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GAIToe: Gait Analysis Utilizing an IMU for Toe Walking Detection and Intervention

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Abstract. Idiopathic toe walking (ITW) is a walking pattern in which a person habitually walks on their forefoot with the absence of heel contact during the gait cycle. Gait rehabilitation can be achieved through behavior modification by employing a wearable device and giving the user immediate feedback. In this paper, we introduce GAIToe, a real-time toe walking detection and intervention platform that remotely monitors walking patterns. GAIToe utilizes an Inertial Measurement Unit (IMU) located in the insole and incorporates a machine learning model to detect different walking, sitting, and standing behaviors. GAIToe identifies these activities with 88% accuracy and provides vibration feedback following consecutive toe strikes. It also provides an Android application to transmit the data and a visual context to monitor the walking patterns. For the preliminary evaluation of GAIToe, we collected activity samples from ten healthy subjects.

Keywords: Idiopathic toe walking · Gait analysis · Wearable sensor · Inertial Measurement Unit (IMU) · Machine learning

1 Introduction

Toe walking is a gait pattern where a person walks on the toes or balls of the feet without the heel touching the ground during the gait cycle. General conditions associated with toe walking include autistic spectrum disorders, cerebral palsy, congenital talipes equinus, developmental coordination disorder, and muscle dystrophy [1,2]. When children first begin to walk, the presence of toe walking is not unusual; however, the heel-toe gait pattern can become persistent as they grow up [3]. If older children persist in toe walking with no signs of neurological, orthopedic, or psychiatric disease, or the cause of toe walking remains unexplained, they are diagnosed with idiopathic toe walking (ITW) [4,5]. A child with ITW habitually walks on the forefoot, but they can perform heel-toe walk for short periods when they are asked to do so [1,4]. The incidence of ITW has been

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estimated at 7% to 24% of the childhood population [6]. Persistent toe walking may induce foot deformities, ankle dorsiflexion limitations, poor alignment of posture, and impaired balance [2,7,8].

Suggested treatments for ITW vary, but the necessity and effectiveness of the treatments are controversial. The recommended approaches to overcome ITW include observation, special training procedures, muscle stretching, orthotic therapy, supportive footwear therapy, serial casting, intramuscular botulinum toxin type A (BTX-A) injection, and finally, surgical heel-cord lengthening [1,3,4,9]. Williams *et al.* [10] proposed a Toe Walking Tool, an online questionnaire to encourage the users to distinguish between ITW and toe walking associated with medical conditions. Their approach was found to be a valid and reliable tool for the diagnosis but does not serve as an immediate treatment to fix toe walking. In [9], stretching exercises and ankle-foot-orthoses are useful to keep adequate ankle dorsiflexion, and BTX-A reduces the development of plantar flexion torque. Engström *et al.* [11] explored the effectiveness of BTX-A with 24 months follow-up, but they concluded that injecting BTX-A did not significantly decrease toe walking. Davies *et al.* [12] studied the geology of ITW and the long-term effects of conservative therapy on gait performance. They concluded there was a reduction in toe walking severity in the active treatment group with casting. However, several studies [3,13] report that conservative treatments do not have any lasting effect on the toe walking, and even after surgical treatment, the failure rate is over 30% [4]. More promising analyses and interventions of ITW still need to be developed and validated.

Variability of gait parameters has been an indicator of health, such as Parkinson's disease [14], cardiovascular disease [15], fall detection [16], and cognitive decline [17]. Gait analysis has been used to monitor patient progress in orthopedics and rehabilitation [18]. A gait cycle (or stride events) contains a stance phase (initial contact, loading response, mid stance, terminal stance, and pre-swing) and a swing phase (initial swing, mid-swing, and terminal swing) [18]. Information about human locomotion includes quantitative measures (i.e., length, speed, and angle) of step, stride, stance, and swing. The traditional clinical assessments to analyze gait parameters rely on subjective or semi-subjective scales [18]. Subjective gait assessment tools, such as the Gait Abnormality Rating Scale [19], Four Square Step Test [20], and Functional Gait Assessment [21], are more likely to have observer variations which affect the accuracy of diagnosis [18]. Objective measurement to characterize human gait is obtainable through advancements in technology, including instrumented walking mats, treadmills, and motion capture systems [15]. These instruments are often expensive, difficult to use, and require a clinical setting to be installed and measured.

The development of wearable sensors and wireless communication encourages remote monitoring of human movements in natural settings. Wearable sensors can be attached to different body locations, such as the foot, waist, chest, wrist, or head [18]. Numerous wearable sensors have been used for the gait analysis: accelerometers, gyroscopic sensors, magnetometers, force sensors, extensometers, goniometers, active markers, and electromyography [15]. A low-power and short-range wireless medium, such as Bluetooth, ZigBee, ANT, Near Field Communications (NFC), are also available for body sensor networks [22]. Recent remote health monitoring systems [17,18,23] utilize a smartphone as a network hub or processing gateway for massive amounts of sensor data. The remote health monitoring system, which is low-cost, portable, and pervasive, enables a new healthcare era.

A real-time assessment system enables real-time intervention. Because ITW is a habitual or behavioral activity among healthy children, behavior change techniques (BCTs) [24] may motivate them to put their heels down. Based on control theory [25], designing a system to record walking activities to compare the daily number of toe strikes and heel strikes can bring positive outcomes to the individuals with ITW. The remote assessment system can prompt a specific goal setting (i.e., achieving more heel strikes) and provide an intuitive interface to review the goals compared to the recordings. These children may not need conservative or surgical treatments with high-cost clinical visits to overcome ITW. The system with wearable sensors can detect continuous toe walking and give just-in-time adaptive intervention (JITAI).

We introduce a remote toe walking monitoring system, GAIToe (**G**ait **A**nalysis utilizing an **I**nertial measurement unit (IMU) for **Toe** walking detection and intervention). The GAIToe uses a single IMU in an insole to detect physical activities such as toe walking, heel-toe walking, standing on toe, normal standing, sitting on toe (sitting heel raises), and normal sitting. It also provides real-time biofeedback with two types of vibrations: a short vibration for 3, 6, or 9 consecutive toe contacts and a long vibration for ten consecutive toe contacts on the ground. The long vibration can be turned off with a heel strike. The sensor data of GAIToe are transmitted to the developed Android application via Bluetooth Low Energy (BLE). The Android application stores the recordings in the cloud-based database and presents the number of toe steps and normal heel-toe steps. Our system affords a portable, non-invasive, low-cost, power-efficient, easy-to-use, and quantitative assessment. Using this system is expected to have positive impact on the population with ITW.

The remainder of the paper is structured as follows. Section 2 explores the related works on utilizing wearable sensors for gait analysis. Section 3 discusses the system specification of the GAIToe, including hardware implementation, power consumption, mobile app development, and the activity recognition algorithm. Section 4 presents the experiments and preliminary evaluation of GAIToe. Finally, we propose our future research direction in Sect. 5 and conclude in Sect. 6.

2 Related Works

Multiple wearable sensors have been proposed to provide information about human locomotion and activity recognition. Liu *et al.* [26] developed a wearable system to detect gait phases using multiple inertial sensors of gyroscopes and accelerometers. The sensor units are attached to the leg segments (the foot, shank, and thigh) using straps. Since many sensors' usability and appearance on the body regions are not practical, several studies have embedded sensors in the shoe or insole. Xu *et al.* [27] proposed a smart insole to compute gait parameters with 48 pressure sensors, a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis compass. Lin *et al.* [28] presented a smart insole that measures plantar pressure with an array of piezoelectric sensors and movement information with inertial sensors. Both studies developed smartphone software for data processing and real-time computing. Sazonov *et al.* [29] utilized five force-sensitive resistors (FSRs) placed on an insole and a 3-axis accelerometer positioned on the back of the shoes. Their sensor system recognized human body posture and activity by employing support vector machines (SVMs). Hegde *et al.* [30] proposed a pediatric smart shoe system for remote activity (sitting, standing, and walking) detection. They placed five FSRs and an accelerometer on the insole and mounted other electronics in the back of the shoes. Carbonaro *et al.* [31] achieved the detection of the gait phases (heel-strike, stance, heel-off, and swing) utilizing two FSRs located on the heel and forefoot and an accelerometer embedded in the forefoot, interfacing with a smartphone through Wi-Fi connection. All of these works are useful to track human locomotion and walking status. However, their complicated systems and algorithms are not designed specifically for toe walking detection and interventions.

Our proposed platform, GAIToe, detects different walking, sitting, and standing behaviors by integrating a single IMU in an insole. We selected an IMU because the shoes' acceleration data were sufficient to identify different gait patterns based on the literature and our experiments. The system costs less than $80.00 before the cost-saving of mass production. The sensor unit is not exposed and does not deform the exterior design of regular shoes. Furthermore, our activity recognition algorithm does not require complex sensor fusion algorithms because we use a single IMU on each insole. The computation of activity recognition is executed onboard; therefore, the portable sensing unit can give real-time feedback without requiring a connection to the server or the other devices for the determination. The developed Android application also provides visual feedback and serves as a data logger. Our platform motivates individuals with ITW to change their walking patterns with continuous remote monitoring in non-clinical settings.

3 GAIToe System Specification

GAIToe is composed of two main components: a shoe sensor unit and a linked smartphone application (Fig. 2). The sensor unit is designed to measure the foot movements using an IMU. It is mounted into an insole to be easily inserted into any running shoes. We programed the sensor unit with a machine learning-based activity recognition algorithm for the real-time toe walking detection and feedback. The readings of the sensor unit are transmitted to an Android application via Bluetooth. The Android application stores the recordings in the cloud-based database. It also displays toe walking and heel-to-toe walking results for the individuals with ITW in order to review their daily walking patterns.

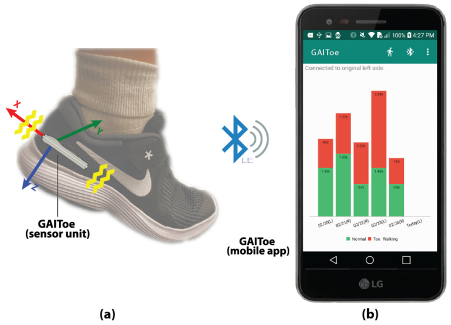

Fig. 1. Components of the system: (a) a sensor unit mounted on the insole and (b) a linked smartphone application. A sensor unit of the GAIToe, utilizing an IMU, detects toe walking and vibrates onboard. It transmits data to the connected smartphone application via Bluetooth.

3.1 Hardware Implementation

We investigated available wearable sensors, wireless data transmission modules, programmable controllers, and rechargeable batteries with small dimensions to develop remote monitoring and real-time intervention systems for habitual toe walkers in natural settings. Our hardware implementation goal was to maximize the utilization of currently available and affordable devices in order to reduce the expense of our custom-designed system.

With all these considerations, Adafruit Feather M0 Bluefruit LE (Adafruit Industries, New York, NY, adafruit.com) [32] development board was chosen. It has an ATSAMD21G18 ARM Cortex M0 processor with up to 48 MHz operating frequency, 32 KB SRAM memory, and 256 KB FLASH. Adafruit Feather provides Bluetooth Low Energy (BLE), low-power, 2.4 GHz spectrum wireless protocol. The Bluefruit LE module (nRF51822) uses the standard Nordic universal asynchronous receiver-transmitter (UART) RX/TX connection profile and enables transmitting data back and forth from an iOS or Android device. Adafruit Feather has a JST connector for 3.7 V Lithium-Polymer (Lipo) or Lithium-Ion (LiIon) battery. We selected an 800 mAh Lipo rechargeable battery as the power supply and connected a slider switch to control it. The built-in micro-USB port on the board allows us to program the microcontroller, as well as automatically switch between USB power and charging the connected Lipo battery at 100 mA. Several indicator LEDs provide the board's status, such as a red LED for power, a blue LED for BLE connection, and a yellow LED for charging. The board's dimension is 51 mm $\times$ 23 mm $\times$ 8 mm, reasonably small for any wearable device.

GAIToe is equipped with an MPU-9250 motion tracking device (9 degrees of freedom IMU). It is a multi-chip module consisting of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer (AK8963). The accelerometer has a measurement range of up to ± 16 g and sensitivity up to 16,384 LSB/g. The gyroscope has a range of $\pm 2000°$/s and sensitivity up to 131 LSB/deg/sec. The

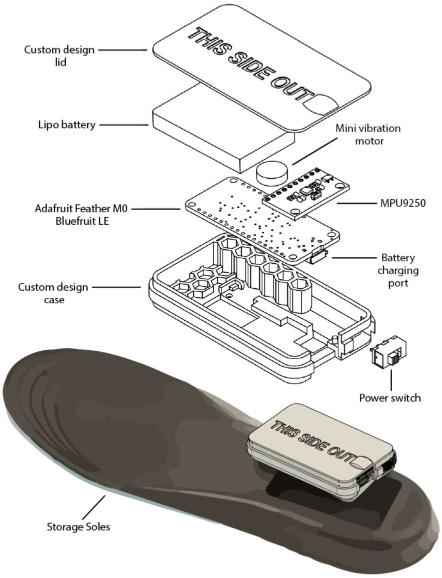

Fig. 2. Circuit components in a GAIToe sensor unit. The custom-designed 40 mm × 72 mm × 14 mm case is mounted on the storage soles and includes all the circuitry, such as an Adafruit Feather board, an IMU, a mini vibration motor, a Lipo battery, and a slide switch.

magnetometer's full-scale range is ±4800 μT, and the sensitivity is 0.6 μT/LSB. Each sensor outputs digitized values through three 16-bit analog-to-digital converters (ADCs). An MPU-9250 communicates with the Adafruit feather board via I^2C bus at 400 kHz. The IMU in the insole is located to contact the calcaneus, the heel bone on the hindfoot, as can be seen in Fig. 1a. It captures the shoe acceleration, angular velocity, and magnetic north.

A mini vibration motor is connected to the Adafruit Feather board to provide real-time biofeedback. When the user is continuously toe walking or consistently standing and sitting on the toe (sitting heel raises), the GAIToe sensor unit produces vibration. Following three, six, and nine consecutive toe contacts (walking, standing, or sitting) on the ground, the GAIToe sensor unit generates 1-s vibration. Following ten consecutive toe contacts, it generates 30-s vibration. The long vibration can be turned off with a heel strike. This vibration generation protocol was defined in consultation with orthopedic surgeons and physical therapists as what would successfully arouse the user's attention regarding toe walking and motivate more heel strikes.

Storage soles [33], insoles with a container space at the bottom, satisfied our need to house the shoe sensor unit and to insert it into any running shoes. Storage soles are made from flexible polyurethane (PU) foam, so they are waterproof and easily trimmed for nearly any shoe size. We designed a case and lid to house the circuitry components and fit them into the storage soles. The case and lid are made by a 3D printer using polylactic acid (PLA), a common plastic filament material. The empty space in the case is filled with hexagons to endure the pressure of human body weight. The custom-designed 40 mm × 72 mm × 14 mm case includes all the circuitry (Fig. 2), such as an Adafruit Feather board, an IMU, a mini vibration motor, a lipo battery, and a slide switch.

3.2 Power Consumption

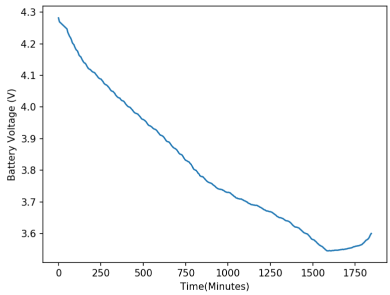

Fig. 3. Battery characteristics of GAIToe sensor unit. A Lipo battery discharge curve with continuous vibrations

The power efficiency of the system is crucial to monitor the foot activity and give continuous real-time intervention. We attempted to emulate a worst-case usage scenario, continuous toe sitting, including a series of vibrations and a transmission rate at 20 Hz. A typical Lipo battery maintains around 3.7 V for much of the battery life, then decreases in voltage just before the circuitry cuts it off. In our experiment, the battery almost consistently discharged the voltage and stayed at the minimum voltage of 3.545 V for 30 min. Interestingly, the battery increased the voltage up to 3.6 V before it turned off (Fig. 3). We figured out that the system lasts 1,845 min (30.75 h) under continuous operation (Fig. 3). Our system fits in clinical settings as well as continuous, pervasive monitoring in naturalistic settings. It requires getting charged every day and does not run out of charge during activities in a day.

3.3 Android Application Development

Our sensor unit is implemented to compute activity detection on the board but does not have a data logging component. We could add data storage, like an SD card, in the unit, but that would require an extra step of transferring data to monitor daily walking patterns. Due to the recent advancements in mobile technologies, smartphones are commonly used as a communication hub in the remote monitoring systems [28,31,34]. We developed an Android app (Fig. 1b) to achieve wireless data transmission, collecting data from our sensor unit via

Bluetooth, and storing the data in the cloud-based database via the Internet. We focused on a design with minimal user interaction.

The Android application includes a specific Bluetooth connection protocol to connect to the GAIToe sensor unit automatically. When the app is launched, it starts to scan and connect to the BLE module using the pre-stored MAC address. When the Bluetooth connection is stable, the UART serial communication between the BLE module and the Android device begins. If the UART service fails within 20 s, the app automatically terminates the BLE connection and scans the BLE module again. The Bluetooth connection can be reset manually by pressing the (three-dot) Connect button on the top right corner of the screen (Fig. 1b). The Bluetooth icon next to the Connect button indicates BLE connection status in four colors: disconnection in red, scanning phase in orange, stable connection with UART in white, and failed UART service in black. The average time for the Bluetooth connection was 5.242 s in an experiment with the LG Phoenix 4 smartphone (which has an Android 7.1.2 Nougat operating system and 1.4 GHz Quad-Core Qualcomm Snapdragon processor). The GAIToe sensor unit transmits the IMU's raw signals, the detected activities, and the generated vibration feedback to the connected app with 20 Hz.

The developed app provides an intuitive visualization of the daily walking pattern. Our app calculates an accumulated number of steps based on the received types of activity from the sensor unit. A stacked bar chart displays the number of toe steps in red bars and the number of heel-to-toe steps in green bars (Fig. 1b). The previous six days' step counts are shown on the first 6 bars while the real-time step counts are shown on the rightmost bar. The app saves the collected data into the cloud-based database every five minutes.

3.4 Activity Recognition Algorithm

In order to achieve the objective of providing a real-time system, we concentrated on developing the activity recognition algorithm on the microcontroller. Wearable IMU signals are sensitive to small foot movements, and the activities cannot be determined by a threshold-based algorithm. Tree-based machine learning models allowed us to achieve high classification accuracy with the IMU signals.

To train the activity classification model, we first collected activity data from 14 healthy subjects recruited from the university community. The subjects were asked to wear our study shoes with sizes vary from youth's size 6 to women's size 11. Then, they performed 200 strides of heel-toe walking and toe walking, as well as 2 min of sitting and standing. We made use of our Android application with an added functionality to save the activity label and the subject ID along with the sensor data in the database.

We extract features from the IMU data to feed the classifier. The magnitude of the 3-axis of accelerometer, gyroscope, and magnetometer is computed using Eq. 1.

$$A_i = \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2} \tag{1}$$

Where i is the index of the signal; and x_i, y_i, and z_i are the three-axis of vectors. A low-pass filter [35] is applied to the vectors of the accelerometer. We derive the roll and pitch angles from the acceleration data [35]. The tilt angles [36] of the 3-axis of each sensor are also calculated.

To train supervised machine learning classification algorithms on our time series data, we process the data by dividing it into windows of 10 data points. Then, according to Eqs. 2 and 3, the mean and standard deviation of each window are extracted as a feature.

$$WindowAverage_t = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

Where x_i is a signal reading with index i and n is the size of the window which here is assumed to be 10.

$$WindowStandardDeviation_t = \left(\frac{\sum_{i=1}^{n}(x_i - WindowAverage_t)^2}{n-1}\right)^{\frac{1}{2}} \tag{3}$$

We selected an extra-trees classifier from Scikit-Learn [37], which had the highest cross-validation (CV) result among other classifiers. This classifier predicts the class by implementing a meta estimator that fits randomized decision trees with sub-samples [37]. Using an extra-trees classifier, we ran the training data with various estimators (1 to 100) and maximum depths (1 to 20). Figure 4 demonstrates the cross-validation scores achieved from examining these estimators and maximum depths. Considering the limited flash memory (program space) on the Arduino-compatible microcontroller and analyzing Fig. 4, the best 10-fold cross-validation (88%) was achieved by setting the estimator to 25 and maximum depth to 8.

To remove the irrelevant features from our classification model, we ran tree-based feature selection [37]. Acceleration pitch and tilt angle mean, gyroscope magnitude mean, and standard deviation of gyroscope raw signal values are the most significant features among the others in our training model. The precision, recall, and F1-score of each label (normal walk, toe walk, normal sit/stand, and toe sit/stand) are reported in Fig. 5. According to Fig. 5, the normal sit/stand label has the highest precision and lowest recall; however, the toe walk label holds the lowest precision and highest recall. All four classes have roughly the same f-1 score.

Further, the leave one subject out cross-validation of the extra-trees with 25 estimators and maximum depth of 8 is 86%. In order to compute the leave one subject out cross-validation, for each subject, we train the classifier on the data collected from the other subjects, and then we test the classifier on the remaining subject's data. Therefore, we make sure that the training and test data are subject-independent.

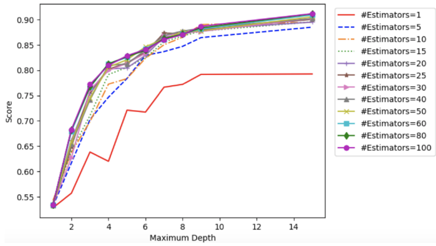

Fig. 4. The extra-trees classification cross validation scores using a various numbers of estimators and maximum depths. Running extra-tree classifier on training data using a various number of estimators (ranging from 1 to 100) and maximum depths (ranging from 1 to 20). The cross-validation score resulted from each run is reported. Then, considering our hardware limitations, the best estimator and maximum depth are selected.

After coming up with the classification model, if activity is determined as normal or toe walking, then the steps counting procedure takes place. Regarding the gait cycle, the forefoot is off the ground during the swing phase, which happens once for each step. Having this in mind and computing peak signals of all the features mentioned earlier, we conclude that nonconsecutive peak signals of gyroscope 3-axis magnitude in window size equal to 10 are an accurate estimation of step counts. To this end, for each window identified as walking, the signal retaining a higher value than the window average is classified as a peak of the window.

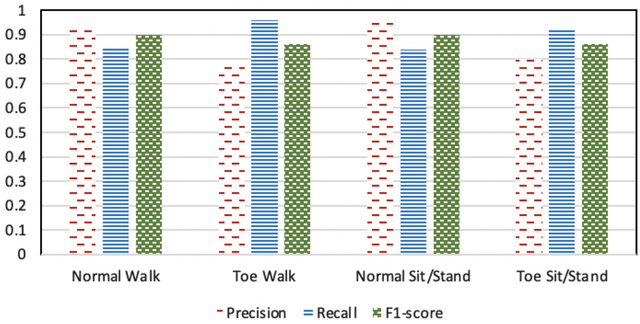

Fig. 5. Precision, recall, and F1-score of all labels. The precision, recall, and F1-score of all classes when running extra-tree classifier on training data with estimator and maximum depth equal to 25 and 8, respectively. The F1-score of all the labels are roughly the same.

Taking into account various walking paces, consecutive peak points are considered as a single step. Figure 6 elaborates an example of the steps count procedure in 2 consecutive windows of size 10. In Fig. 6, among the first 10 consecutive values of gyroscope magnitudes, the 1st, 5th, 6th, 7th, and 9th values are higher than the average of the window. Due to the sequence of 5th, 6th, and 7th signals; signals that indexed as 6 and 7 are not labeled as a step. Accordingly, static windows of gyroscope magnitude signals are processed one after another. As an example of handling consecutive windows in Fig. 6, the last signal (index 9) of the first window is marked as a step. Incidentally, the first signal (index 10) of the second window carries a higher value than the mean signal values of the second window. Since the first window's last signal and the second window's first signal are consecutive, the last one is not perceived as a step. We programmed the microcontroller by integrating the exported C code of the extra trees classification model and step counts procedure.

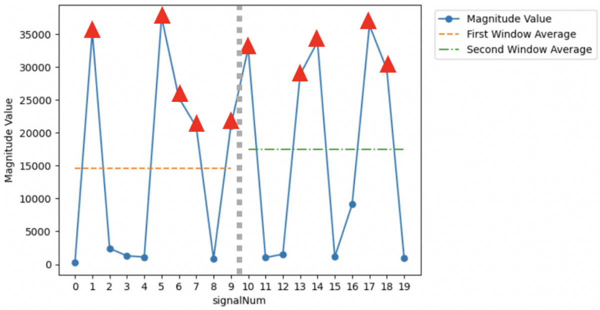

Fig. 6. Steps count peak detection in successive windows. An example of step counts procedure through 2 consecutive windows of gyroscope 3-axis magnitude. The windows are separated with a grey vertical dashed line. The average of each window is depicted using a horizontal dashed line. The signal values with a higher value than the average of their window are marked with red triangles. (Color figure online)

As previously explained in the Hardware Implementation section, to prevent users from continuous toe steps, after each third, sixth, and ninth successive toe step detection, a short vibration with a duration of a second is generated, and there is a long vibration with a duration of 30 s after the tenth successive toe step detection. The long vibration is halted as soon as a heel strike is perceived. Regarding the heel strikes detection in our machine learning classification, any activity labeled as normal heel-to-toe walking, normal sitting, and normal standing is remarked a heel strike. The same intervention procedure takes place for being on the toes while sitting or standing. In this case, every 400 ms of sitting or standing on toes is taken in to account as a step unit for the procedure. Giving these vibrations can notify the individuals about their continuous toe steps and remind them to put their heel down.

4 Experiments

Ten healthy adults (between the ages of 21 and 44) volunteered to try our GAIToe in their running shoes for the preliminary system evaluation. They attempted six activities: 100 strides of toe walking, 100 strides of normal heel-to-toe walking, 2-minute toe standing, 2-minute normal standing, 2-minute toe sitting, and 2-minute normal sitting. We instructed the participants to perform these activities correctly and then supervised them in order to obtain clear data. Subjects were asked to walk at a comfortable pace on level ground. This data was synchronized with the connected Android device.

Figure 7 shows the results of our activity detection and steps count algorithm evaluation. There is no incorrectly detected toe step during normal heel-to-toe walking of all subjects. However, within 100 toe steps of some subjects, there are incorrectly detected normal steps varying between 2 to 9. The average accuracy of normal heel-to-toe step counts and toe step counts are 93.6% ± 3.2 and 84.1% ± 5, respectively.

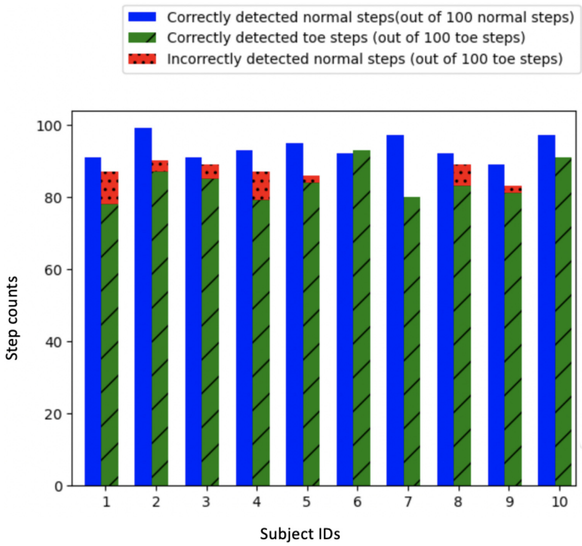

Fig. 7. Number of steps detected per subject. Results of steps detection and count. The solid blue bars show the number of correctly detected heel-toe normal steps through 100 heel-toe normal steps. There is no incorrectly detected toe step within normal walking. The green hatched (//) bars are the number of correctly detected toe steps out of 100 toe steps. Finally, the red dotted bars show the number of incorrectly detected heel-toe steps through 100 toe steps.

To evaluate our vibration protocol performance, we kept a record of the short and long vibrations while subjects walked for 100 toe steps. Table 1 reports the number of short and long vibrations within correctly detected toe steps. Any incorrectly detected normal steps through 100 toe strikes disrupt our vibration policy. If all the correctly counted toe steps were consecutive and all the packages have been delivered via the board to phone Bluetooth communication, the number of expected short and long vibrations would be what is recorded in the last two rows of Table 1.

Table 1. Number of short and long vibrations within 100 toe steps per subject. Reporting the number of short and long vibrations along with the number of correctly detected toe steps out of 100 toe steps. The expected number of short and long vibrations based on the correctly detected toe steps are reported in the last two rows as well.

Subject ID	1	2	3	4	5	6	7	8	9	10
Number of correctly detected toe steps	78	87	85	79	84	93	80	83	81	91
Number of short vibrations	20	27	26	23	25	28	24	25	24	28
Number of long vibrations	6	8	7	6	8	9	8	8	8	9
Expected number of short vibrations	23	26	25	24	25	28	24	25	24	27
Expected number of long vibrations	7	8	8	7	8	9	8	8	8	9

5 Future Work

We are actively recruiting children with ITW through the local children's hospital. We will provide a pair of Nike Revolution 5 FlyEase running shoes to the subjects as a constant measurement instrument. These running shoes have a wraparound zipper that is convenient for inserting and removing our insoles. The subjects and their parents will be educated to alter the insole based on their shoe size and install our software on a study Android device to monitor subjects' daily toe and heel-toe steps. We will ask the subjects to run our Android app in the background and wear the waist bag with the smartphone while trying our shoes. They will be responsible for charging the system every day. The subjects will benefit from real-time feedback when they have a series of toe walking. We will examine our system's effectiveness and robustness through their behavior change regarding their walking patterns.

Since IMU signals are sensitive to a small movement, we can reduce the signals' noise by applying various signal processing techniques. We will enhance our detection algorithm to reduce possible false positives in different situations, such as taking a stair or walking on the uphill path. The repeated usage and pressure on the circuitry container can break our custom-built sensor unit because it is located underneath the hindfoot, a place within the foot region that holds high pressure values [38]. We need to validate the robustness and durability of the system through a long-term assessment. Moreover, we can extend our study to identify the IMU-based gait parameters of ITW. GAIToe may enable orthopedic experts and researchers to investigate the detailed gait parameters and foot movements of ITW in natural settings. It may become an assistive tool to develop a more effective intervention technique.

6 Conclusion

In this paper, we proposed GAIToe, a remote-monitoring system for activity recognition and improving walking patterns of individuals with habitual toe walking. GAIToe provides a wearable, portable, energy-efficient, and low-cost platform for pervasively monitoring walking patterns in daily life. Our sensor unit, utilizing an IMU, is designed to be inserted into any running shoe. The proposed activity recognition algorithm is developed to identify different activities and give real-time biofeedback. It has been validated through an experiment on ten healthy subjects. The connected Android app provides visual feedback regarding walking patterns. Our system has the potential to improve an individual's walking behavior. Furthermore, their orthopedist can monitor the patient's progress remotely.

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