, resulting in a database of 700 gait data sets across ten users.

Measurement Platform

The system was designed and developed in-house using an ARM Cortex M3 core ultra-low power micro-controller with Bluetooth version 2.0, an MPU 6050 3-axis accelerometer and a 3.74 V Lithium polymer (LiPo) battery with a voltage regulator for power supply. The accelerometer consists of microstructures whose capacitance changes due to external forces. This capacitance change is converted to voltage values (Roy et al. 2016). The sensor has a pair of three 16-bit ADCs for digitizing the output. The sensor has a minimum full-scale range of ±2 g and a maximum full-scale range of ±16 g.

The sensed data is transmitted via UART from the micro-controller to the Bluetooth module HC-05 V2.0. This module is further paired to a smartphone, where all the computation is performed through a mobile application. Figure 16.1 shows the architecture of the system.

The proof of concept of the device and how it is worn is depicted in Fig. 16.2.

In the next section, the explanation of how the sensor data was preprocessed, how the human walking was recorded and how gait features were extracted is provided.

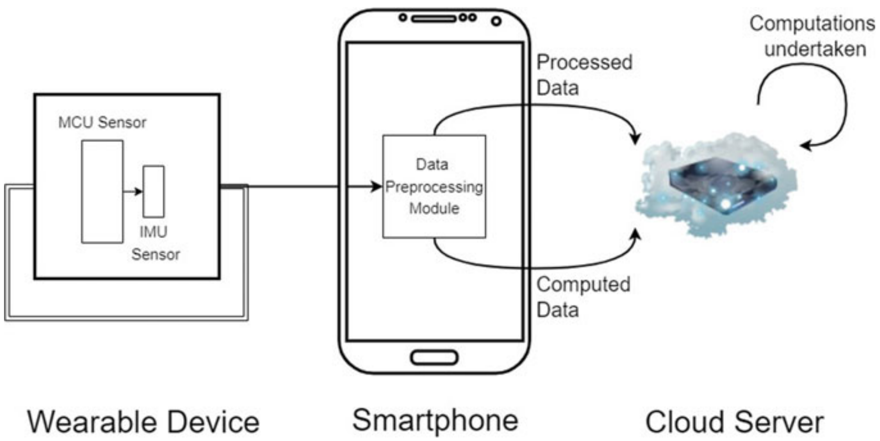


Fig. 16.1 Architecture of flow of the application

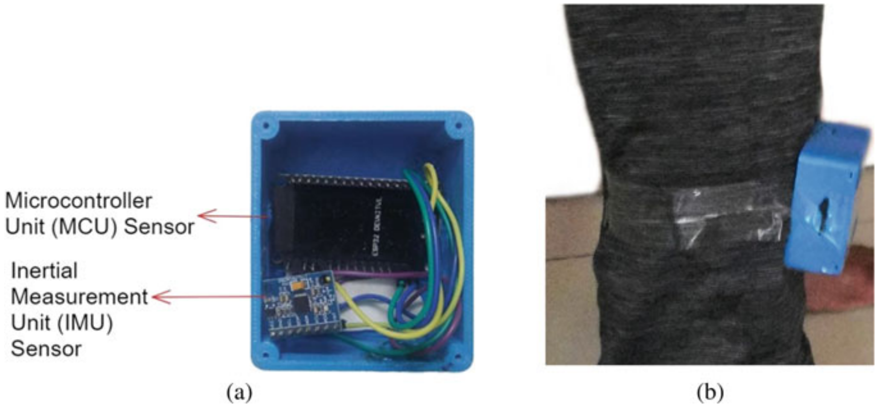


Fig. 16.2 **a** The sensor along with the micro-controller unit is shown on the right and the Bluetooth IC on the left. **b** The device fixed to a band and wrapped around the ankles

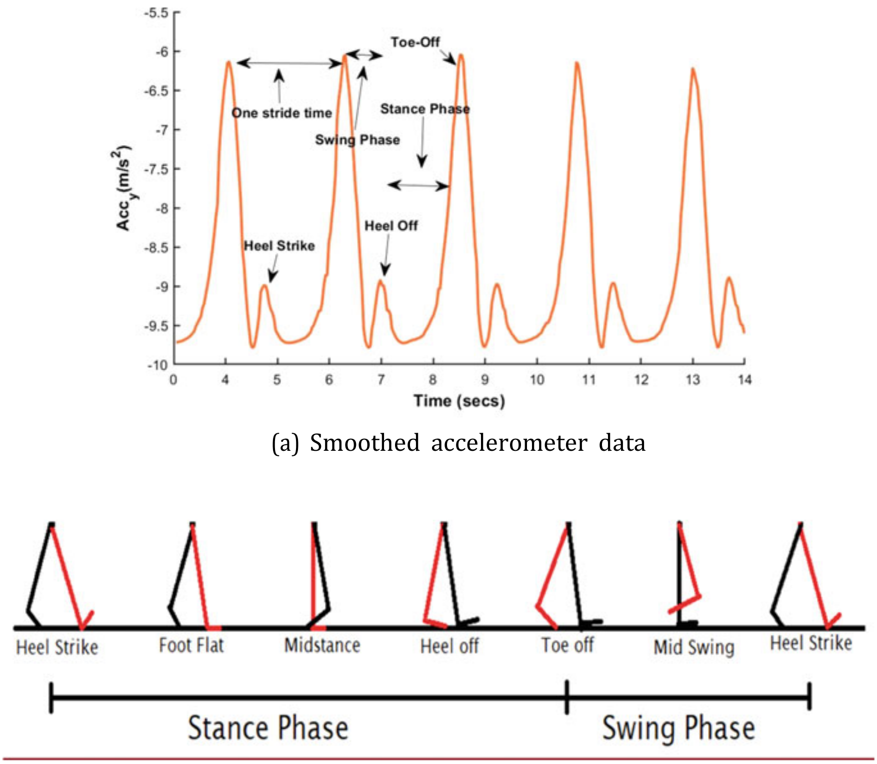
Data Processing

The data from the wearable device was sampled at 50 Hz. The data was sent to a cloud database through a smartphone which was later converted and downloaded in CSV format for analysis in MATLAB (version 2022a). Basic filtering techniques were applied to smoothen the raw data. The data from each user was named *UserID day*1 *normal* and *UserID day*1 *Abnormal* to preserve anonymity. All data was sent to MongoDB, where the data is stored and can be exported in CSV format. Figure 16.3 shows the screenshot of the sample data.

Figure 16.4a illustrates the smoothed accelerometer data captured from one individual who wore the device and walked a distance of 10 m, and the corresponding

acc_x (m/s²)	acc_y (m/s²)	acc_z (m/s²)	Time since start	HH-MI-SS_SSS
-0.1085	9.5662	-0.7045	10	14:56:46:805
0.2361	9.4418	0.042	26	14:56:46:821
0.1667	9.4992	-0.2834	41	14:56:46:836
-0.1516	9.7218	-0.403	57	14:56:46:852
-0.5033	9.4155	-1.1568	74	14:56:46:869
-0.6732	9.6236	-0.8673	90	14:56:46:885
-1.0178	9.65	-0.5036	106	14:56:46:901
-0.9747	9.6524	-0.3887	122	14:56:46:917
-0.8599	9.449	-0.5347	138	14:56:46:933
-0.4555	9.3652	-0.7237	153	14:56:46:948

Fig. 16.3 The accelerometer (*acc x*, *acc y* and *acc z*) data across 3 axes are stored along with the timestamp



(a) Smoothed accelerometer data

(b) Gait phases

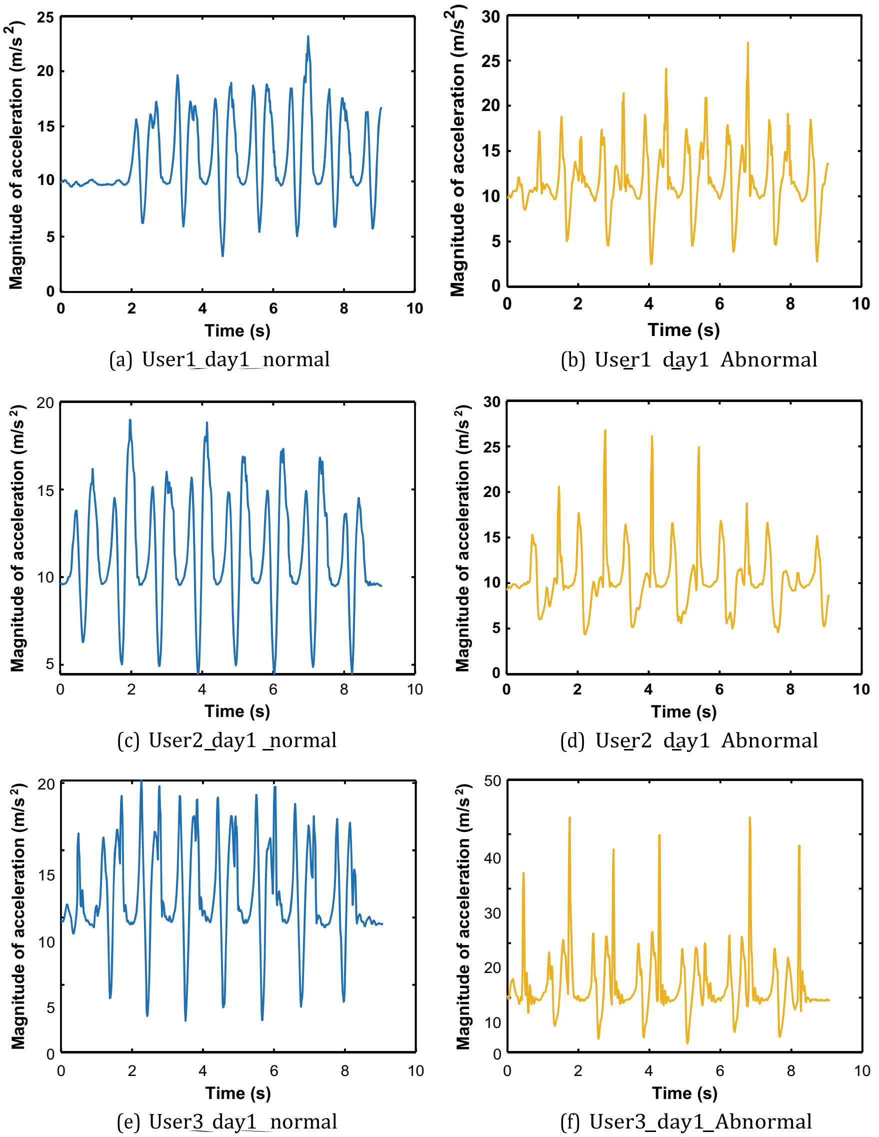
Fig. 16.4 **a** The gait cycle starts at heel strike and ends at heel off. The stance phase is from heel strike to toe-off and the swing phase is from toe-off to heel strike of the other leg. **b** The various gait phases are identified in the smoothed accelerometer data

gait phases are shown in Fig. 16.4b. The device placement was suggested by an orthopedic and sports bio-mechanics expert who tested the device in the lab themselves. The location of the device (Fig. 16.2) assists in capturing the force exerted while walking.

Figure 16.5 compares normal gait and limping gait patterns of a volunteer.

Detection of Gait Changes

With the proposed device, user's gait can be stored and analyzed for sudden changes so as to diagnose potential chronic ailments early. Let us look at intra-subject differences in stride times between normal and abnormal walking samples. Figure 16.6 provides a statistical comparison of stride duration for both walking patterns of six



(a) User1_day1_normal (b) User1_day1_Abnormal

(c) User2_day1_normal (d) User2_day1_Abnormal

(e) User3_day1_normal (f) User3_day1_Abnormal

Fig. 16.5 One cycle of gait starts at heel strike and ends at heel off. Stride Length is the distance between successive parts of heel contact of the same foot, and stride time is the corresponding time taken for one stride length. To calculate the stride length, two consecutive heel strikes are considered as the start and end of a stride because when the heel hits the ground, a transient intense force is exerted, resulting in a peak acceleration

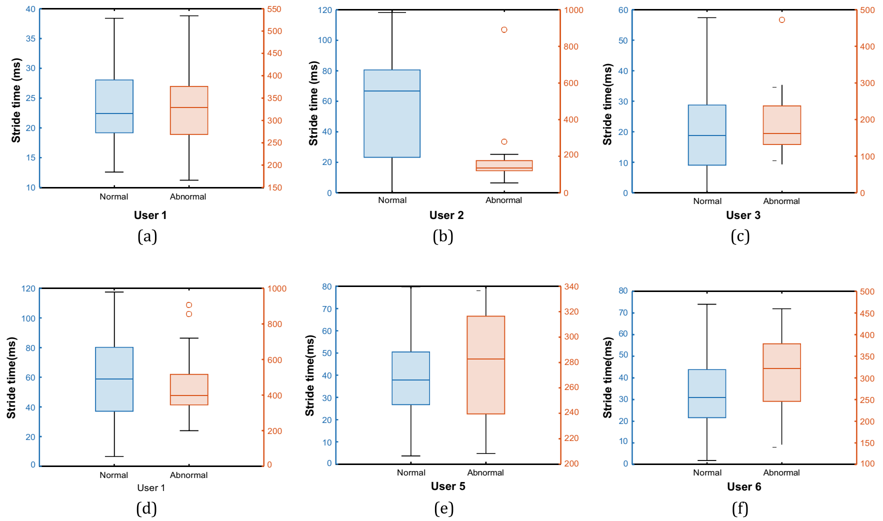


Fig. 16.6 Stride time variations of volunteers: For each box plot, the median and inter-quartile values are in different ranges, confirming that there were significant individual variations in walking between normal and limping

volunteers. This difference clearly provides a quantitative comparison and indication of one's gait changes.

The novelty of this work is to facilitate a personalized classification or identification of abnormality in gait. In other words, classifying a person's gait as normal or abnormal from a pool of gait samples belonging to different persons does not help in analyzing the degree of change in gait. Instead, performing an intra-volunteer gait pattern comparison will help to observe how one's gait patterns change over a period of time.

For instance, the heel strike and heel off features of one user are identified, the stride length is extracted and the stride time is computed. Further, the average change in stride times over each day is computed and changes are observed as shown in Fig. 16.7.

A smartphone app has been designed as explained in section "Measurement Platform". The interface of the app is shown in Fig. 16.8. The interface is self-explanatory. The stakeholder (orthopedic, physiotherapist) has given a list of his patients post log into the app. Once a particular patient is selected, his/her historical gait parameters are available. Further options include visualizing the sensor data along with the gait parameters extracted by the algorithm at the server.

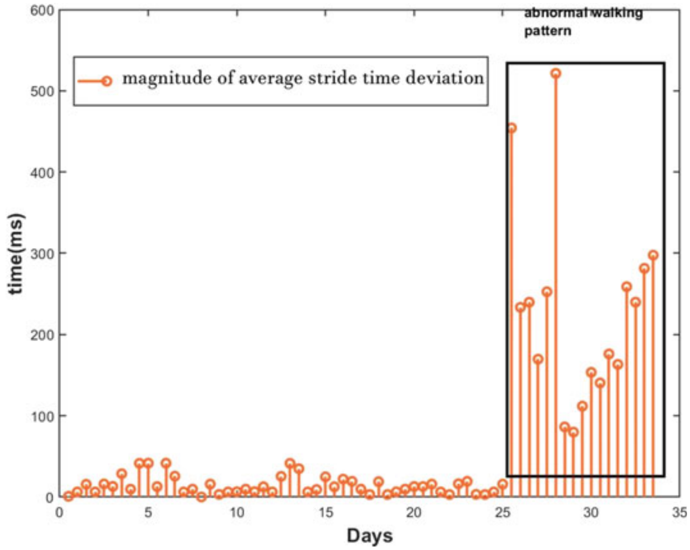
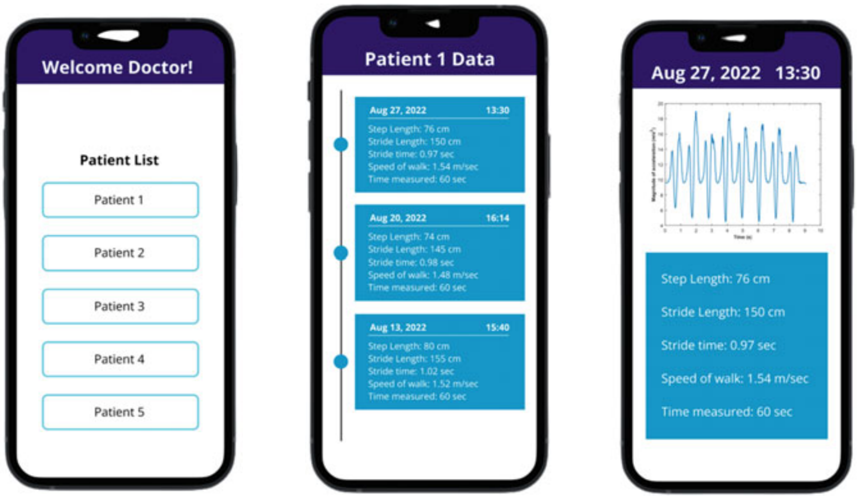


Fig. 16.7 As we can see, most of the deviations are negligible but due to limping the stride times increased. This can be observed between days 25–33. Such sudden but slow changes in stride time could indicate difficulty in walking which if noticed earlier could assist in an early diagnosis by the medical personnel



(a) List of patients whose data is available

(b) History of gait data of the patient

(c) Measured Gait data of a patient

Fig. 16.8 Flow of the screen interface of GaitTracker, the mobile application

Conclusions

This work presented a device that can provide personalized gait monitoring and detect sudden changes. The novelty of the work lies in packaging together a solution that is inexpensive, portable and easily usable. The device can be used at a clinic for regular checkups, where the digital records of each patient's gait patterns are stored for diagnosis. The work is currently looking at predicting when and how much one's gait could change if the current trend of abnormality is observed. With healthcare prediction being a positive trend, this device can play a vital role in the pre-diagnosis and diagnosis of gait irregularities. In future, this work can be extended to the device being worn on both the legs and the gait patterns being measured simultaneously so as to cover a broader scope of gait patterns.

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