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Abnormal Gait Detection using Wearable IMU Sensor via IoT and Alert for Condition Monitoring of Elderly People

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Keywords:

Gait detection; elderly healthcare internet of things (IoT); inertial measurement unit (IMU) sensor

ABSTRACT

Gait detection is a type of analysis that can detect patterns of walking in a person. In this research, a wearable sensor is used to detect the walking pattern of the user. This wearable sensor will alert the user if abnormal gait is detected. Result from this project is the gait analysis is performed on stance and swing phases of a walk. Sensor 6-axis Inertial Measurement Unit (IMU) decided to be used in this device with Arduino Nano 33 IoT and analysis is done based on the results monitored in ThingSpeak. The data obtained from sensor in Arduino Nano 33 IoT is sent to ThingSpeak to be converted into csv file which is then readable by MATLAB software. Result obtained from the analysis is then concluded into the programming code of Arduino which then the Arduino board can identify the gait by itself based on the analysis done after collecting data.

1. Introduction

When a person grows older, their capabilities and strength lessen. Not only the body can fall sick easily, but also the body cannot handle more than simple tasks as elderly. Usually, there is no one that can always accompany elders unless it involves in their job scope. So, there is a need for something that can monitor elders effectively in case of emergency. Gait detection is a walking pattern detection which can identify a person's defection when walking that is different from usual patterns that may cause by injuries, underlying conditions or problems with the legs and feet. This will help identify if there's underlying conditions that the user may not notice in the first place.

The number of elderly people is rising significantly as compared to overall population which lead to an ageing population in Malaysia and an increasing number of elderly folks who live alone especially in rural area [1]. Most older people prone to trip or fall when they live alone in their home. This project focuses on fall or injury during physical activities. When and elder fall, there's a

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probability of physical injuries that could occur like sprain or broken leg. Falls among nursing home residents are linked to a high personal and societal illness burden due to their body are not as able as a younger person. Therefore, strong early identification methods of residents at risk are required to initiate and customise individual intervention programmes.

Gait analysis using walking patterns also have their own issues with the method of acquiring the data like the use of the sensor. The sensor used need to be accurate so that it can compare with datasets of gait analysis. An extended architecture is presented by Sethi, Bharti and Prakash [2], along with the history of gait analysis, parameters, machine learning methods for marker-based and marker-less analysis, applications and performance metrics. A set of repetitive motions made by the lower extremities that propel the body forward with the least amount of energy expended is referred to as a gait. To estimate the lower extremity characteristics and afterwards study the impact of medicine, both sensor-based and sensor-less procedures are utilised. Gait analysis generates valuable information about healthy and unhealthy gait patterns. The objective method of gait analysis was not so accurate and had adverse effects on the diagnosis of a disease and then treatment of the disease.

In a study of a free field gait analysis by Unger *et al.,* [3], the aim of this study was to test the capability of a free field gait analysis insole to determine fall risk. The average resident age was 88.2 years (range 78–99), 15 residents had at least one fall event. There was no significant correlation between clinical assessment and fall risk, but there were moderate correlations between different temporospatial parameters and risk. An open go-insole (Moticon ReGo AG) with 13 sensors, a three-dimensional accelerometer and a temperature sensor was used to measure plantar pressures, resulting forces, acceleration and temperature. Baseline gait analysis over 1 week was performed with all nursing home residents over the age of 75 years with no acute lower extremity injury or chronic systemic illness distorting the gait pattern (e.g.Parkinson's Disease). Based on the introduced protocol in a limited patient cohort, further large-scale studies should now determine the effect of prevention measures triggered by gait analysis, the specific risk reduction and the associated personal and socioeconomic advantages.

Pierleoni *et al.,* [4] describes a dataset of gait measures acquired to validate the use of wearable sensors in gait analysis. The subjects carried out a motion task wearing the wearable sensors and reflective markers of the stereophotogrammetric system. During the motion task each subject walked over an 11-meter-long walkway according to its own course. This makes the dataset useful for the development, testing and validation of algorithms for estimating gait parameters.

Inertial measurement units (IMU) [5,6], including accelerometers and gyroscopes, can support the assessment of gait regularity. This study by Scalera, Ferrarin and Rabuffetti [7] compares gait-regularity assessment by autocorrelation analyses performed on accelerometer and gyroscope data. Twenty-five adult healthy subjects walked steady state on treadmill at three speeds. Four IMUs were attached on the trunk, pelvis, wrist and ankle.

The work by Matsumoto *et al.,* [8] was to determine if locomotive syndrome in the general senior population was related to gait variability measured using an accelerometer. The following were evaluated: demographic data, assessments of body function and structure (bone mass, grip strength, muscle mass and postural alignment) and gait characteristics. Utilizing a wireless tri-axial accelerometer connected to the third lumbar vertebra process by a trunk belt, gait variability analysis was based on acceleration. Based on the results of the 5-question Geriatric Locomotive Function Scale, the 7 participants were categorised as either having or not having the locomotive syndrome. 41 (22.3%) of the 223 participants had the locomotive syndrome. Locomotive syndrome patients had decreased autocorrelation coefficients in all three directions. Of the autocorrelation coefficients, only gait variability in the vertical axis remained a significant independent related with the locomotive syndrome using multivariate logistic regression analysis with correction variables. A screening approach for the locomotive syndrome in the general senior population may be developed utilising gait variability based on analysis of autocorrelation coefficients in the vertical axis recorded with an accelerometer, according to this research. Other works by Kaur *et al.,* [9,10] also looks into multiple sclerosis differentiation using multi-stride dynamic in gait and Parkinson's Disease gait dysfunction using deep learning.

Article by Steinmetzer *et al.,* [11] measure gait abnormalities such as asymmetry of the lower limbs to evaluate the diagnosis more objectively. For the measurement they use inertial measurement unit (IMU) sensors and force sensors, which are integrated in wristbands and insoles. To end the battery life of wearable devices, they only save data of the activity gait within the wearables. Using convolutional neural network (CNN) they achieved an accuracy of 94.7% of the activity gait recognition.

A study by Desai *et al.,* [12] mentioned that they used the Logistic Regression Classifier to classify the daily activities and the fall in their experiment. Machine learning based classifier algorithms like random forest, SVM were implemented. But these algorithms require high computation power which is not possible on a 32-bit micro-controller. The algorithm has been developed which can be leveraged to build a quick response safety airbag system for protection against the fall. The product is extremely low cost and can be implemented on a simple microcontroller. The complete duration for the detection is 0.25 seconds owing to the time required for I2C communication with Motion Sensor MPU6050.

In paper by Gujarathi and Bhole [13] an IMU-based gait analysis technique that leverages angles from the accelerometer and gyroscope sensors in the MPU6050 to pinpoint the various stages of each gait cycle when a person is walking. The heel strike and toe off variables are identified using the initial contact (IC) and terminal contact (TC) detection methods in the gait analysis algorithm and the gait parameters are then derived from those gait features. For gathering gait signals, two MPU6050 sensors were mounted on the shanks of each leg. For experimental purposes, each subject was instructed to go along a straight corridor for 40 metres at a typical pace. Using the HC-05 Bluetooth module, the gait signal data collected by the Arduino Uno microcontroller is then wirelessly communicated to the Android app Blueterm. The software stores the data it has gathered in a text file on the device it is installed on. This information is subsequently analysed using a MATLAB-developed algorithm to extract a period of walking-related events, such as stride length, stance length, step length, cadence, etc.

In this study by Zhao *et al.,* [14], a dual foot-mounted inertial measurement unit (IMU) gait analysis system, also known as an inertial navigation system, has been designed (INS). By utilising an inequality-constrained Zero-VelocityUpdates (ZUPT)-aided INS algorithm, such a system can offer a useful method for calculating gait parameters. In contrast to employing an optical motion capture system, experiments were conducted while level walking down a straight line, which has less restrictions for the working environment. Both healthy volunteers and people with cerebral thrombosis are sought for comparison purposes. The experiment's findings showed that gait analysis using foot mounted IMUs might provide a close evaluation of gait problems, which might be useful to medical practitioners as they develop a treatment strategy.

This research by Chanchotisatien and Vong [15] describes an end-to-end monitoring system for individuals with foot or ankle disabilities. Three primary components make up the system: a wearable controlled ankle motion (CAM) boot with inertial and load sensors, a web application that displays sensor data as visual feedback and the use of machine learning and deep learning to examine walking behaviour and gait. The CAM boot uses an accelerometer, a gyroscope and load cells as sensors. Sensor data from the CAM boot is wirelessly sent to the database. The web application retrieves sensor data from the database and displays several graphs to provide visual feedback on the patient's walking habits. Machine learning and deep learning models are trained to identify and distinguish between seven actions carried out by the patient using sensor readings received from the database. Six classifiers and three dimensionality reduction techniques are investigated and compared.

An Internet of Things (IoT) systems provide a straightforward yet effective capacity to work with 9 various devices and applications by sharing information. IoT services oversee sending messages to the platform's linked clients. An IoT platform called ThingSpeak collects and saves sensor data in the cloud while also creating IoT apps. The ThingSpeak IoT platform offers programmes that enable the use of MATLAB to analyse, display and take action on their data. The Arduino Nano 33 IoT with Wi-Fi module can transmit sensor data to ThingSpeak. An IoT-enabled gait assessment [16] for habitual monitoring on is looking at better remote gait assessment using IMU-based wearables [17-20] and algorithms mature in their corroboration with alternate technologies, such as computer vision, edge computing and pose estimation.

The motivation behind the project is an attempt to make wearable sensor that can detect the walking patterns of normal and abnormal gaits. The project also aims to notify the user when abnormal gait is detected via ThingSpeak. It also has an objective to evaluate the performance of detection system in terms of accuracy. Wearable sensors are a convenient method of diagnosis that does not restrict the user like a heavy machine or device would. It can easily be carried along in the user's daily live like a normal electronic device like a mobile phone would. This method would help especially for elders since their movement are even more restricted and cannot go to hospital for every diagnosis with ease without help from others.

The wearable sensors device in this research also aimed to be equipped with IoT. IoT in this context means that the wearable sensor can integrate with internet through Wi-Fi module which is included in the wearable sensor. The device would send information gained from the sensor through an app on a mobile phone regarding the gait analysis performed and fall detection. This makes sure that help can come faster for the user since this device is targeted mainly for elders where they are prone to fall easier due to many underlying conditions that may affect their gait.

The purpose of this study is to assist the elderly in their daily life. This study will assist users in taking safety precautions even in the event of an emergency, such as tumbling downstairs. This will allow emergency personnel to respond faster when they receive calls depending on the gait identified. The user's family will be able to watch the user's stride and any falls that occur while they are not present. The detection technology in the wearable sensor can also predict disease based on the irregular walking pattern. For example, the wearable sensor can compare the aberrant pattern of an undiagnosed locomotive syndrome user to existing data and determine that the user has the same syndrome.

This paper presents gait detection for detecting normal and abnormal gait using 6-axis Inertial Measurement Unit (IMU) wearable sensor motion signal on the people via IoT and using MATLAB for normal and abnormal classification. The remainder of the paper is organized as follows. Section 2 describes the methodology of a walking gait data collection and classification of normal and abnormal walking gait detection. Next, in section 3 discussed the experimental result of gait detection performances. Finally, section 4 provides the concluding remarks and point out the ideas for future extension of this work.

2. Methodology

This research is on the detection of normal and abnormal gait using a wearable sensor motion signal collected from user/people the via IoT. In this project, a dataset of walking patterns will be collected among elderly participants using a wearable sensor that consists of an accelerometer and gyroscope sensor which is 6-axis Inertial Measurement Unit (IMU) of the Arduino Nano 33 IoT. The sensor will be placed on the user's shank. The dataset will be classified into normal and abnormal gaits. The gait abnormality is based on the walking data collected and compared with normal person's data including situations when the participants fall during data collection. Analysis of the gait detection will be performed to determine the accuracy of detection system. Besides, an alert message will be sent to the user through ThingSpeak when abnormal gait is detected.

Figure 1 shows the block diagram of the wearable sensor for gait detection. The block diagram consists of two inputs, one microcontroller and one output. The controller of the system is Arduino Nano 33 IoT board which comes with an IMU (LSM6DS3), combining an accelerometer and a gyroscope that acts as an input of the system and the board also comes with Wi-Fi® connectivity for internet connection of an IoT applications. All the data obtained is then transferred to the output of the system which is ThingSpeak IoT Cloud. When battery power is available and Wi-Fi is connected, the system operates. It quickly transfers data to ThingSpeak's IoT Cloud.

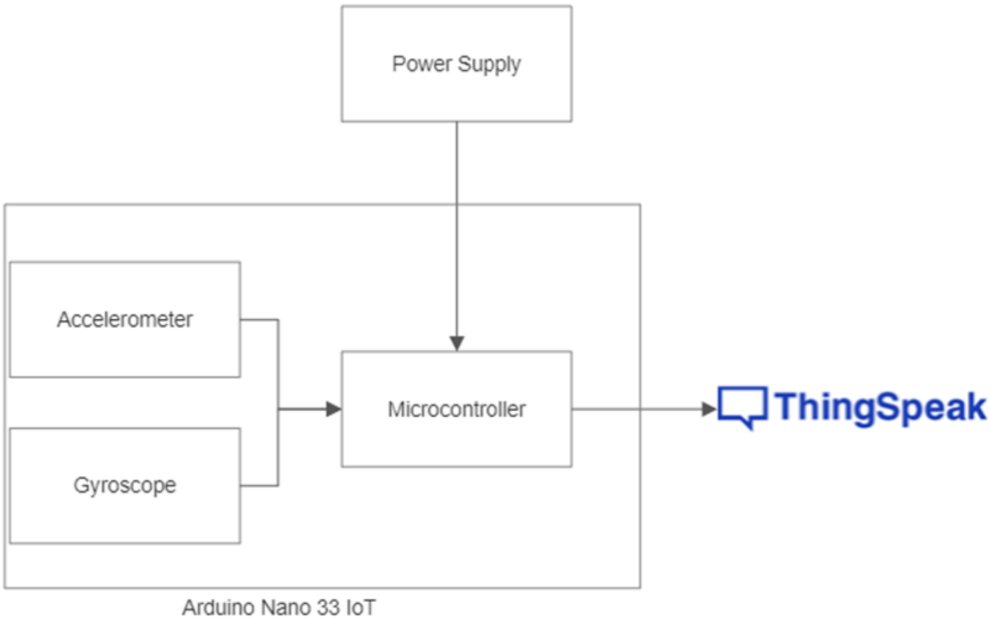

Fig. 1. Block diagram of wearable sensor for gait detection

2.1 System Overall Flowchart

Figure 2 shows the overall flowchart of this project. After setting up the wearable sensor on user's shank as illustrated in Figure 3 and powering the device, the sensor reads the data of accelerometer and gyroscope during walking. The sensor is powered by a power bank so that the user can move freely without bound by cables. The data of the sensors then is sent to the cloud platform, ThingSpeak via Wi-Fi connection. The data in ThingSpeak would show the waveform of each sensor data which are accelerometer's x-axis, y-axis and z-axis and gyroscope's x-axis, y-axis and z-axis. Once the user starts moving, the wearable sensor keep checking for abnormal gait through the 6-axis IMU.

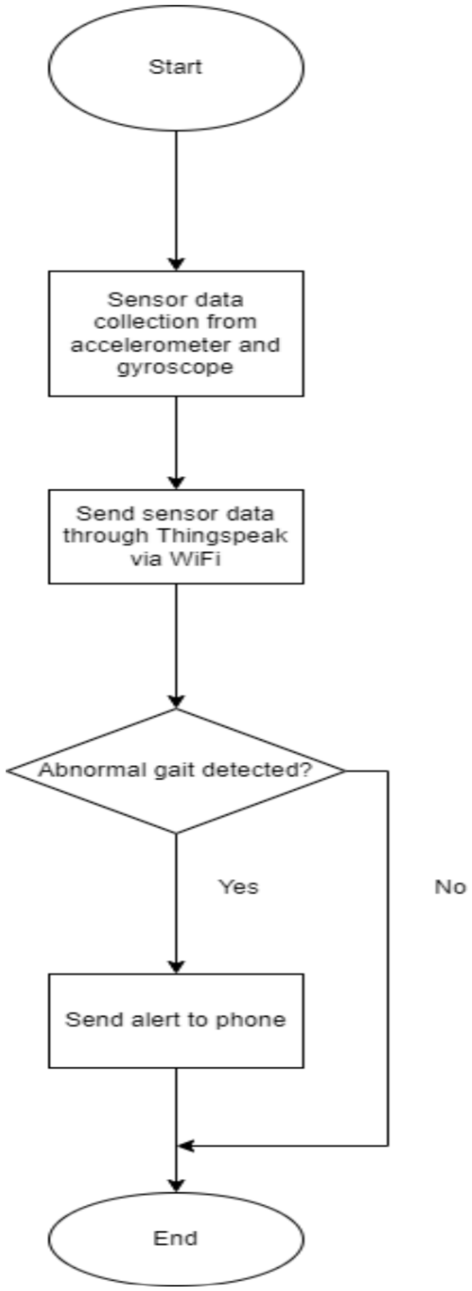

Fig. 2. System overall flowcharts

The collected data is classified in term of normal and abnormal gait walking condition via MATLAB Classification app. The microcontroller then sends the signal to IFTTT using webhooks when abnormal gait walking condition detected. The webhooks are set in the Arduino Nano 33 IoT's code using the Arduino IDE. IFTTT then proceeds to send a notification to phone indicating that abnormal gait is detected. IFTTT (If This Then That) is a free online-based tool that individuals use to build networks of straightforward conditional statements or "applets," that manage tiny jobs between web services and the Internet. Examples of changes that can be monitored to determine a course of action include those that take place within other web services like Gmail, Facebook, Instagram or Pinterest. In this project, the platform is used to receive webhooks from Arduino board and send an alert when a certain condition is met for the wearable sensor.

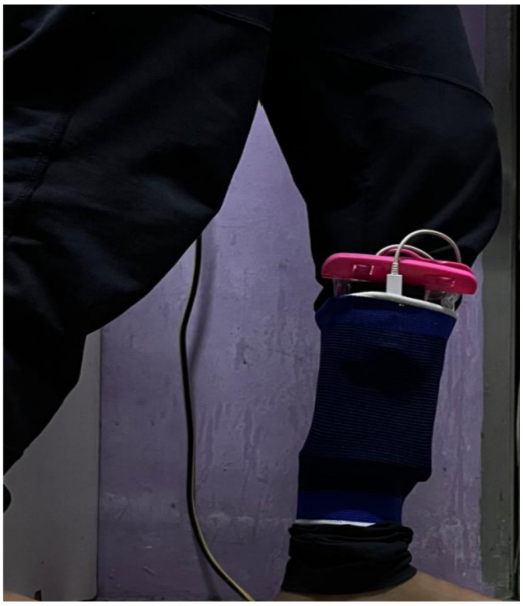

Fig. 3. Arduino Nano 33 IoT on shank

2.2 Accelerometer and Gyroscope Data Collection via Integration with ThingSpeak

Data collection in this research was through the sensors data which then was labelled each run for normal and abnormal gait. The wearable sensor was applied to the shank with custom-made fabric and connected to Wi-Fi to record the data in ThingSpeak. ThingSpeak is an IoT analytics platform service that allows user to aggregate, visualize and analyse live data streams in the cloud. The platform can receive data from devices, create instant visualizations of live data and send alerts using web services like Telegram.

The collected data is also stored in an online database and can be accessed in forms such as CSV or JSON. The data comprises of accelerometer and gyroscope sensor readings taken while walking. Approximately 40 sessions of normal and aberrant gait were collected. Each session was divided into two classes: normal and abnormal. After labelling, 23 sessions are normal, while the rest are aberrant.

2.3 Classification of Walking Pattern using MATLAB

MATLAB is a software that has many usages including classification. MATLAB provides an application called Classification Learner App that allows to run classification without needing to construct a single code. This app also able to provide a great result for analysis purpose such as the confusion matrix diagram, the scatter plot and the others. Figure 4 shows the process of using the classification learner. MATLAB's Classification Learner is a tool that allows users to train and compare different types of classification models using machine learning algorithms. It can be used to classify gait based on accelerometer and gyroscope data collected from a wearable sensor.

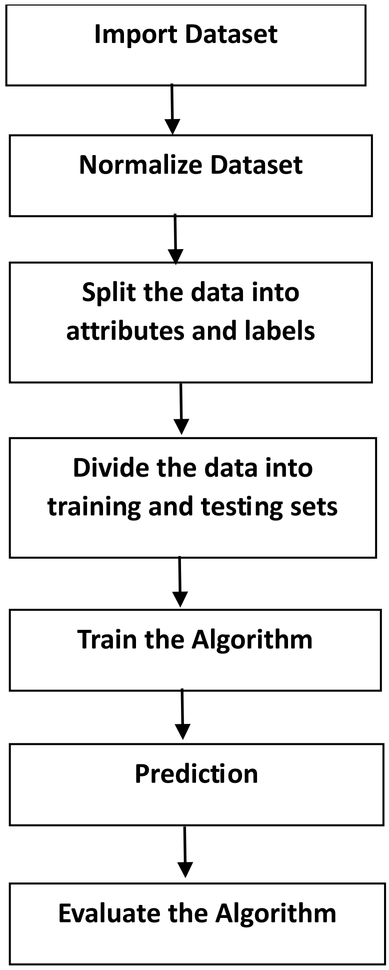

Fig. 4. Flowchart of classification of walking gait

To use Classification Learner to classify gait, the first step is to prepare and pre-process the accelerometer and gyroscope data. This may include cleaning the data, removing outliers and normalizing the data to a consistent scale. The pre-processed data is then divided into a training set and a test set. The training set is used to train the classification models, while the test set is used to evaluate the performance of the models.

Once the data is prepared, the user can then use the Classification Learner app to train and compare different types of classification models on the training data. Some popular classification models that can be used to classify gait include Decision Trees, K-Nearest Neighbours, Support Vector Machines and Neural Networks. The user can select the appropriate model based on the characteristics of the data and the specific classification task. The user can also use the app to tune the parameters of the selected model to optimize its performance. Once the model is trained and fine-tuned, it can be tested on the test data to evaluate its performance. The results of the test can be used to evaluate the model's accuracy, precision and recall and to make any necessary adjustments to the model.

Finally, the inference model can be used to classify new gait data from the wearable sensor in real-time. The model can be integrated into a software program or app that can run on a smartphone or other device to provide real-time feedback to the user on their gait patterns.

In the beginning of this step, first is to import the dataset, which the dataset is taken from ThingSpeak and cleaned up. The data that is taken is the Accelerometer data and Gyroscope data. Then, the data is normalized, must be in csv file because that is the only way the program is able to read the file. The data is split into training set and testing set, being 80% and 20% respectively. Next, the algorithm is applied, for this method there is no specific algorithm used. A few algorithms are used to evaluate the performance with the actual result.

The running classifier will make prediction on its accord based on the data given which is already labelled for normal and abnormal. The normal condition is one which the user is in healthy condition and has no underlying pain or injury that cause their walking pattern to be unusual. Finally, the final step in the classification process is to evaluate the obtained result in term of accuracy.

For classification of normal and abnormal walking pattern, the data collected from volunteering users. This is so that the data collected can be easily classified to each of the gait category which are normal and abnormal. To determine whether a gait is normal or not, data from ThingSpeak is classified beforehand with each session. MATLAB is also used by inputting the collected data for accuracy and evaluating performance. The data were input into the classification learner where 80% of the data were used as training set while the remaining 20% of the data were used for validation set. MATLAB is a software that has many usages including classification. MATLAB provides an application called Classification Learner App that allows to run classification without needing to construct a single code. This app also able to provide a great result for analysis purpose such as the confusion matrix diagram, the scatter plot and the others.

3. Results

This section discusses the results obtained for gait detection data collection for normal and abnormal classification via IoT. Firstly, the data collection via ThingSpeak for normal and abnormal pattern dataset. Finally, the notification alert is sent via IFTTT if abnormal pattern is detected by system.

3.1 Data Collections

Figure 5 and Figure 6 display the results collected via the ThingSpeak IoT platform throughout the data collection sampling. The results include samplings of both normal and near-fall gait walking conditions. Data obtained is based on multiple samples of people with no known complication with their legs for the normal gait data and people with injuries for the near-fall abnormal data. Each session is recorded and put into csv file for easier reading of the data.

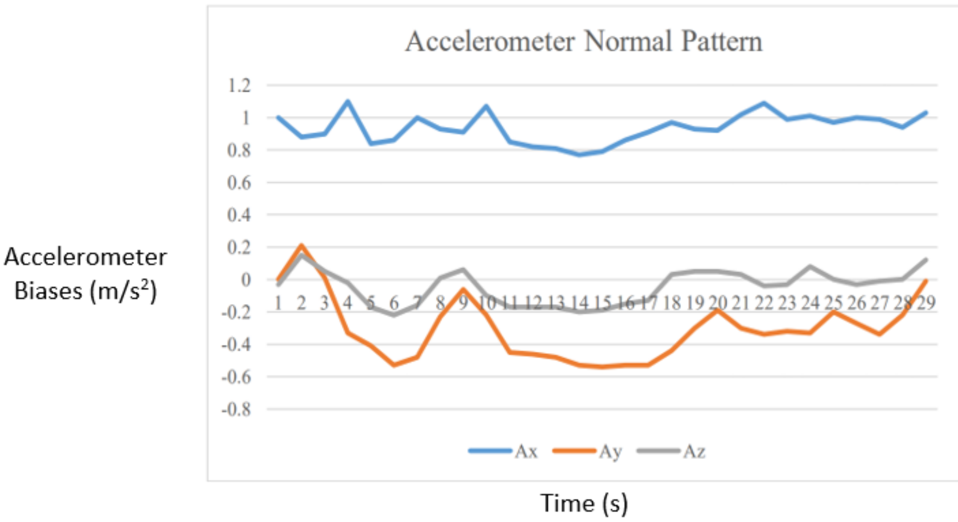

Fig. 5. Normal accelerometer pattern gait

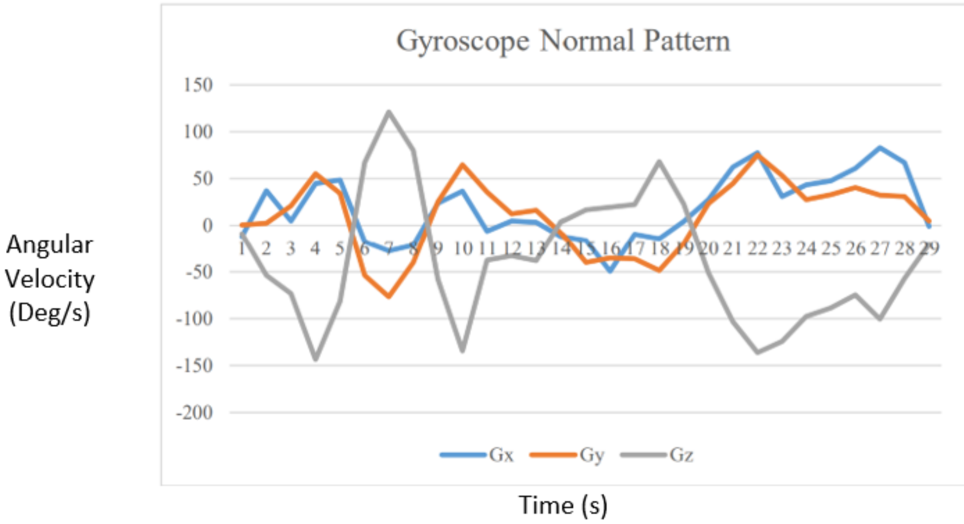

Fig. 6. Normal gyroscope pattern gait

As fresh data takes time to update, the data acquired using this method is not entirely dependable. One way to avoid this issue is to use a premium account, which allows the data to be updated every second. Data obtained is based on multiple testers with no known complication with their legs for the normal gait data and people with injuries for the abnormal data.

Based on the patterns of the waveform that were obtained during data collection, the collected data can be compared to one another between normal gait walking and near-fall abnormal walking gait condition. The figures depicted are examples of the waveforms for near-fall abnormal walking gait condition. The data gathered on aberrant gait is displayed in Figure 7 and Figure 8 or accelerometer biases value and the gyroscope angular velocity value respectively.

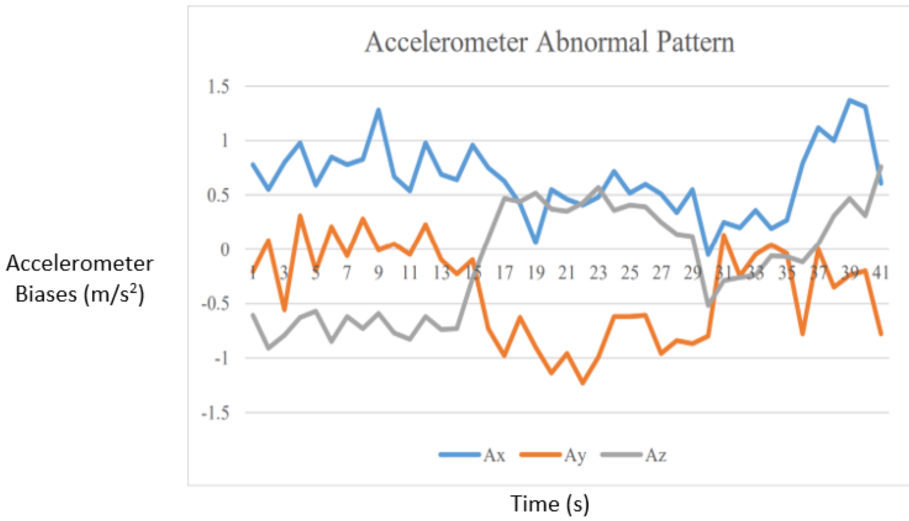

Fig. 7. Abnormal accelerometer pattern gait

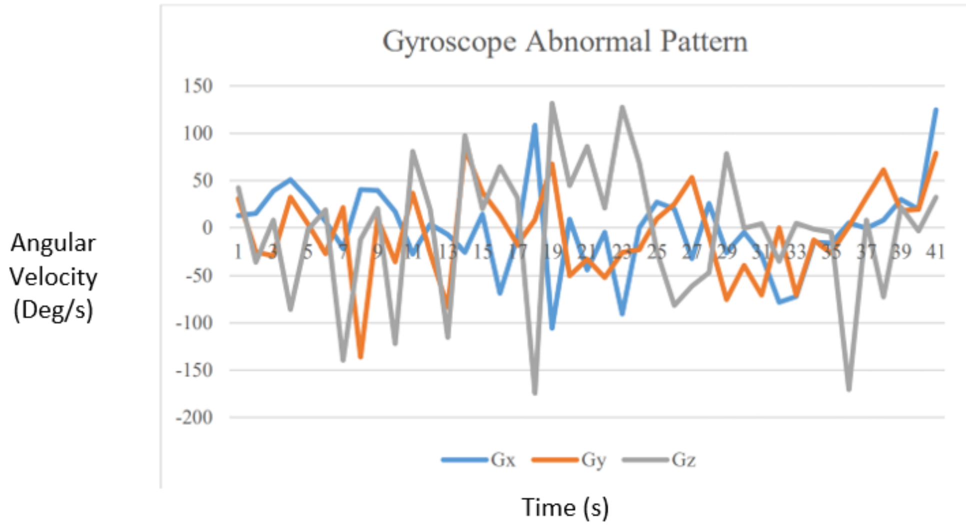

Fig. 8. Abnormal gyroscope pattern gait

Given how different the results are, it is possible to see the distinctions between normal and abnormal data. When walking normally, accelerometer data shows more linear patterns; when walking abnormally, the waveforms show more chaotic patterns. While for gyroscope data, the waveform correspond to the phase of gait during walking and the abnormal waveform also seems more chaotic. The number of spikes in the waveform is higher in the near-fall abnormal gait walking condition than in the normal gait walking condition due to the smaller but more frequent step of walking movements.

3.2 Abnormal Gait Detection and Alert

Figure 9 shows the notification received the moment the wearable sensor detects an abnormal gait. Prior to sending of notification alert to elderly caretaker, the acquired data are categorized as either normal or abnormal by using a MATLAB Classification app. The Inference model of the walking gait is put in live action to produce result on live data collected from collected 6-axis IMU sensor on microcontroller.

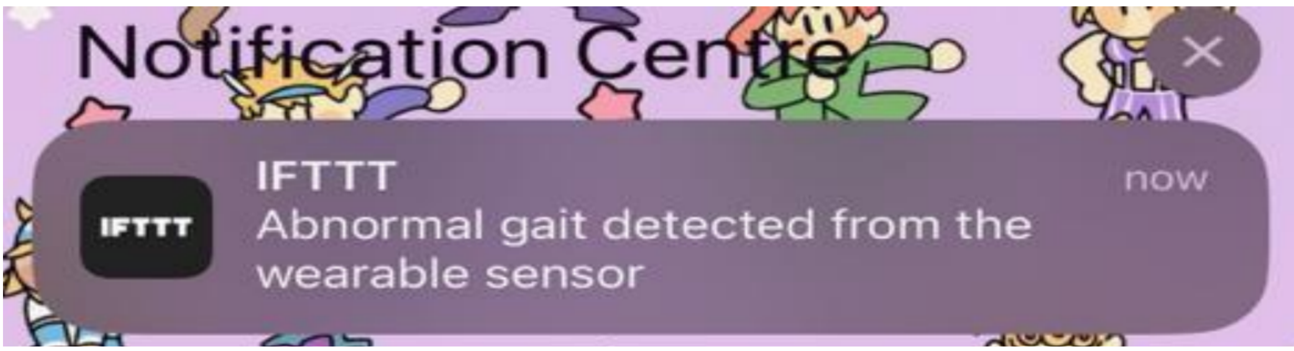

Fig. 9. The IFTT notification alert when abnormal gait detected

After verifying that inference model with the live data waveform of an abnormal gait walking waveform condition is met , then an abnormal gait walking condition is detected. Then the server notifies the caretaker via phone that an abnormal walking gait stride has been identified and detected. The system was configured to send a notification alert only after a classification of an abnormal gait walking waveform condition is detected. If preferred, the trigger and notice can be configured to do additional tasks, such as sending an email.

4. Conclusions

As a conclusion, the objective to produce a wearable sensor that can detect the walking pattern of normal and abnormal gaits using a wearable sensor is achieved. By using Arduino Nano 33 IoT, the wearable sensor avoids some of problem that could happen from connecting sensors and Wi-Fi module with microcontroller manually since the Arduino board already includes both features. Analysing the data is difficult with the limitation of using IoT which does not allow data at smaller interval. Thankfully some of the patterns are easier to see than other even though the accuracy of analysing manually is worse than doing it with machine learning. The aim to notify the user when abnormal gait is detected via ThingSpeak is also able to be done using webhooks and sending it to IFTTT as a notification alert to caretaker. Blynk is tested before opting for ThingSpeak but the platform does not allow exporting data to CSV or JSON and also unable to keep the data online more than a week in the free version unlike ThingSpeak which saves the data up to a year.

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