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Human Activity Recognition Using a Mobile Phone Device

Thesis presented by

Rabih Abou Fakher BSc (Honours)

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University College Cork

School of Computer Science and IT

Head of the School of Computer Science: Professor Cormac Sreenan

School of Mathematical Science

Head of the School of Mathematical Science: Professor Finbarr O'Sullivan

Supervisor: Professor Ken Brown

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Abstract

The aim of this thesis was to discover if a mobile phone app could be used to collect data in the workplace and in healthcare facilities. I wanted to design an app to generate and label human activity using sensors from a mobile phone. The data was collected from the Accelerometer, Gyroscope and Magnetometer sensors which are embedded in most mobile phone devices.

This thesis investigates how this form of data collection could be of assistance to construction workers, health and safety officers, pharmaceutical company employees, medical professionals and educators. The objective is to analyse Human Activities from data collected.

The paper reviews how this form of data collection could be a practical and efficient in a variety of working environments. It explores the opinions of a variety of professionals on the feasibility of using mobile phone sensors in observation and employee safety to reduce injuries and to react promptly to workplace accidents and emergencies.

I have used a variety of well known classification algorithms including K-Nearest Neighbours, Random Forest and Gradient Boosted Trees to analyse the data collected. Decision tree classifiers showed the best performance recognizing human activities with an accuracy rate of 84.9%.

Acknowledgements

I would like to thank my supervisor Professor Ken Brown for his continued guidance and support throughout this thesis. He set me on the right course and was very helpful during the entire process, answering questions and offering ideas. Your guidance and mentorship will always be remembered. I have learned a lot from you and am truly grateful.

I would like to thank Sebastian Scheurer for his data set on human activity in Emergency First responders. This was a very well structured project and laid the foundations for my own research. Thank you for being available to answer emails and allowing me to access your data set. I understand now how much time can go in to collecting such data and am thankful that you were willing to share this data set with me.

I had many volunteers in this project who gave up many a Saturday to help me collect data. Thanks to Joao Viegas, Marcos Dias, Larissa Soshnikova, Jenny Reid, Carmel Reid, Barry Reid, Cathy Reid, Declan Power, Nicole Magee, Ethan Power and Isaac Power. I recognize the hours spent to help me create this data set. Your friendship and willingness to help out have been greatly appreciated.

I am indebted to my employers at 8 West who ensured that I could effectively juggle work and study over the last two years. They facilitated my course with flexible work hours and the opportunity to work remotely. This has made it possible to complete this Thesis paper. Throughout the years they were interested in my course work and allowed days for study and preparation. I was promoted to Senior Developer during this period which kept my enthusiasm for both occupations high. I thank you for this time and support. I hope that I can utilise the skills and new technologies in 8 West for the benefit of the company.

A special thanks to Alec Reid, Martin Hurley, Emer O'Neill, Laura Gaffney and Clodagh O'Flaherty who answered questions on how this method of Data collection could be used in the workplace. This made the project more interesting to imagine the real life possibilities for the app. It was enjoyable talking to each of you and exploring the future potential of this project.

I would like to especially thank my partner Lucy Reid who proofread my thesis and supported me during the busiest summer. She now understands more about Data Analysis and Statistics than she ever wanted or needed to know. Thank you for everything.

Table of Content

Chapter One: Introduction and Background

This thesis was inspired by a recent U.C.C paper Human Activity Recognition for Emergency First Responders Via Body-Worn Inertial Sensors (2017). This paper outlines how I.M.U sensors were used to track and predict the movement of Firefighters in emergency rescue situations. The data was collected in a supervised trial with volunteers who performed 17 tasks such as falling on to a mattress, walking, standing still, running and lying down. These activities were tracked using sensors which when analysed could be used to accurately recognise the position and activity of firefighters as they navigate dangerous rescue operations. These ideas laid the foundations for thesis. One objective was to discover could a standard mobile phone be used in the place of separate movement sensors.

Mobile phones are widely available. They are already equipped with an abundance of sensors including accelerometers, magnetometers and gyroscopes. These sensors were used in the original thesis on Firefighter Movements. In addition, all of these smart phones are connected to a network which means data can be streamed at an incredible pace by phone based technology. The phones are able to automatically recognise human activities discretely and without much imposition to the user. It makes good common sense to use a phone based app to collect this Data. So I interviewed several employees and employers in a variety of fields to clarify which activities would be most important to track in their work environment.

These are some of the thoughts and queries of these professionals.

Emer o' Neill, a highly respected physiotherapist in the Bons Secour Hospital Cork, was quite interested in the very accessible nature of this app. Many of the elderly patients in this Cork hospital have been utilising a similar sensor to track patient activity while in the care of the hospital. Ms.o Neill outlined how motion sensors played an emerging role in physiotherapy services. She was intrigued by the fact that the app could be used on the patient's mobile phone. The patients often dislike the bulky nature of the ankle and wrist sensors. The mobile phone app supplies the elderly patient with a discretion that cannot be achieved by the larger more invasive trackers.
Also this would be a more affordable method of tracking a patient's movements. This is could help to motivate and remote supervise rehabilitation patients who often do not maintain their daily exercise routines after their discharge from hospital. Unfortunately the rehabilitation services for stroke patients and the elderly are very overwhelmed in this country and perhaps a remote data collection app could help to provide a more efficient and cost effective tool for ensuring the patient engages in a sufficient amount of daily activity. Ms. o' Neill was enthusiastic about this method of tracking the daily activity of the patient, highlighting that the self esteem of the patient could be increased by simply using their phone as opposed to being hooked up to an ankle sensor. Going forward the app could be used to raise an alarm if a patient has fallen. The app could monitor and analyse the symptoms of Parkinson's disease. This could offer a method of monitoring the patients tremors, balance and activity in a non-invasive and discrete fashion. In a paper by Muhammad Atif he proposes a prototype which has “potential to emerge as a tool

in diagnosing and predicting the pace of the disease and a possible feedback system for rehabilitation of patients suffering with Parkinson Disease" (2011,p.3.)
In the same way this could help medical professionals to track epileptic seizures. An article from the journal of Neuroengineering and Rehabilitation further supports Ms. o' Neill's ideas on
sensor data collection saying "Home based motion sensing might assist in falls prevention and help maximize an individual's independence and community participation" (Rodgers,2012).

Alec Reid, a foreman in Novartis, outlined to me the need for quick and fool proof method of tracking the employees in a large pharmaceutical plant. He described the "dead man's switch." This is to be activated if the operator becomes incapacitated, such as by falling or losing consciousness. The dead man's switch is an alarmed sensor in the operators walkie- talkie.If the walkie-talkie is laying flat for an unusual period of time the foreman is alerted. This is a clever precaution. The operator presence detector is used in most pharmaceutical factories in Ireland. Operators working with heavy machinery or toxic chemicals are monitored throughout the day. This mobile phone app could enable large pharmaceutical companies to supervise every member of staff not just those working in the more dangerous areas of the plant.

Laura Gaffney, a health and safety office for Helsinn Birex Pharmaceuticals, spoke to me of sensor use for operators working in isolated areas. They also used the operator presence detector which she referred to as the "Man down switch." This is used to speed up injury response time.

Martin Hurley, a construction manager based in Dublin, also showed an appreciation for this form of data collection. He would use an app like this for advancing construction safety management. It would make real-time construction safety management a possibility. It is vital to respond quickly to onsite emergencies or accidents and this kind of remote tracking could be lifesaving in terms of speed and supervision. It could track dangerous behaviour or alert the construction manager of possible falls or injuries on site.

In general, this data collection app could improve safety in the workplace. There is ongoing debate about the use of I.O.T in schools and child care facilities. This form of Data collection could provide information on child activity and help with pupil safety in school environments. However this would not comply with current data protection rules of the Department of Education and would not be cost effective. I spoke with a primary school teacher, Ms. Clodagh O' Flaherty. She was less enthusiastic about this method of data collection as it would be distracting and counterproductive in a classroom management situation. However she thought it would be of interest to parents and teachers of children with certain special needs such as Autism who can be prone to wandering and can be a flight risk. The phone sensors and movement trackers could ensure the safety of a child who has a tendency to flee from overwhelming or demanding situations. The app could track the movement and coordinates of the missing and possibly distressed child in a meltdown. She was interested to know what role I.O.T wearables or Phone sensor apps could play in helping adults with high functioning autism to manage and analyse their daily activity and possibly help to record and evaluate times of stress and movements such as flapping or rocking. This could help to reveal the antecedent trigger for sensory meltdowns and moments of high anxiety in adults with autism.

Going forward this phone sensor data app could be used in a wide variety of workplaces to assist and improve employee safety. If this method proves that this form of data collection is feasible this tool could be used to speed up injury response times and improve workplace safety. I will examine this data collection app in the areas of accuracy and feasibility and discuss its potential for use in various workplaces.
There are many classification problems which occur with this sort of data collection. Humans come in all sizes and move in different manners. One could argue that to accurately predict activities you would have to monitor the user over a long period of time and become accustomed to their personal gait and mannerisms. I hope to prove that regardless of the individual the app can predict the activity by analysing the patterns. I wondered if for optimal accuracy is there a need for supporting different users with different needs and demands. I will use volunteers between the ages of 10 and 65 to test this theory. This is one of the questions I hoped to resolve with my analysis.

I endeavour in this thesis to create an Android App which can stream sensor data to analyse subsequently. I hope to show that mobile technology is strong enough to collect movement data efficiently. I would like to conclude whether this position in the armband is more or less accurate than attaching a sensor to the shoulder strap of the firefighter air tank. If this experiment works successfully this method could be a cheap and more accessible form of movement tracking in industry and healthcare. Rather than invest in sensors and complex programmes the user could use their mobile device in conjunction with the sensor app.
I would like to examine whether the sensors in a phone could compete with the wearable IMUs as in Scheurer's paper. I would like to assess the feasibility of using data streaming apps and phones in various workplace environments. Could they replace wearable movement sensors in the this area? Are the accelerometer, gyroscope and magnetometer in an Android phone suitable for data collection in the area of activity recognition?

Basis of This Research

The very foundation of the thesis was based on a study that was proposed to me by my supervisor Professor Ken Brown. The paper "Human Activity Recognition for Emergency First Responders Via Body-Worn Inertial Sensors" in which Scheurer (2017) describes an experiment during which he gathers data from 11 volunteers. Scheurer was interested in the Fire Safety aspect of Human activity recognition. He hoped to reduce firefighter injury and death and to shorten response times in the event of a fall or loss of consciousness. This idea really intrigued me and after thoroughly analysing this paper I was fascinated. I decided to speak to other professionals and see in what other workplaces this type of Human Activity Recognition could improve services and general health and safety practices. I met some very interesting and innovative people on this investigation.

Scheurer used IMU sensors attached the strap of the Firefighter shoulder apparatus. As I was hoping to expand this project to other workplaces I decided to simply use a sports armband attached to the users forearm. I also decided that in the interest of accessibility and affordability I would design and create an app that could be used on any smart phone device. An android app was developed for proof of this concept. I read many papers which followed the same topic Bao and intille's (2010) paper described how the volunteers wore 5 biaxial accelerometers as they performed a variety of very similar activities. This was another interesting article. The wearing of 5 separate sensors seems impractical for daily monitoring and remote supervision in the workplace. This further encouraged me to create this mobile app.

Scheurer used adult volunteers of the same size and age profile to generate the data. I was interested to see how different users in a wide range of heights and ages might alter the accuracy of the data. My nephews and nieces volunteered to help the adult volunteers in collecting data.

GBT, k-Nearest Neighbors (kNN) and Support Vector Machines (SVM) models were used in Scheurer's analysis. The analysis showed that Gradient Boosted Trees (GBT) can be used to recognise up to 17 human activities for monitoring first responders during operations, with subject-independent and -dependent accuracy of over 73% and 97% with fewer misclassifications and distributed more evenly among the target classes, than kNN or SVM. The high accuracy was impressive and I hope to match his results with the phone sensor data. I am planning to use the same models and especially the decision trees classification methods since they seem to fit best for the accelerometer, gyroscope and magnetometer sensor data.

Scheurer's paper set me on the right track and inspired this research which became my every waking thought. I wanted to expand and improve his theories and make this form of injury response more available to employers in a wider range of workplaces.

A Brief Outline of the Chapters

Chapter Two outlines how the android app was developed and how the data was collected, processed and prepared for analysis.
Chapter Three will analyse the data using a variety of classification techniques to predict the activities and evaluate these classification models. The best model fit for this dataset is found on page 24 with accuracy of 84.9%.
Chapter Four I will answer the questions posed in the introduction, make conclusions and outline some future work and ideas of how this project could be enhanced going forward.

Chapter Two: App Design, Data Generation & Processing

Sensor Types

This trial will use the following three sensor types.

The Accelerometer is a device which measures changes in gravitational acceleration in a given axis. When stationary an accelerometer measure 1 g-force because of the earth's gravitational pull which registers at 9.81 metres per second. Often, in a mobile device, several accelerometers are combined to create multi axis accelerometers.This will enable the analyst to measure the presence of motion, the speed and position of the user and can also measure any repetitive movements or vibrations.

The Gyroscope within the device is used to measure orientation and velocity. This is measured in revolutions per second and can aid the analyst to accurately predict movements by measuring the speed of the rotations.

The Magnetometer will give the magnetic field intensity on the three axes relative to the device. The magnetic field of a certain point is directional and has magnitude measured in microtesla. This helps the analyst to determine a repetitive pattern of direction in the activity. The magnetometer can be affected by magnetic interference. The phone itself may contain magnetized metals or have magnets embedded in the device. However, phone technology can calibrate these inner device magnetic forces so that they do not interfere with the magnetometer sensor. Unfortunately, there is often magnetic objects or forces in the surrounding environment which can affect the data as it is collected. With larger volumes of data and constant model training, the model should be enabled to recognise these outliers and behaviours.

Due to the nature of sensor data that is sent from different devices there is usually outliers. These outliers could affect the classification if they lie far outside the average range.

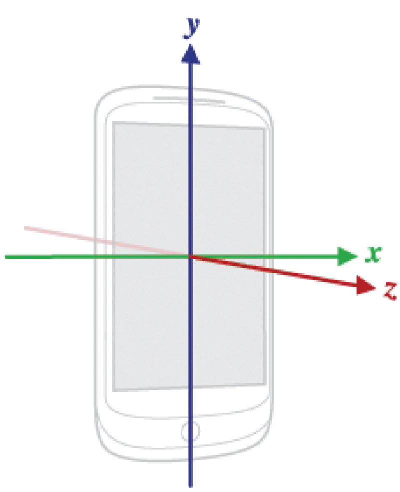

Figure 1.
Coordinate system (relative to a device)
Unknown (2018)

Phone Apps Creation and Implementation

The following diagrams illustrate the two apps which were created to collect data, the sender (Figure 2) and observer app (Figure 3). The former is used by the participant who has the device in a sports armband on their forearm. The latter is used by the observer who will instruct the participant and label the activities as they are performed. Both apps are android apps.

Sender App

The sender app was created to run as a service in the background for collecting the data and sending it to an endpoint where it can be analyzed in real time (this functionality would be very beneficial after the analysis model is created) or it can be stored and analysed afterwards when all the data needed has been collected. This is a a proof of concept and the main purpose is to collect and send the data in the background, so most of the options below are only created to ease data collection for the initial analysis which is necessary to build the Analysis Model.

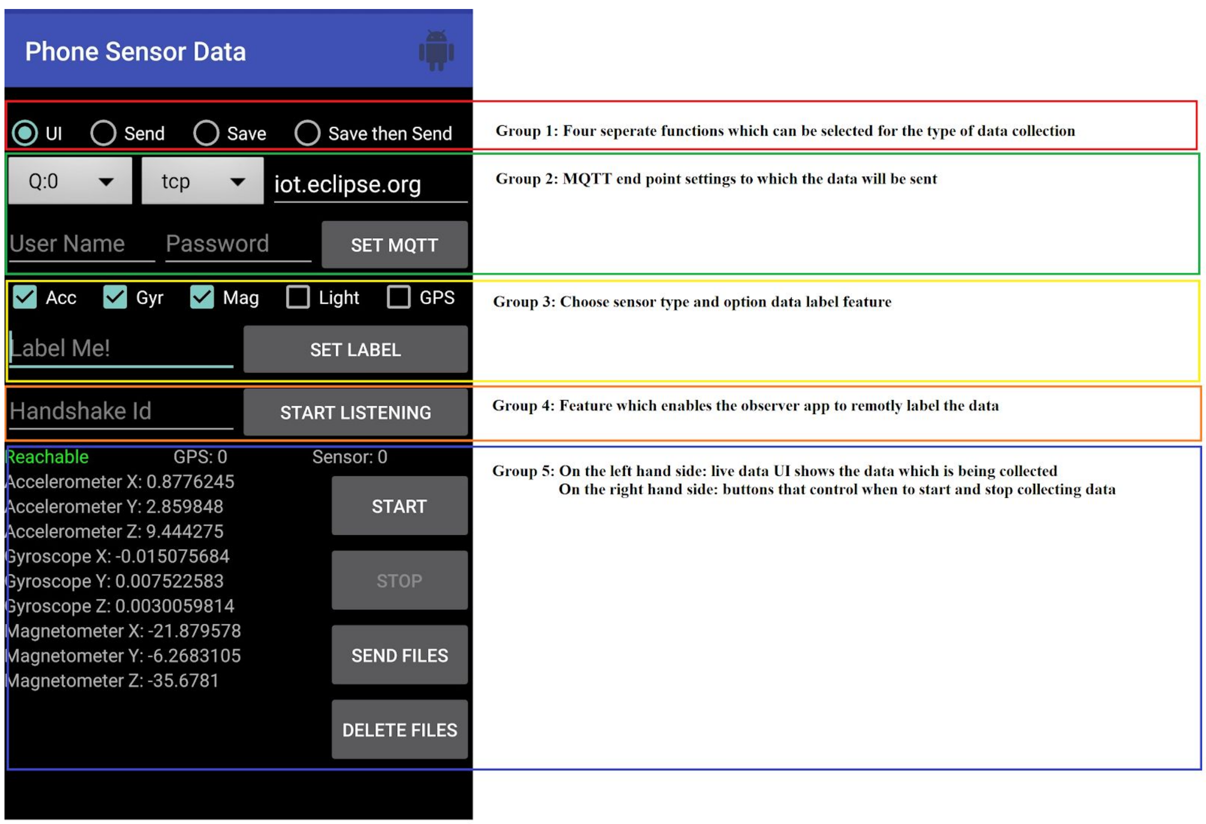

Figure 2. The sender app

Group 1: Gives the user the ability to choose an option which suits their settings

- UI Option: prints the real time sensor data on the screen (group 5 section).
- Send Option: sends the raw data to MQTT endpoint (group 2 section).

- Save Option: saves the raw data into a file on the phone.
- Save then Send Option: saves the raw data into a file in the phone and sends the file automatically after a certain amount of the data has been collected (For this trial this option was selected. Data was collected in groups of 90 samples. This helped in a low network bandwidth as opposed to sending the data for each individual sample).

Group 2: MQTT endpoint settings (MQTT is a lightweight and flexible network protocol designed to provide very efficient communication across Internet of Things devices).

- QOS dropdown menu allows the user to select the MQTT quality 0,1 or 2. The higher the quality the better guarantee of the data delivery on network bandwidth cost.
- Type of the communication dropdown menu where it allows the user to select between tcp or ssl (encrypted communication).
- The URL textbox for the endpoint address.
- Username and password text boxes in case the MQTT server is authenticated.
- Set MQTT button for apply MQTT options selected.

Group 3: The data types to collect.

- Five checkboxes represents the sensors that can be selected for the data collection (Accelerometer, Gyroscope, Magnetometer, Light and GPS).
- The label textbox is an optional feature which can be used to label the data in the absence of the observer app).
- Set Label button is used to apply the label textbox changes.

Group 4: Feature to enable communication between the sender and the observer app.

- Handshake Id is an id that both users agree on to enable communication between the two apps, this Id is mainly used so the observer app can communicate with multiple sender apps at the same time.
- Start Listening button is used to tell the sender app to wait for commands from the observer app as to when to start and when to stop collecting data and what label value should be set.

Group 5: This section is used for information and control.

- The left hand side of the screen prints the real time values of the data in case UI option is selected.
- It also shows if the endpoint is connected or can be reached.
- It also shows a counter of how many raw data sent per run.
- The right hand side includes four buttons to control the data collection
    - Start button to start the service of collecting data.
    - Stop button to stop the service of collecting data.
    - Send Files to send the files in case of Save Option was selected.
    - Delete Files to delete the files when done.

Observer App

The observer app was created to control the sender app remotely and to label the data while being sent. This app was created to provide an easy way to label the data being sent by the sender app while it's running. These labels are needed for the classification analysis models when the data is being analysed. This app was necessary as it helps for accurate labeling.

Once the data has been recorded and analysed, the observer app will no longer be necessary unless is needed for labeling more data.

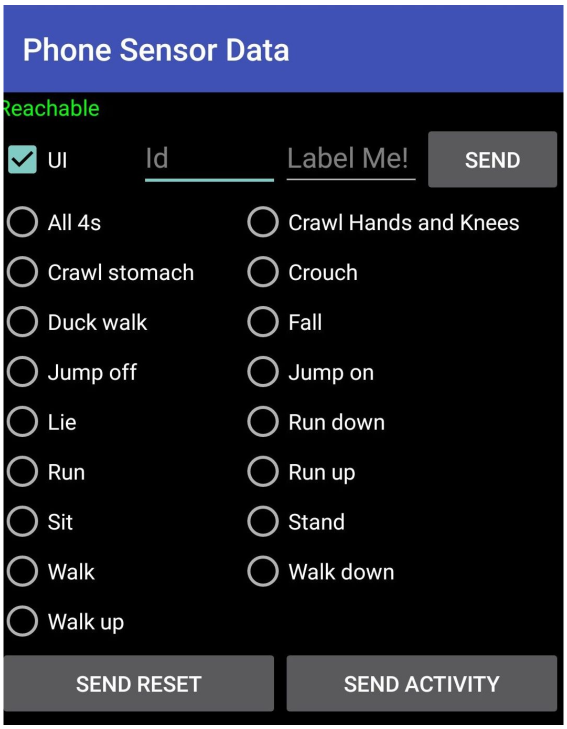

Figure 3. The observer app

The observer app has the following features:

- The Id textbox is used to fill the sender app handshake Id agreed on.
- Label textbox is used for custom labels.
- Send button is used to send the custom label.
- Seventeen radio buttons are used to have a fixed label value.
- Send Activity is used to start the sender app data recording the selected activity.
- Send Rest is used to stop collecting data on the sender app and to reset the sender label value.

Limitations and Challenges

People carry their phones in different ways. Often in pockets, handbags or in one's hand. The orientation of the phone can affect the sensor data. However when we consider that this app will be used mostly for medical and workplace investigation it is not implausible that the user will carry the phone in an armband which has been designed for the purpose of data collection. In addition, once enough data has been collected in different settings this could eliminate this problem going forward.

The model, functionality and battery life of the device can alter the feasibility of this app. Different devices rely on various operating systems and have slightly variant calibrations. To function effectively the app must consume the lowest possible amount of battery. There are many problems which make mobile phone data collection impractical including interrupting phone's actual functionality and battery life and the inflexibility of movement sensor recognition. Although most phones have these three sensors some phones are missing one or other of the sensors. This could limit the opportunities for wide ranging data collection. Also there is a challenge in the differing hardware used in different phones even in the same brand and model which leads to outlier samples which are not as similar to the samples collected from a different device. However once enough data has been collected over a larger period of time and using a wider variety of phone models this problem maybe once again overcome.
For this trial data was collected using two different devices the Nexus 6p and the Xiaomi Mi A1.

Gathering Data

I gathered volunteers on a one to one basis to collect some original data. I chose the activities which the professionals I interviewed concurred could be most beneficial to workplace data tracking. The most common activities were standing, falling, running, walking, sitting, lying down and crawling. I had particular interest in the falling activity and the static activities which may indicate and injury or loss of consciousness. These activities are already monitored in pharmaceutical plants using very simple sensors in operators walkie-talkies. The volunteers I chose were of all ages from ten years old to 65 years of age. I chose these to avoid bias in the data.
A chair, a mattress, a treadmill and a sports armband for the Android mobile phone were used during the date collection process. I aimed to use similar modes of data collection with my volunteers performing activities for the recommended amount of time and adhering to the instructions given in the Human Activity Recognition for Emergency First Responders paper. I strapped the mobile device to the participants upper arm as sports armbands are widely available.

Processing and Storing Data

Once the data run (a group of samples for a certain activity) is sent from the android App using MQTT protocol, A stream process was developed using Node-RED (a programming tool for wiring together APIs and online services) to listen to the MQTT topic where the data is sent. As the data is received we process the run, sample by sample, and store the samples into files for analyzing afterwards.

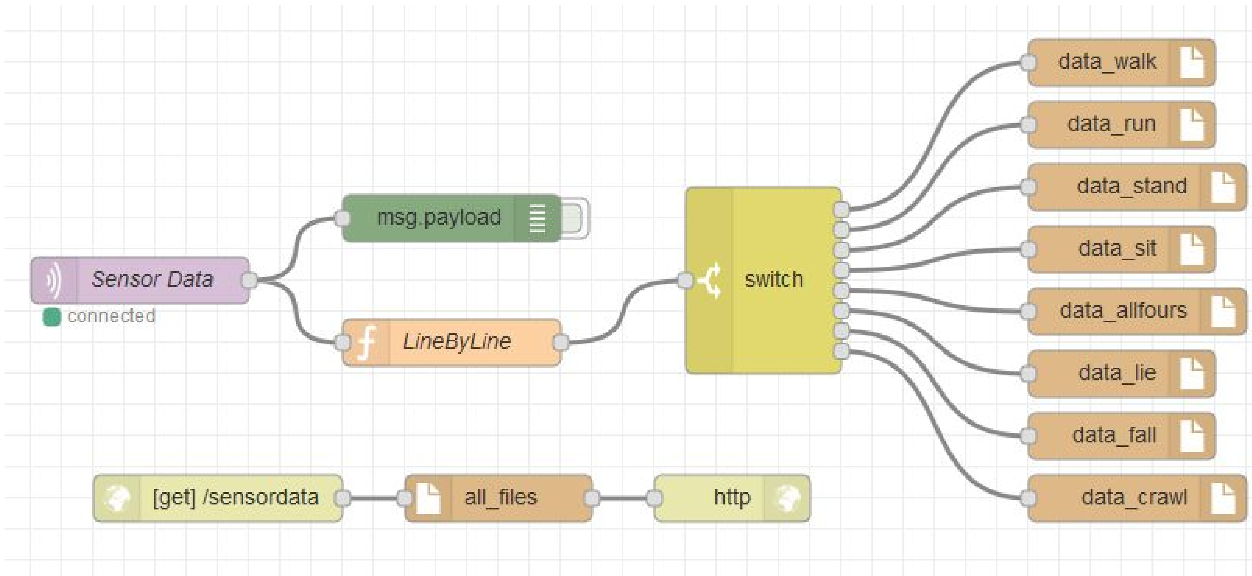

Figure 4. Data processing and storing.

Exploring Data

There are two main differences between the data collected by the Human Activity Recognition for Emergency First Responders Via Body-Worn Inertial Sensors (2017) and the data collected by the android phones for this thesis. The data collected by Sebastian Scheurer is larger than this current data set. Scheurer's dataset contains 518889 samples while this data set is smaller at 135482 samples.
Generally this is considered as a small data set simce sensors collect large volumes of data at all times.
In Scheurer's data set each sample produced by I.M.U sensors is a combination of the three accelerometer, gyroscope and magnetometer data. Whereas the mobile phone data each sample represents an individual sensor data on its own either accelerometer, gyroscope or magnetometer. It is produced this way in the phone due to the fact that some devices do not have all three types of sensor. This means every three samples of the mobile data set represents one sample of Scheurer's original dataset. This means the size of the phone dataset is even smaller than it appears when compared with the I.M.U sensor dataset. Given the considerable difference of the two datasets sizes, it would be interesting to compare the accuracy of the results and conclusions

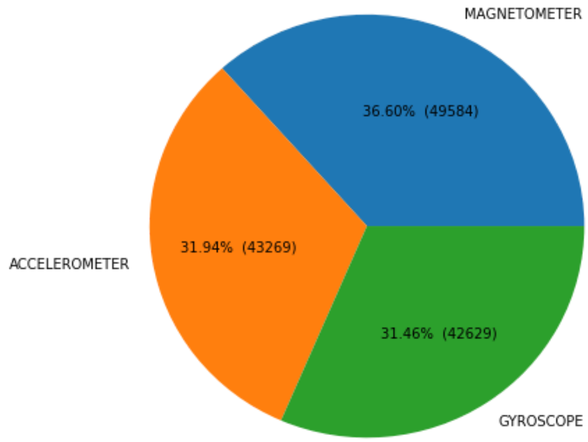

Figure 5.
Data distribution between different types of sensors.
This shows that the data samples collected are equally distributed between the sensor types and there is no data imbalance in this data set.

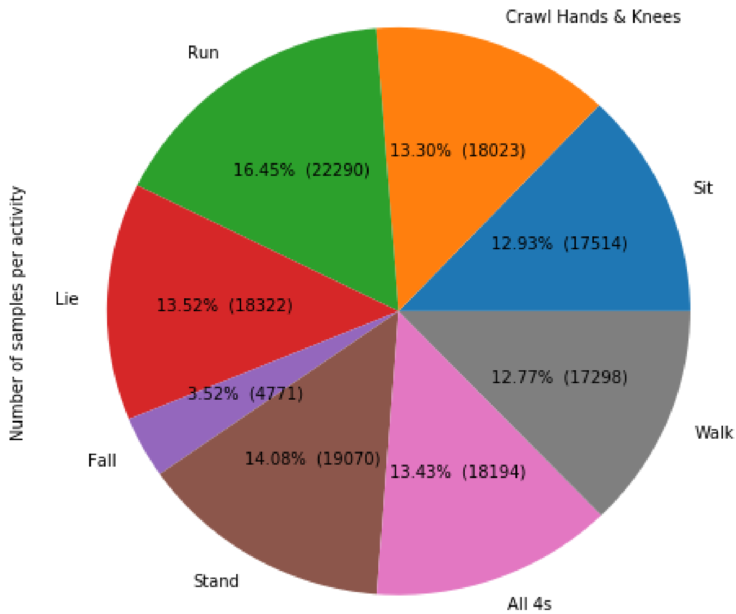

Figure 6.
Data distribution between different Activities.
This shows that the data samples collected are equally distributed between Activities except for the falling activity. The falling activity has shorter samples and less samples as not all the participants were in good enough health to complete this task safely.

Running versus Walking Activities Cluster Graphs

There are more cluster graphs available in Appendix A.

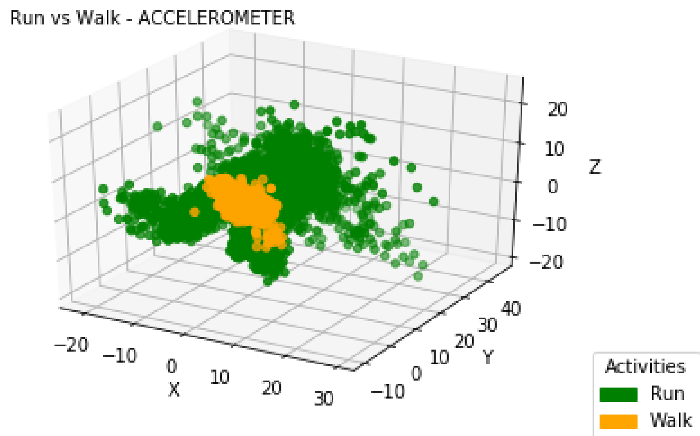

Figure 7.
Accelerometer data comparing running and walking. The running points are in a wider range.
There is an overlap.
The scope is smaller for the walk cluster.

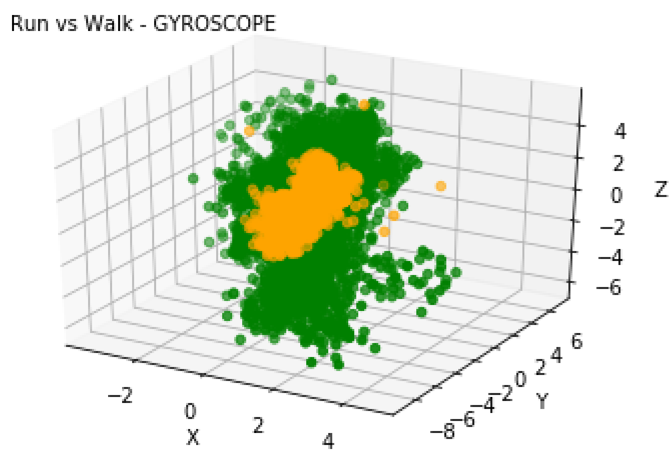

Figure 8.
Gyroscope data comparing walking and running. There is an overlap.
The run activities cover a larger area. The walk cluster is smaller and overlaps with the run cluster. There are some significant outliers in the walk data.

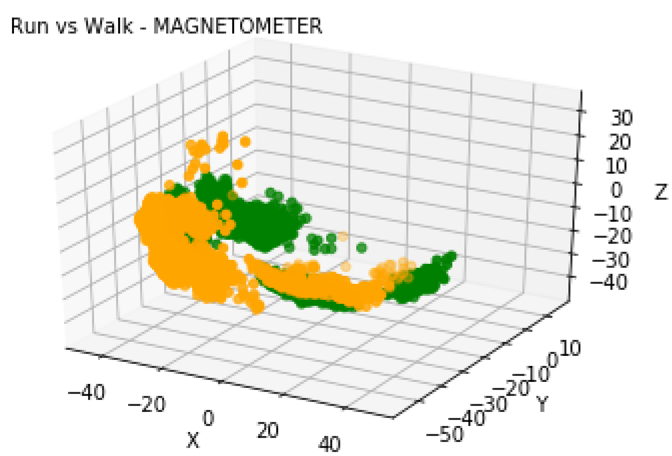

Figure 9.
Magnetometer data comparing running and walking. These two sets are clearly recognizable from one another.

Falling Activity Pattern Graph

Trend graphs illustrate the pattern of each activity by graphing a random run from each activity. All three trend graphs are from the same Fall. The sensors are event based, triggered at their own uptime. There are more pattern graphs available in Appendix A.

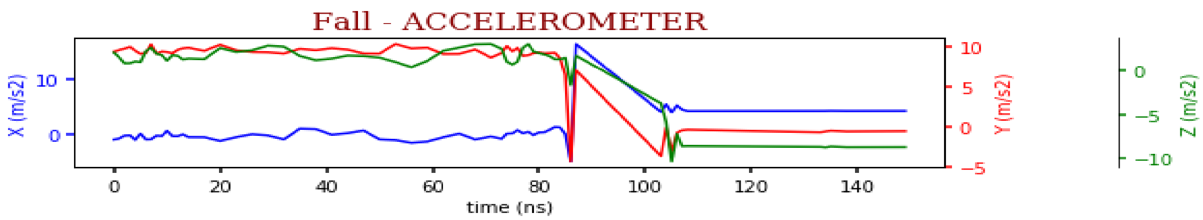

Figure 10. The graph shows a sudden and dramatic change in the otherwise steady pattern.

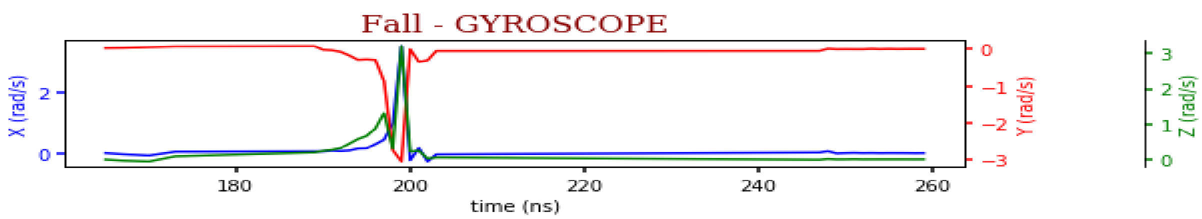

Figure 11. The graph shows a clear fall. The graph is steady with a sudden spike at the time of the fall.

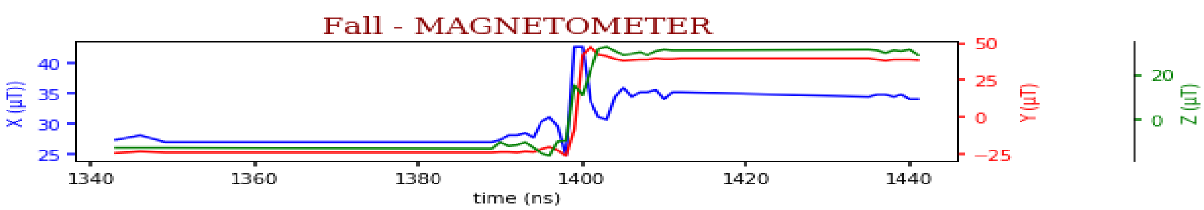

Figure 12. A very clear spike before stabilising again.

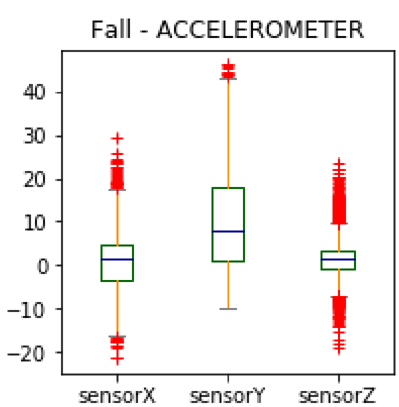

Figure 13. Normal amount of outliers for sensor data.

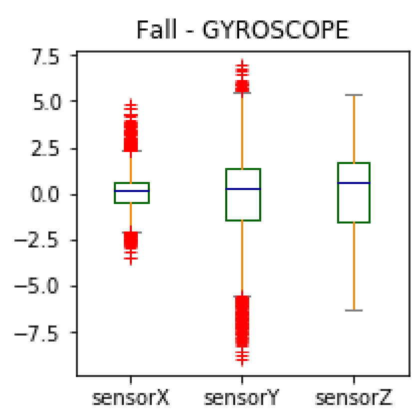

Figure 14. Small amount of outliers, no extremes for sensor data.

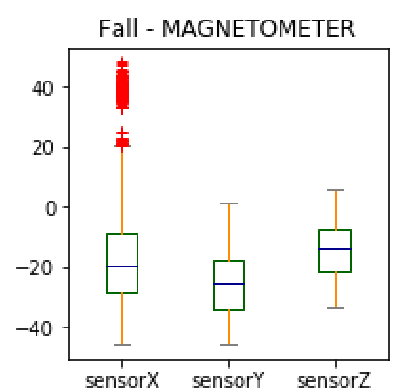

Figure 15. Only outliers in the x axis. All within a normal range.

Human Activity Sensor Data Distributions

The diagrams below illustrate the best fit distribution of each axis on each sensor type for the human activity dataset used in this trial.

Below are two groups of graphs.

Group A: Sensor Data Distribution
The data distribution for each axis (X, Y and Z) values per sensor type (Accelerometer, Gyroscope and Magnetometer) is represented in a histogram.

Group B: Best Distribution Fit
The best distribution fit with the least residual sum of squares between the distribution histogram and the data histogram are represented in group A.

Group A: Sensor Data Distribution

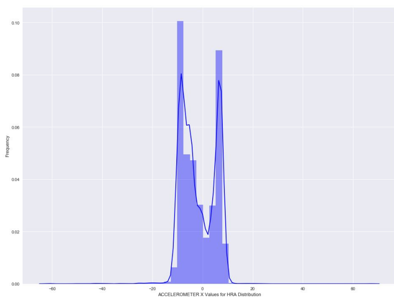

Figure 16.
Distribution for Accelerometer X Values.

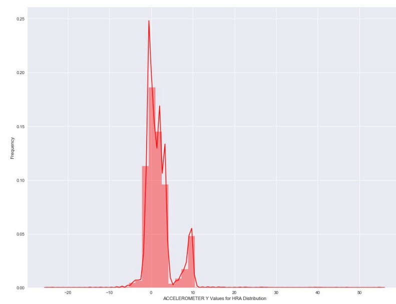

Figure 17.
Distribution for Accelerometer Y Values.

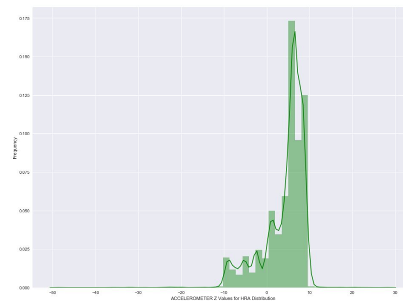

Figure 18.
Distribution for Accelerometer Z Values.

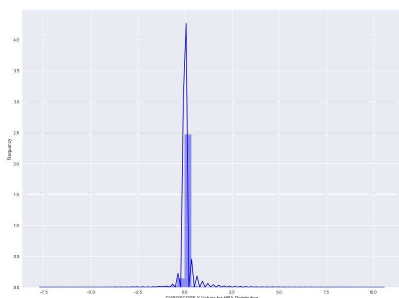

Figure 19.
Distribution for Gyroscope X Values.

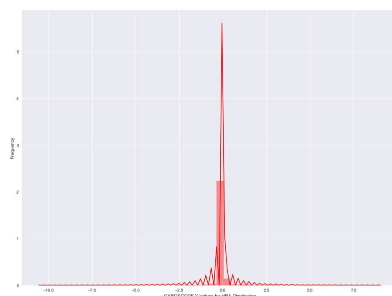

Figure 20.
Distribution for Gyroscope Y Values.

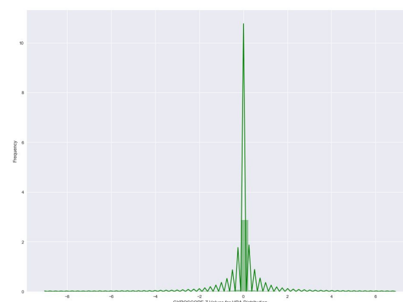

Figure 21.
Distribution for Gyroscope Z Values.

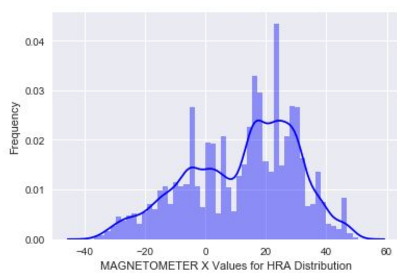

Figure 22.
Distribution for Magnetometer X Values.

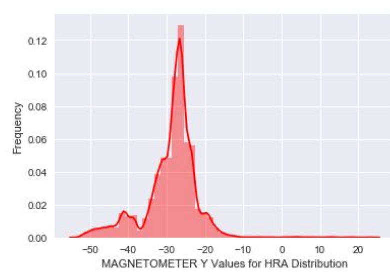

Figure 23.
Distribution for Magnetometer Y Values.

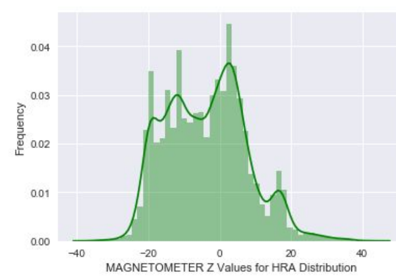

Figure 24.
Distribution for Magnetometer Z Values.

Group B: Best Distribution Fit

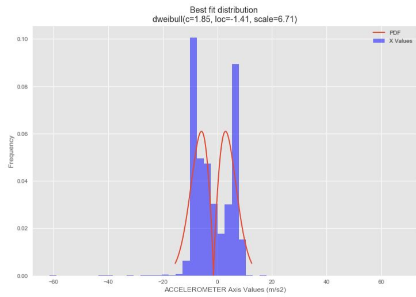

Figure 25.
Best distribution fit for Accelerometer X values is dweibull(c=1.85,Ioc=-1.41, scale=6.71)

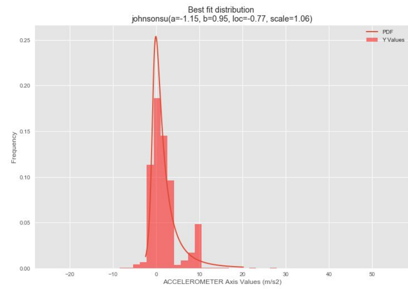

Figure 26.
Best distribution fit for Accelerometer Y values is johnsonsu(a=-1.15, b=0.95, Ioc=0.77, scale=1.06)

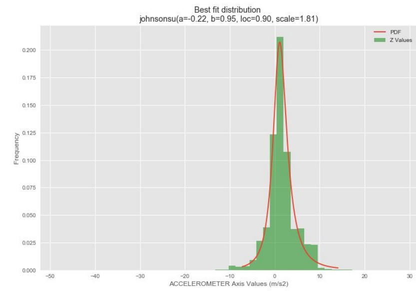

Figure 27.
Best distribution fit for Accelerometer Z values is johnsonsu(a=0.22, b=0.95, Ioc=0.90, scale=1.81)

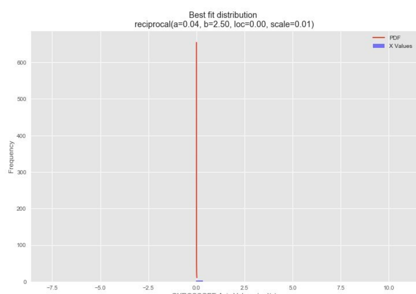

Figure 28.
Best distribution fit for Gyroscope X values is reciprocal(a=0.04, b=2.50, Ioc=0.00, scale 0.01)

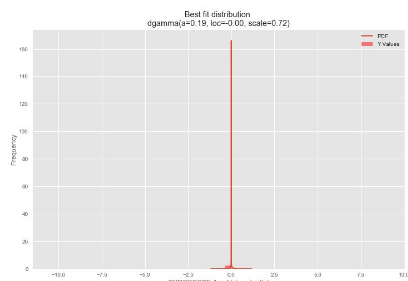

Figure 29.
Best distribution fit for Gyroscope Y values is dgamma(a=0.19, Ioc=0.00, scale=0.72)

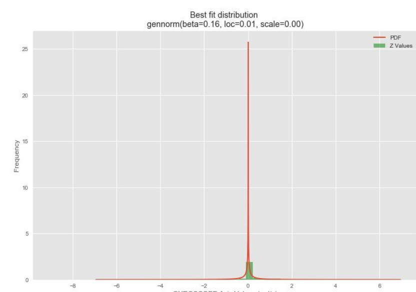

Figure 30.
Best distribution fit for Gyroscope Z values is gennorm(beta=0.16, Ioc=0.01, scale=0.00)

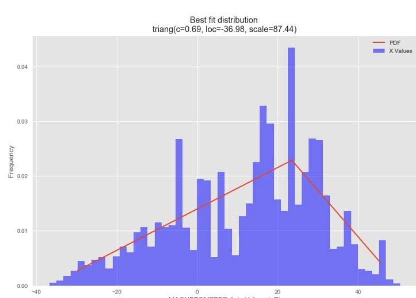

Figure 31.
Best distribution fit for Magnetometer X values is triang(c=0.69, Ioc=36.98, scale=87.44). This could be split into a multiple distributions.

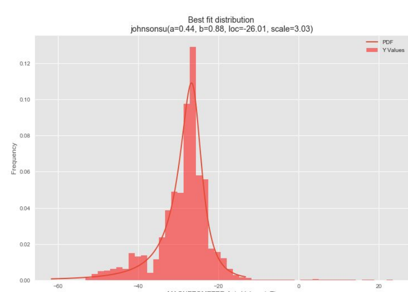

Figure 32.
Best distribution fit for Magnetometer Y values is johnsonsu(a=0.44, b=0.88, Ioc=26.01, scale=3.03)

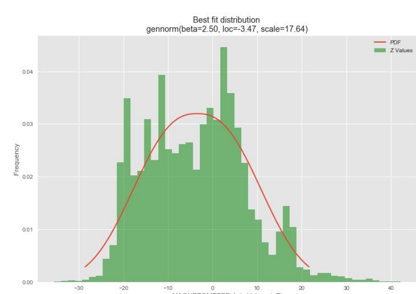

Figure 33.
Best distribution fit for Magnetometer Z values is gennorm(bta=2.50, Ioc=-3.47, scale=17.64). This could be split into a multiple distributions.

Chapter Three: Modelling and Evaluation

The dataset was split into a training dataset of 70% and a testing dataset of 30%.
K-nearest neighbors, RandomForest, Gradient Boosting Tree and SVM libraries were used to analyse and classify this dataset.
K-fold CV and Bootstrap techniques where used ,in each of the classification algorithms above, to improve performance and to avoid overfitting by picking the best parameters for this dataset.

KNN

Here I consider one of the simplest and best-known classification methods, K-nearest neighbors (KNN).
An activity is classified by a majority vote of its neighbours.
My knowledge of KNN came directly from the course and for more details the book "An Introduction to Statistical Learning. Springer (2013) gives detailed instructions and guidelines which have been invaluable to my research.

KNN Results

Results below for different k values:

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
A	77.7	76.5	78.0	78.3	78.6	78.9	78.9	79.0	79.0	79.1	79.1	79.1	79.1	79.0	79.0	79.0	79.0	79.0	78.9	79.0

k	21	22	23	24	25	26	27	28	29	30	40	50	60	70	80	90	100	200	300
A	79.1	79.25	79.1	79.21	79.1	79.1	79.1	79.1	79.0	78.8	78.5	78.1	77.8	77.4	77.3	77.0	76.8	74.5	72.8

The above table shows the K value and accuracy associated with it.
Green signifies an increase in accuracy compared to the previous accuracy.
Red signifies a decrease in accuracy compared to the previous accuracy.
Orange indicates that the same accuracy is maintained as the previous accuracy.
As the table above outlines any accuracy of 78% or higher has a K range of between 3 and 50.
The best accuracy is 79.2508% in which K = 22.

Confusion Matrix

K = 22	Sit	All 4s	Crawl Hands & Knees	Fall	Lie	Run	Stand	Walk
Sit	5375	406	71	63	442	67	314	36
All 4s	310	4652	296	105	382	1	575	58
Crawl Hands & Knees	3	2	3653	171	10	466	12	227
Fall	5	2	68	702	10	16	12	47
Lie	363	419	49	133	4894	28	238	9
Run	1	0	769	110	9	5782	7	235
Stand	346	409	100	121	199	3	5056	103
Walk	22	3	662	186	21	470	25	5090

Green signifies an accurate prediction, e.g. Sitting was classified right 5375 times.
Red signifies the activity which is most often mistaken for another, e.g. Sitting was incorrectly classified as Lying 363 times.

The data set recorded for the activities lying, All 4s and sitting are quite similar and therefore are often confused with one another. Although each has a high accuracy success rate they appear to overlap often and affect the recognition ability. This is most likely because all three activities are low to the ground static activities.

Another trio which appears to overlap are the dynamic activities such as running , walking and crawling on one's hands and knees. They all as outlined in the trend graphs have a very lively pattern due to the strenuous nature of the activities.

The confusion matrix shows that the crawl hands and knees has a high confusion rate with running. The higher result here could be cause for concern.
There is also a high inaccuracy rate in the falling activity which can be justified by the smaller number of falling samples.

Cross Validated k Value

In general, the optimal value for K will depend on the Bias-Variance tradeoff. A small value for K provides the most flexible fit, which will have low bias but high variance. In contrast, larger values of K provide a smoother and less variable fit and so changing one observation has a smaller effect on the prediction.

A good classifier is one for which the test error is smallest. A number of techniques like k-fold CV and bootstrap can be used to estimate this quantity using the available training dataset.

Results of k-fold CV technique with 10 folds for best accuracy are as follows k=15 with accuracy 79.57472

Results of Bootstrapped technique with 10 reps for best accuracy are as follows k=20 with accuracy 78.84236

The code results available for both techniques can be found in Appendix B.

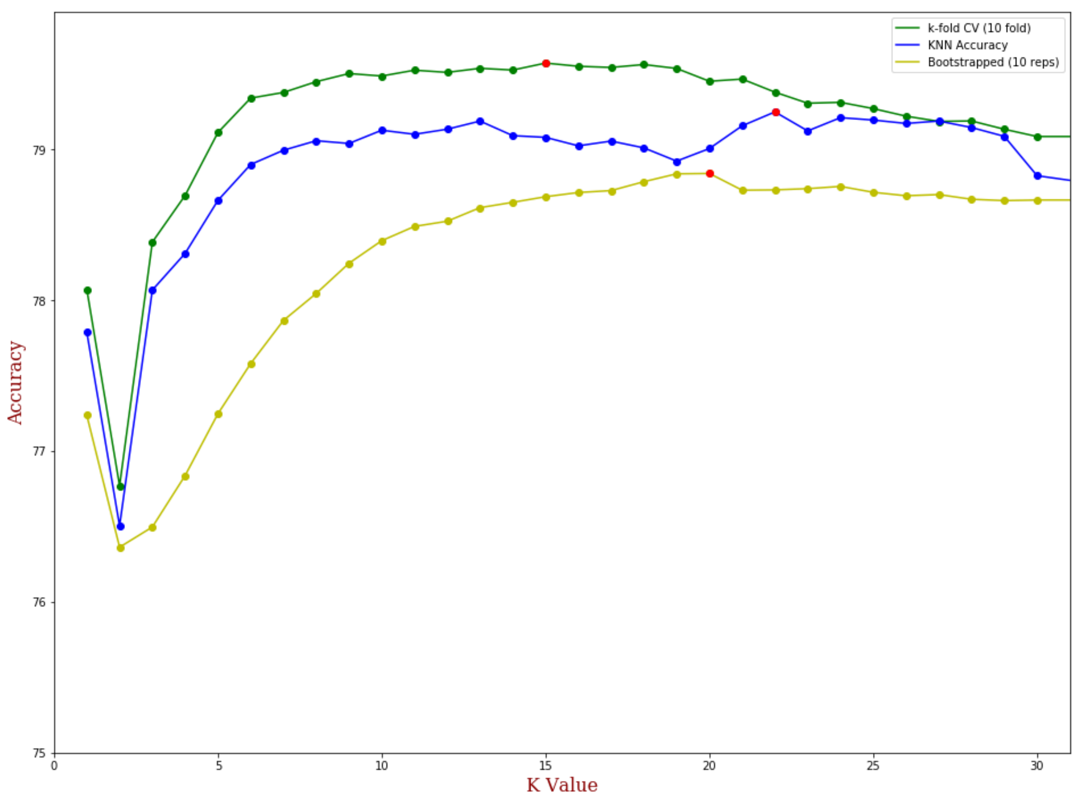

Figure 34. The true test accuracy is shown in blue, the 10 reps Bootstrapped estimate is shown as a yellow line, and the 10-fold CV estimate is shown in green. The red dots indicate the maximum of each of the accuracy curves.

Random Forests

Here I consider one of the best-known decision trees classification methods, Random Forest.
Random Forest train with the bagging method. The general idea of the bagging method is that a combination of learning models increases the overall result.
My knowledge of Random Forest came directly from the course and for more details the book "An Introduction to Statistical Learning. Springer (2013) gives detailed instructions and guidelines which have been invaluable to my research.

Random Forest Results

Results below for different mtry values with the default ntree (500).
mtry is the number of variables randomly sampled as candidates at each split.
ntree is the number of trees to grow.

mtry	Accuracy
1	0.7083361
2	0.8487877
3	0.8487652
4	0.8490804

The best accuracy is 84.9% in which mtry = 4.

Cross Validated mtry Value

If a random forest is built using m = p, then this amounts simply to bagging. Which is our case above mtry = 4. Using a small value of m in building a random forest will typically be helpful when we have a large number of correlated predictors.

A good classifier is one for which the test error is smallest. A number of techniques like k-fold CV and bootstrap can be used to estimate this quantity using the available training dataset.

Results of k-fold CV technique with 10 folds for best accuracy are as follows mtry=2 with accuracy 80.73728 %
Results of Bootstrapped technique with 10 reps for best accuracy are as follows mtry=2 with accuracy 80.44371%
The code results available for both techniques can be found in Appendix B.

Cross Validated ntree Value

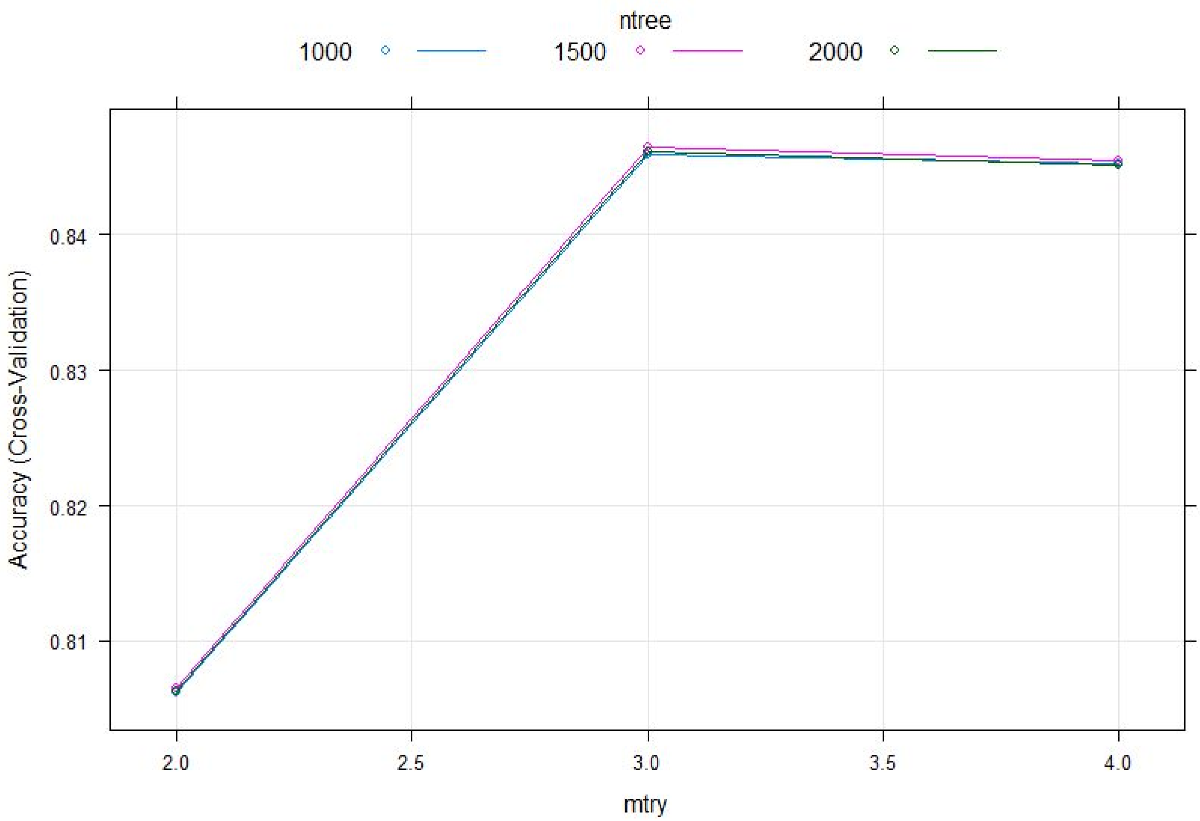

Figure 35. The best value for mtry found using grid search is 3. The best value of ntree found using grid search is 1500 with accuracy of 84.64655%

Gradient Boosted Trees

Gradient Boosted Trees is another well known decision trees classification method.
The aim is to reduce both bias and high variance of learners by averaging lots of models fitted on bootstrapped data samples generated with replacement from the training data.
My knowledge of Gradient Boosted Trees came directly from the course and for more details the book "An Introduction to Statistical Learning. Springer (2013) gives detailed instructions and guidelines which have been invaluable to my research.

Gradient Boosted Results

Gradient Boosted Model which generates 1000 trees and the default shrinkage parameter lambda= 0.001 (learning rate) returned 72.0073% accuracy for the phone dataset.

Cross Validated shrinkage λ Value

The results below reflect cross validation technique with a different value of the shrinkage parameter λ. Which led to an improved accuracy of 10%.

shrinkage λ Value	K-fold CV Accuracy
0.002	0.6302206
0.003	0.6756712
0.004	0.6946581
0.005	0.7107891
0.006	0.7204658
0.007	0.7304705
0.008	0.7364328
0.009	0.7424627
0.01	0.7478558
0.02	0.7811888
0.05	0.8204841

The code results can be found in Appendix B.

There was dramatic improvement with changing the learning rate shrinkage parameter with accuracy of 82% but according to Ridgeway "It is important to know that smaller values of shrinkage (almost) always give improved predictive performance. That is, setting shrinkage=0.001 will almost certainly result in a model with better out-of-sample predictive performance than setting shrinkage=0.01. … The model with shrinkage=0.001 will likely require ten times as many iterations as the model with shrinkage=0.01" Ridgeway (2007).

So I reran the model keeping the shrinkage parameter constantly set to the default value of 0.001. I increased the number of trees to 2000 trees. The accuracy result was down by 9% with value of 63.01627%.

Chapter Four: Conclusions and Future Work

The data which I have collected using an Android phone has returned 84.9% accuracy. I can thereby conclude that phones are a feasible device to record and track data. I agree with Angus Wong's 2010 paper in which he highlights how cellphones are excellent mobile computing devices.
"Increases in the computational power of mobile processors, improvements in mobile operating systems, and the popularity of mobile broadband make cell phones the best candidate for sophisticated mobile computing devices." (2010, p.1.)
The phone app I designed was very easy to use and an effective tool for generating and processing data. Due to its success I can state that this is indeed a feasible way to collect this kind of data.

Children over the age of ten can be used to track data in the same way as the older candidates if instructed in a controlled environment for short intervals. The data collected was very similar across the range of ages who volunteered. I can conclude that the age profile within the range of 10 to 65 did not affect the recognition ability of the app.

When I compare the accuracy of scheurer's experiment in which he attaches the IMU sensor to a shoulder strap to the original dataset in which the mobile device is attached to the users arm, it is clear that both positions are effective in data collecting.

The IMU classification results showed that Gradient Boosted Trees (GBT) can be used with accuracy of 97%."Scheurer (2017)"
The Phone Sensor classification results showed that Random Forest Trees can be used with accuracy of 84.9%.

Decision trees classification methods returned the best accuracy in both datasets. Given the big difference in the size of the datasets the performance of the classification algorithms would be different. I would expect that adding more samples to the phone sensor dataset will improve the accuracy to match the IMU accuracy.

I suspect that due to the different types of sensors in different phones discussed in this research caused an effect on the data generated from the phones, which might led to an overfitting using Gradient Boosted Trees model for this dataset. Hence Random Forest Trees was a better fit as the bagging technique is good for reducing variance.

For this thesis the raw data which was received directly from the sensors was used to build the classification model. In this way, the time series nature of this data was ignored. The model could have been created to take in to consideration the time series data by extracting and building features from the time series data initially (mean, min, max and the variance of the run samples) and then applying the existing classification techniques like the ones used in this thesis KNN, RandomForest.

Going forward to enhance this study it could be interesting to model the data in time series nature and compare and contrast them with this model. Deeper investigation into this could make the foundations of further, comparative study.

Due to the mass marketed nature of these devices and the discretion of their wearing it make good sense to use these in industry and medicine going forward. As a future work I would love to proceed into improving the stream processing to analyse the data in real time and continue to improve the model as oppose the way it was done in this research where it was there to collect the data and store them for analysis process afterwards. This way could give us a great insight into what activities have a strong approximation relationship to each other like running then walking. This could lead to even better streaming human activity recognition. For example in the case of a someone losing consciousness after running which would be spotted at real time. This could save valuable time and lead to quick response times to accidents and emergencies in the workplace.

The study has proved that phone sensors are a highly effective tool in data collection of human activities. The controlled nature of the sender and observer app ensured accurate labelling of data as it was recorded.

I predict a much higher dependence on mobile phone devices in human activity recognition. Having interviewed professionals in a different fields, I imagine this form of data collection will become commonplace in many workplace environments. This has exponential potential in the fields of medicine and health and safety.

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Appendix A - Graphs

Included in appendix A are three types of graphs

a) Cluster graphs to compare the sensor data of the two activities.
b) Trend Graphs illustrate the pattern of each activity by graphing a random run from each activity, All three trend graphs are from the same activity. The sensors are event based, triggered at their own uptime.
c) Box Plot graphs represent the features of the data set per activity and per sensor type.

Sitting versus Standing Activities Cluster

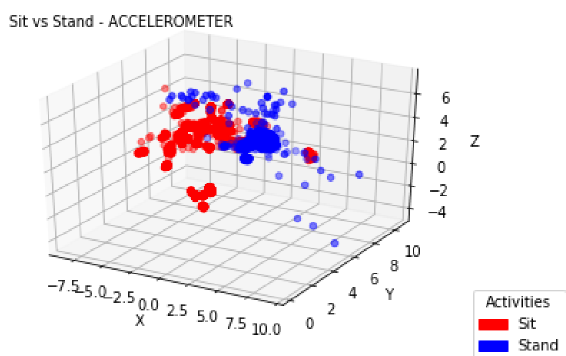

Figure 36.
Accelerometer data of sitting and standing. There is a clear scope between the two activities. There are not many overlapping samples.

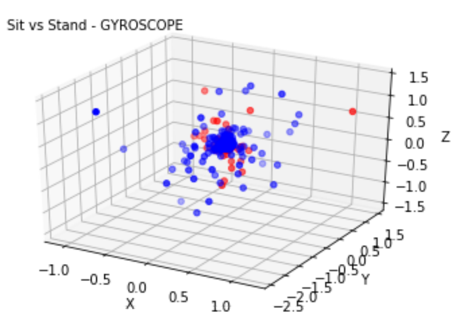

Figure 37.
Gyroscope comparing sitting and standing. These points are overlapping and difficult to distinguish as they appear to be on the same scope.

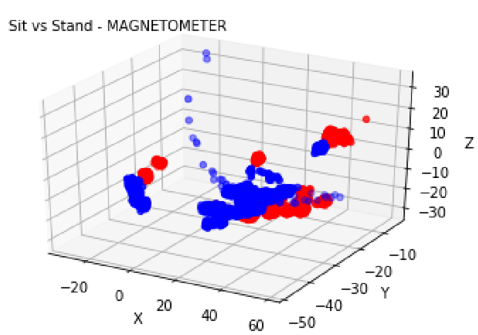

Figure 38.
Magnetometer comparing sitting and standing. There is some distinguished clusters but there is an overlap in places.

Lying versus Falling Activities Cluster

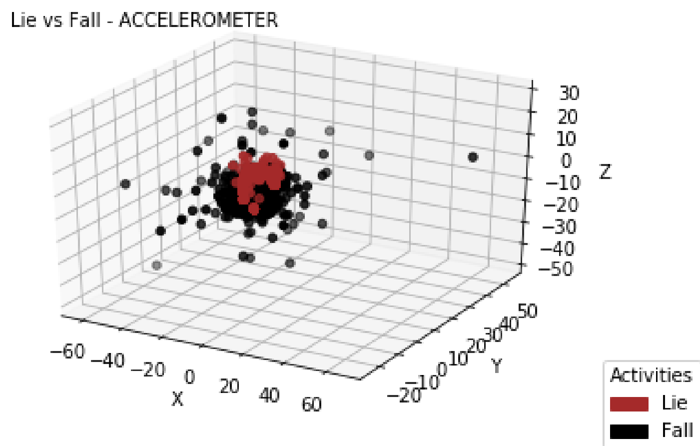

Figure 39.
Accelerometer data comparing lying and falling, the activities overlap here.

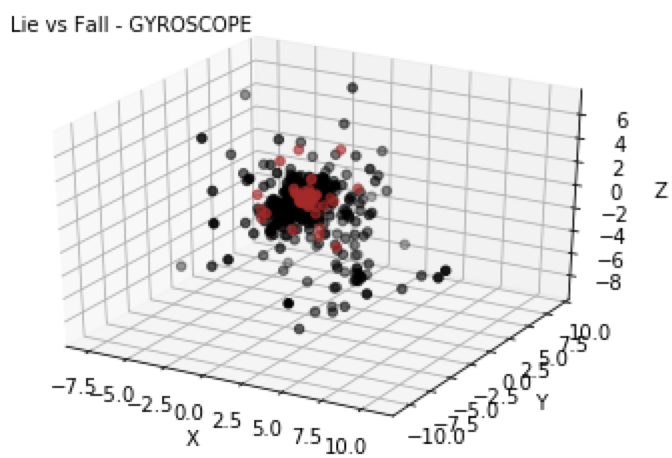

Figure 40.
Gyroscope data comparing lying and falling. There is significant overlap in these activities.

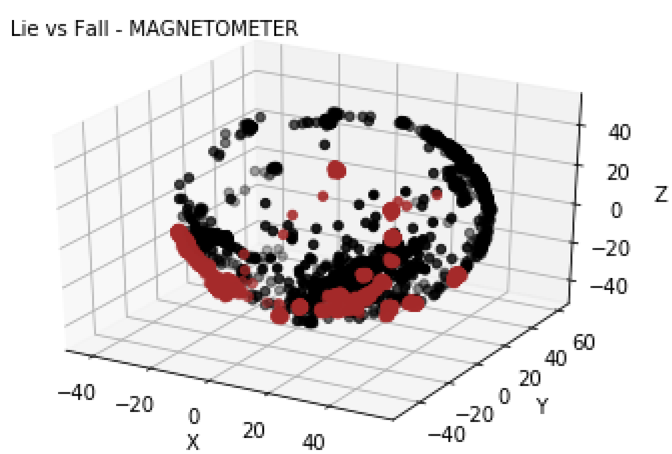

Figure 41.
Magnetometer comparing lying to falling. The two activities or easily distinguished from one another. There is overlap.

All Fours versus Crawling on Hands and Knees Activities Cluster

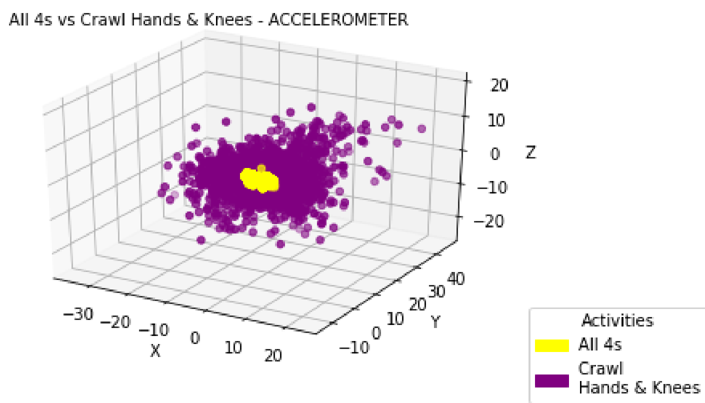

Figure 42.
Comparing all fours to crawling. The activities are quite easily distinguishable. The scope is grouped with an overlap.

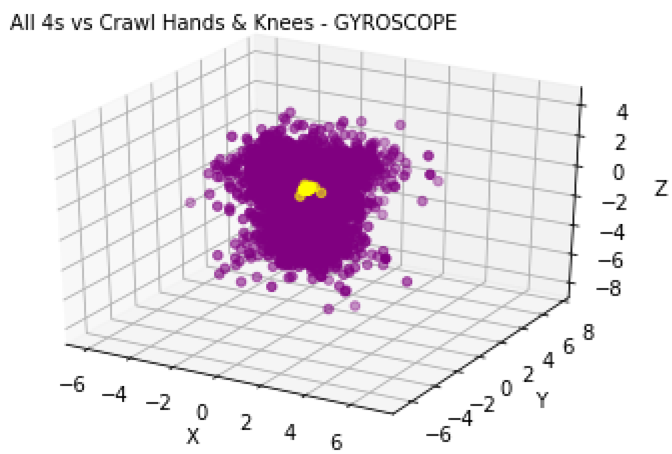

Figure 43.
Gyroscope comparing all fours and crawling. The activities can be determined from one another. There is a large amount of overlap but the scope is grouped.

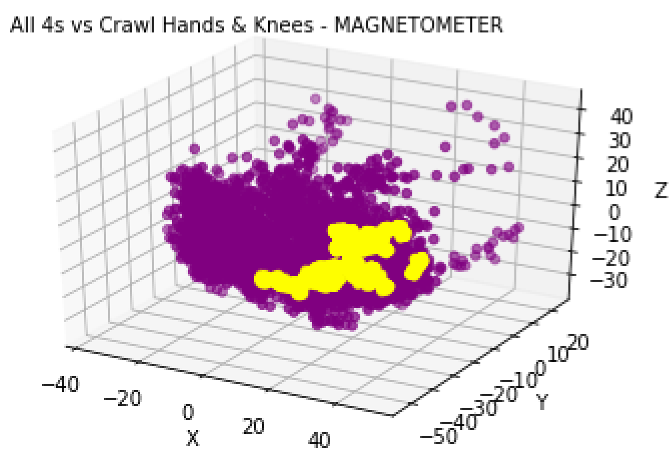

Figure 44.
Comparing all fours with crawling. The activities are distinguished however there is a large amount of overlap but the scope is grouped.

Lying Activity Pattern

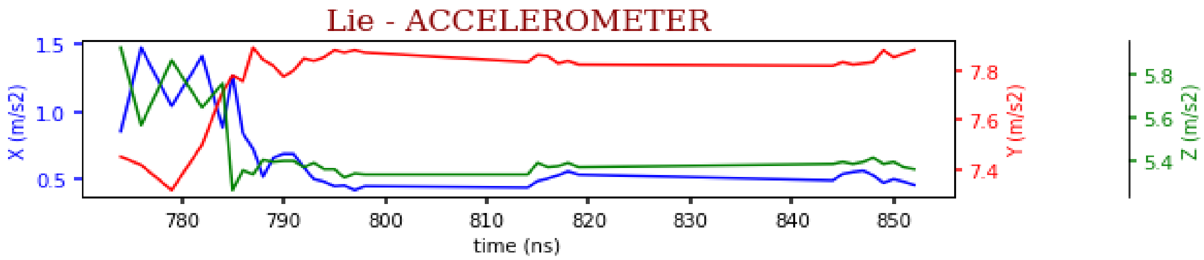

Figure 45. The Accelerometer data for the lying activity indicates that there is little motion in the acceleration pattern.

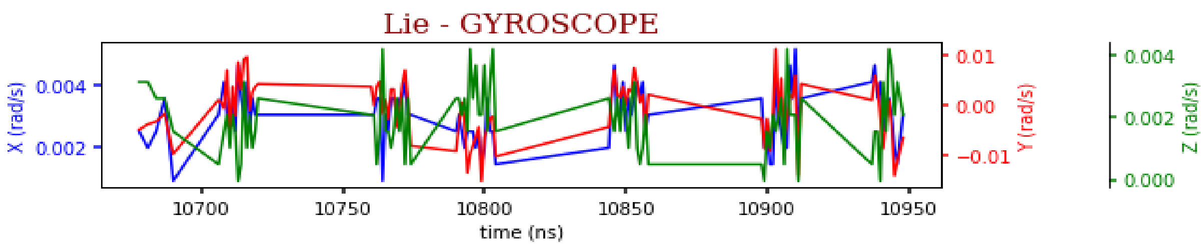

Figure 46. The Gyroscope graph shows a very clear and distinct pattern within a narrow range.

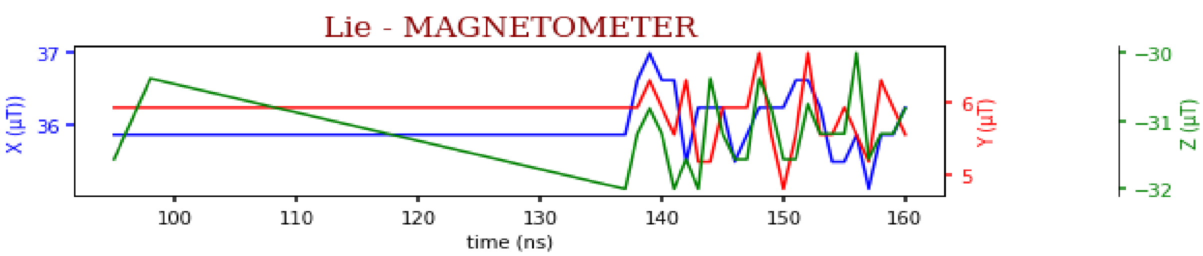

Figure 47. The Magnetometer fluttered towards the end of the graph. The range is very narrow.

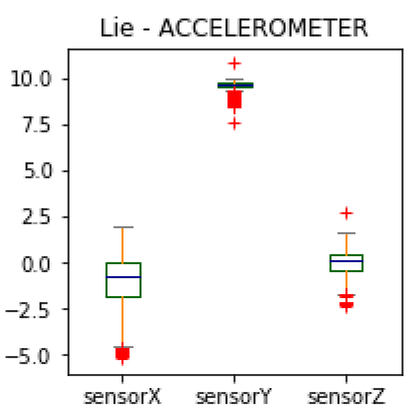

Figure 48. Outliers in close range.

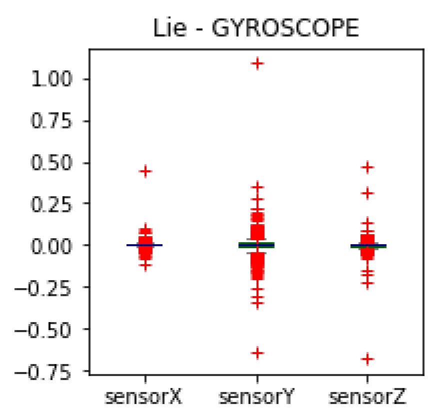

Figure 49. No abnormal outliers.

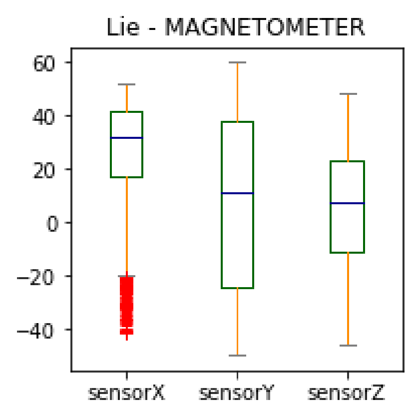

Figure 50. Only x axis outliers.

Walking Activity Pattern

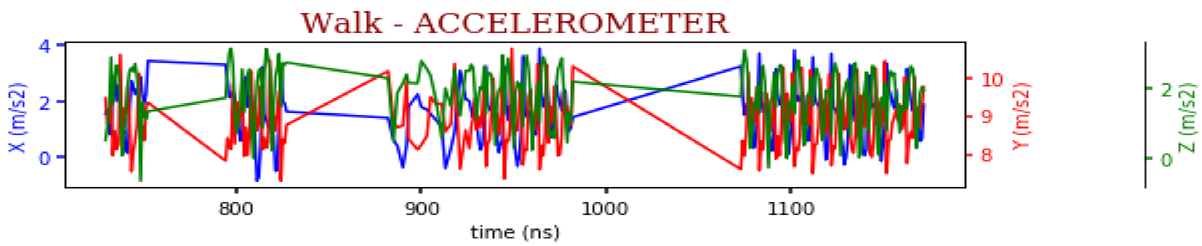

Figure 51.The Accelerometer graph has a very distinct and definite pattern

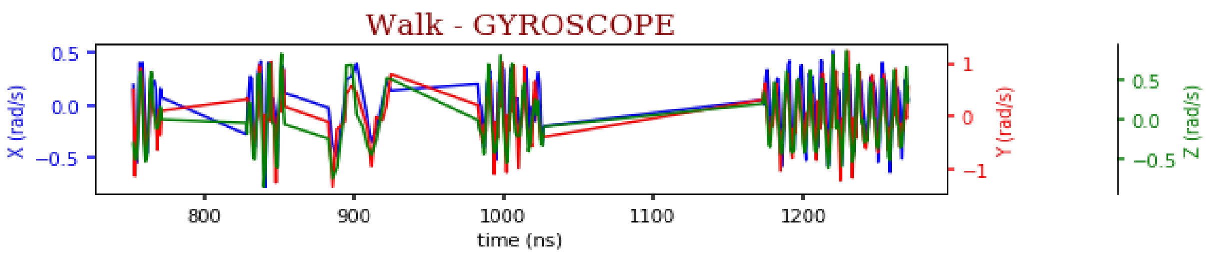

Figure 52. The Gyroscope trend from the walking activity shows a distinct pattern.

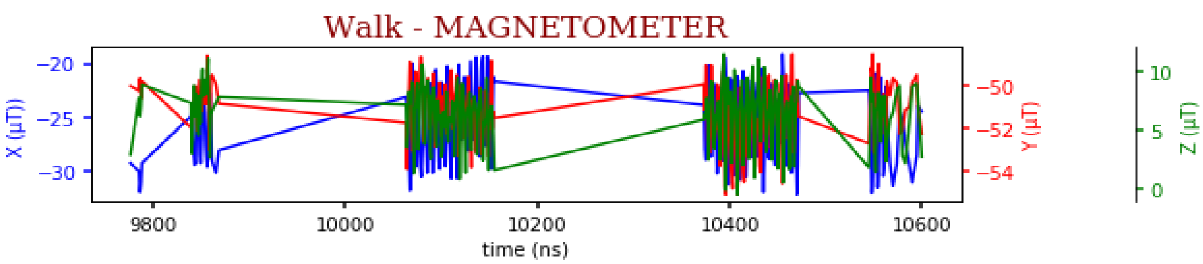

Figure 53. The Magnetometer graph has a very steady pattern of minor rises and falls. It is a very rhythmic pattern.

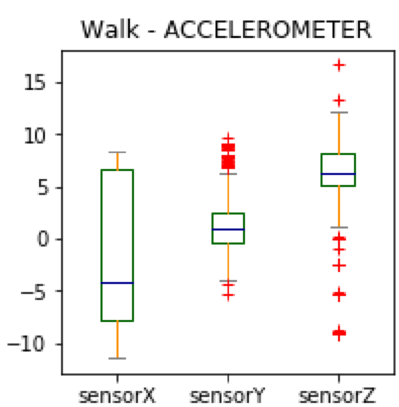

Figure 54. No major outliers.

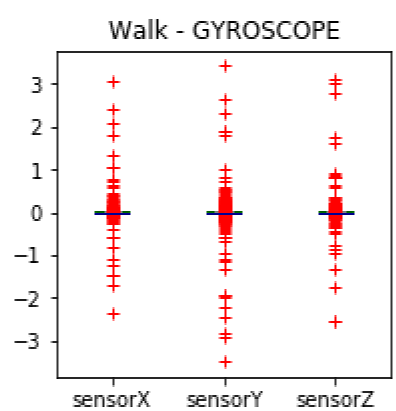

Figure 55. Outliers in close range

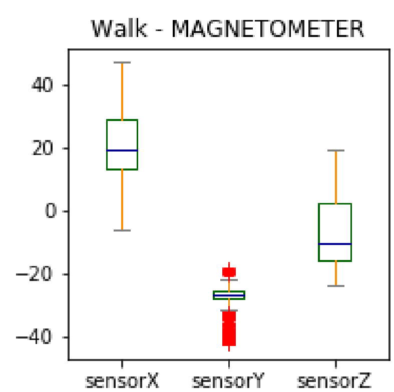

Figure 56. Outliers in Y axis only.

Running Activity Pattern

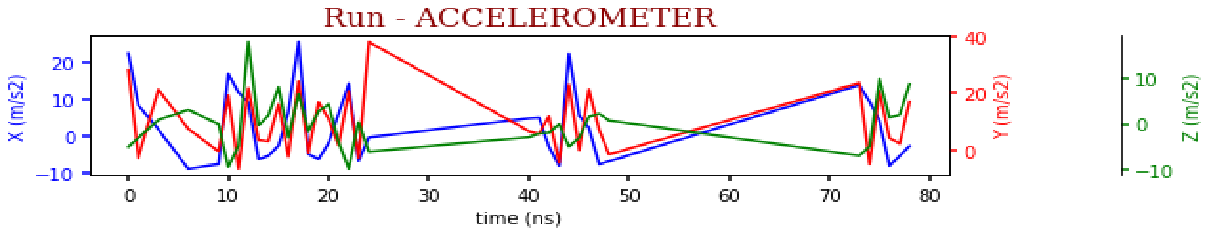

Figure 57. The accelerometer for running shows a rhythmic pattern. It show great highs and lows and irregular bouts of activity.

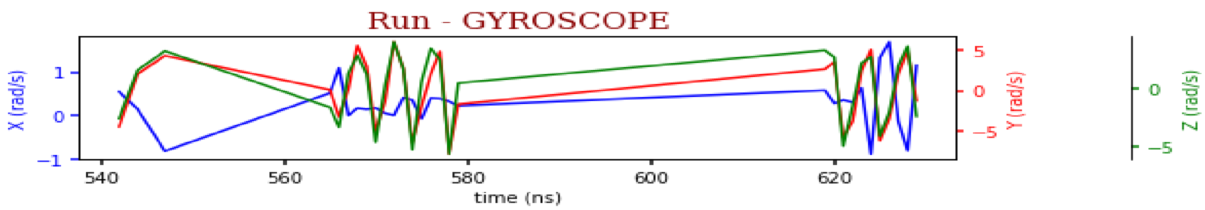

Figure 58. The gyroscope date indicate lulls and then small changes to orientation. This is maybe the indicative of the runners arm moving during the exercise.

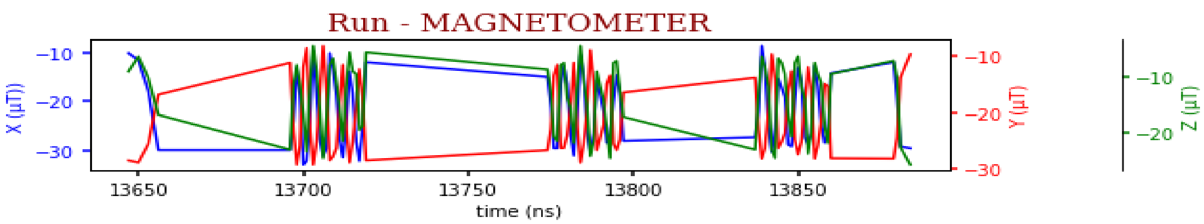

Figure 59. The magnetometer shows rhythmic pattern. The pattern fluctuates in a fluid up and down motion

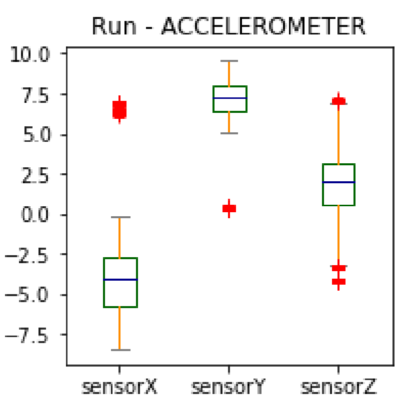

Figure 60. Normal amount of outliers for sensor data.

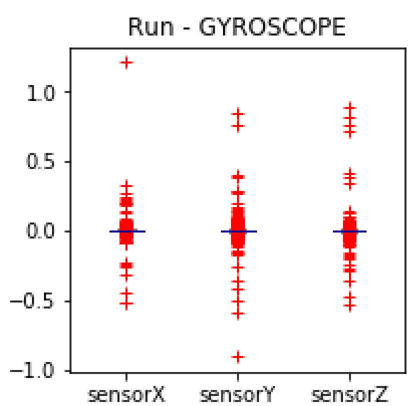

Figure 61. Outliers in very close range.

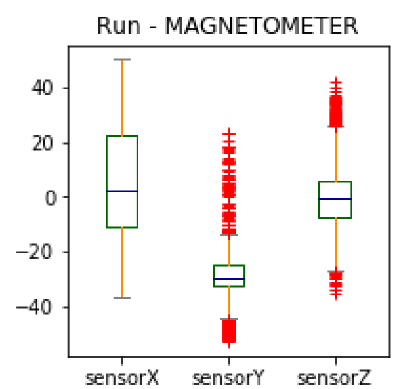

Figure 62. Some close range outliers in Y and Z axis.

All Fours Activity Pattern

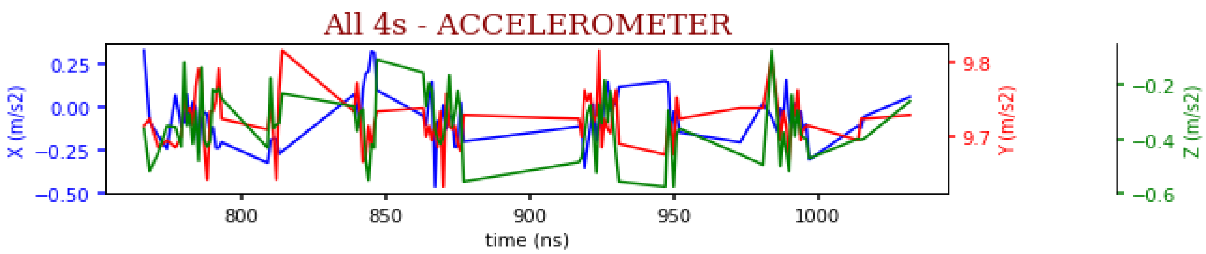

Figure 63. The range for this trend is quite small indicating the static nature of the pose. The fluctuations may indicate rhythmic breathing of the volunteer.

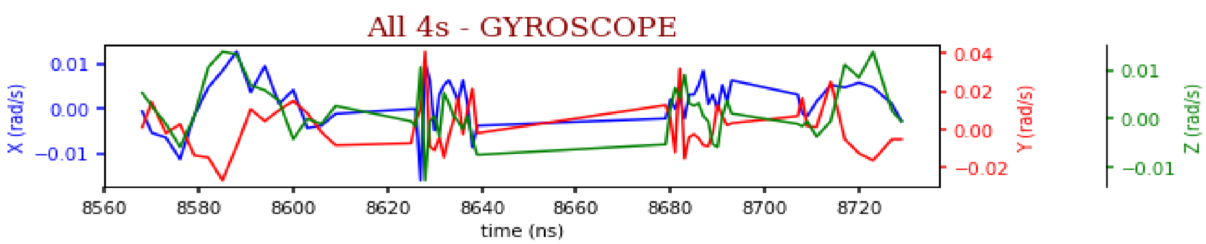

Figure 64. It is clear that this is a static pose as there is only small fluctuations in the graph.

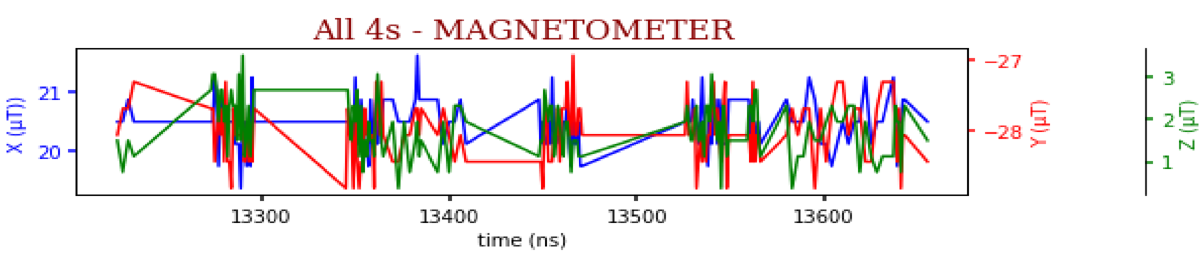

Figure 65. The trend graph for this static activity has a pattern with little magnetic field change.

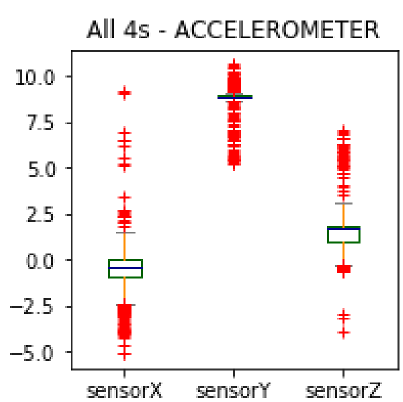

Figure 66.Very close range outliers.

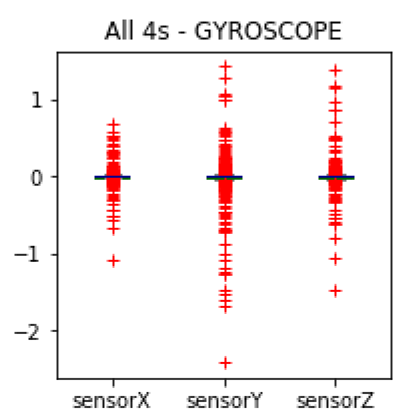

Figure 67. Very close range outliers.

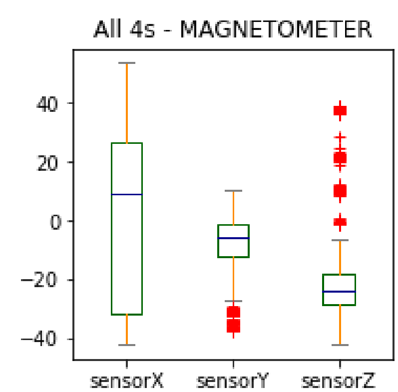

Figure 68. Normal amount of outliers for sensor data.

Standing Activity Pattern

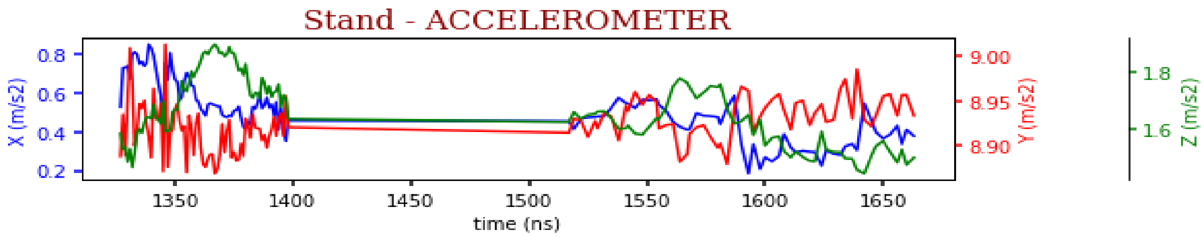

Figure 69. The graph reflects the static nature of standing and breathing. There is a rhythmic change and rest pattern. There is little rise and fall in this trend graph.

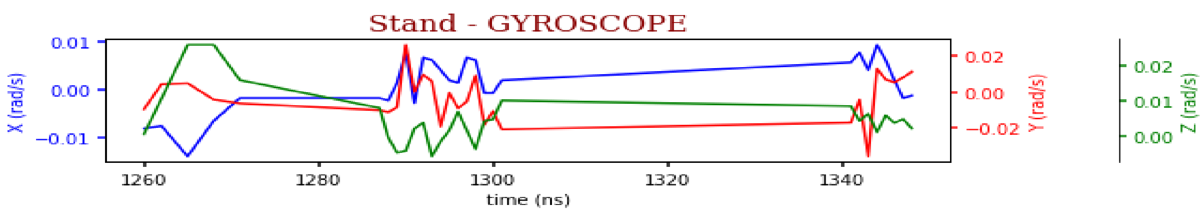

Figure 70. The Gyroscope data is exceptionally close due to the static nature of the pose.

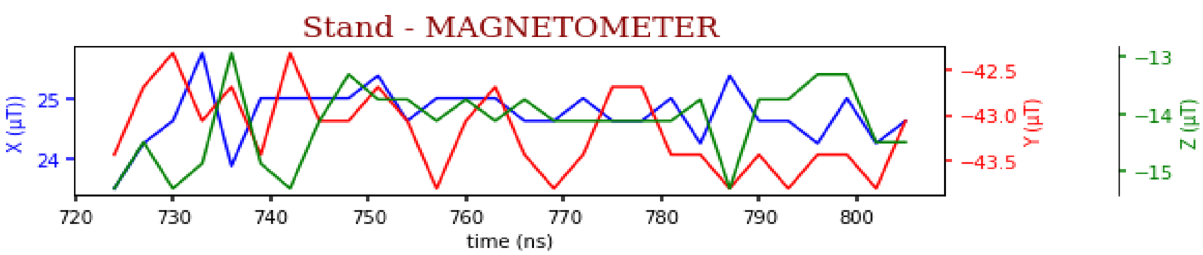

Figure 71. The graph undulates in a regular pattern.

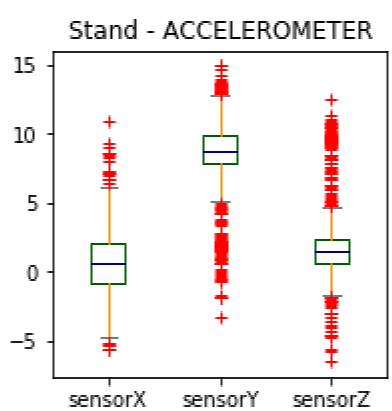

Figure 72. Close range outliers.

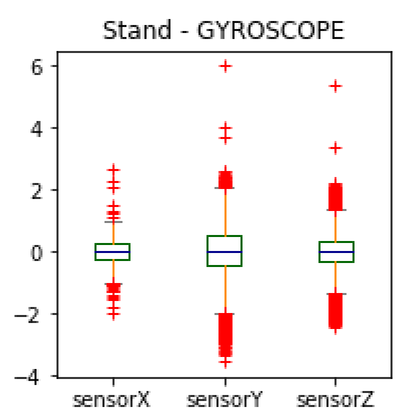

Figure 73. Normal amount of outliers for sensor data

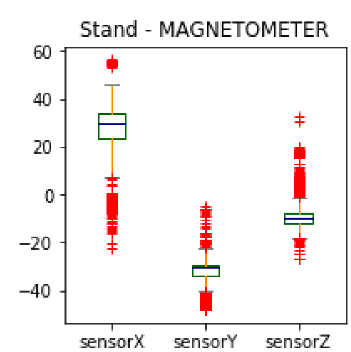

Figure 74. Normal amount of outliers for sensor data

Crawling on Hands and Knees Activity Pattern

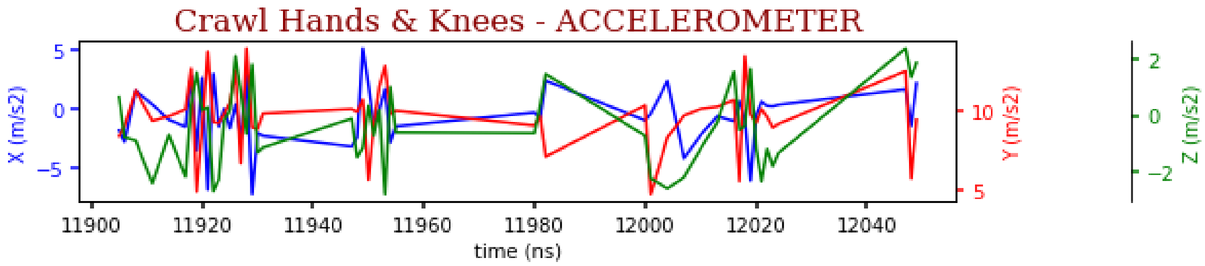

Figure 75. There is regular pattern to crawling with little noise.

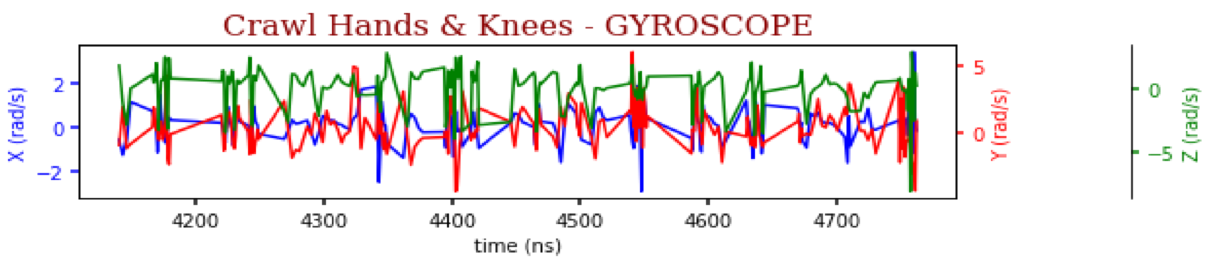

Figure 76. Crawling with Gyroscope data has a very low range and many small fluctuations.

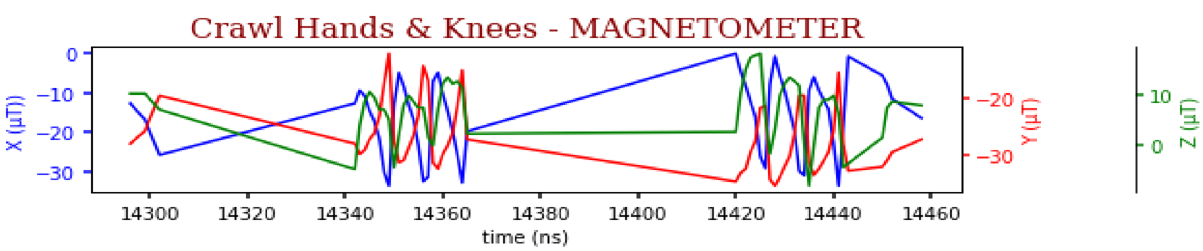

Figure 77. The crawling data has a set pattern here.

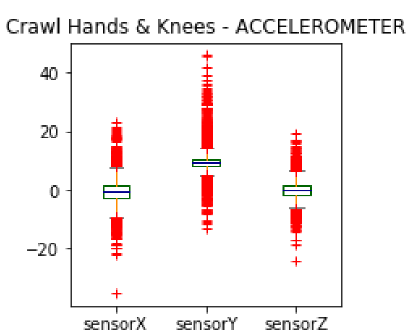

Figure 78. Close range of outliers.

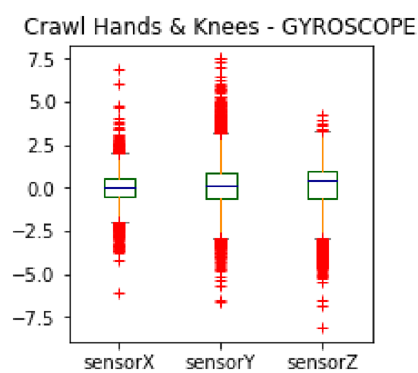

Figure 79. Close range outliers

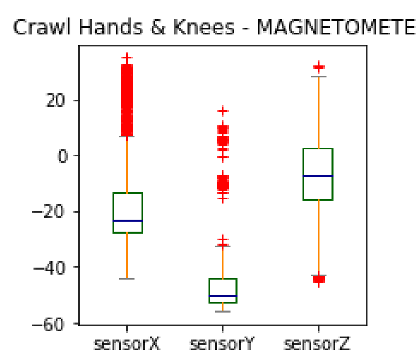

Figure 80. Normal amount of outlier for sensor data.

Sitting Activity Pattern

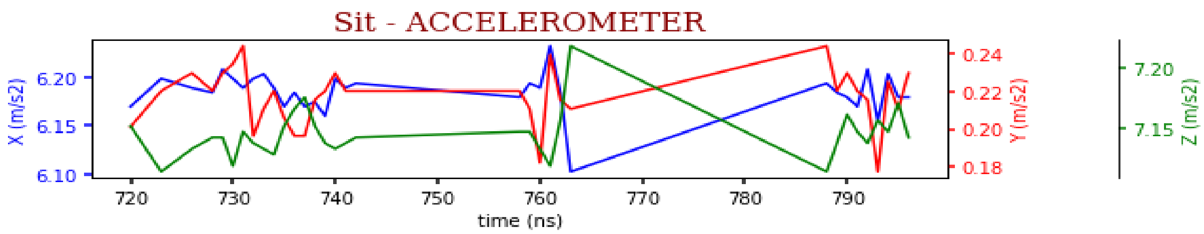

Figure 81. There are very small fluctuations in the accelerometer data here. The range is very close.

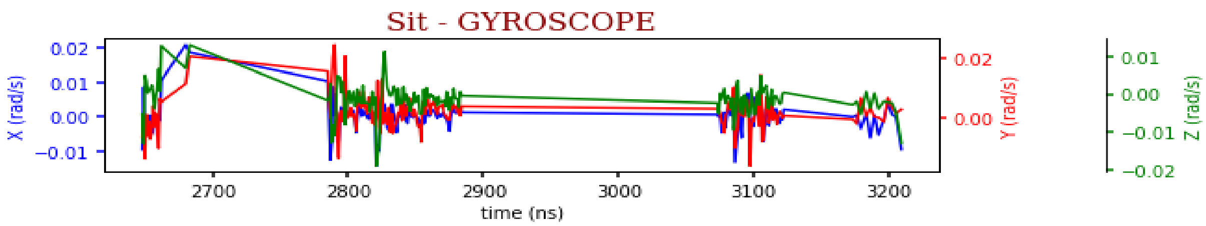

Figure 82. Again, similarly to the accelerometer data set, there is an extremely close range. The regular fluctuations again may indicate small changes in orientation due to inhaling and exhaling.

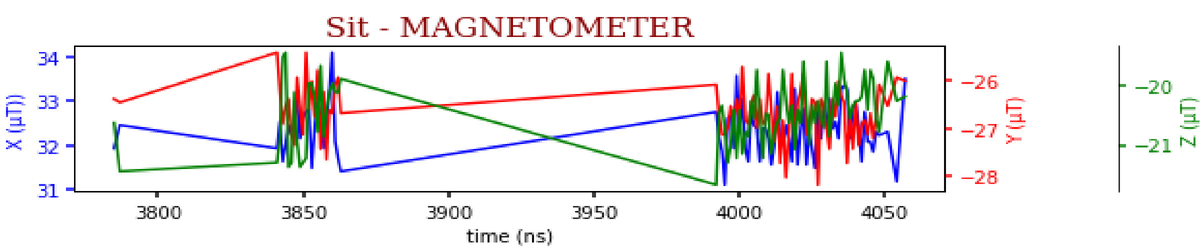

Figure 83. The magnetometer trends zigzag dramatically after a lull.

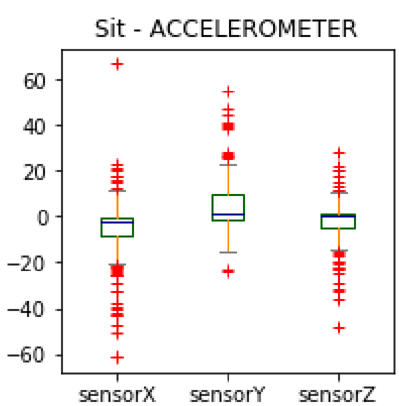

Figure 84. Close range outliers

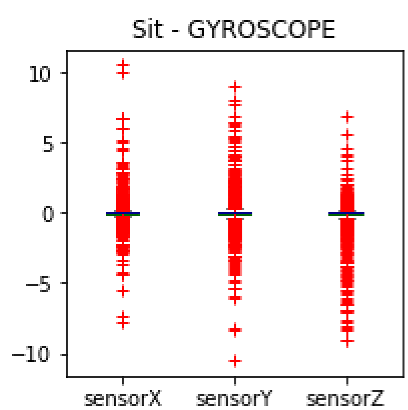

Figure 85. close range outliers.

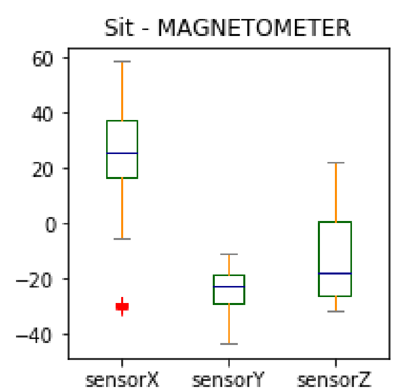

Figure 86. No outliers which cause concern .

Appendix B - Results

Results of k-fold CV for KNN

k-Nearest Neighbors

103651 samples
4 predictor
8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 93285, 93285, 93286, 93285, 93285, 93287, ...
Resampling results across tuning parameters:

k	Accuracy	Kappa
1	0.7807353	0.7465027
2	0.7677011	0.7314223
3	0.7838708	0.7499511
4	0.7869678	0.7534638
5	0.7911355	0.7582344
6	0.7934222	0.7608639
7	0.7937983	0.7612705
8	0.7945123	0.7620818
9	0.7950525	0.7626849
10	0.7948885	0.7624893
11	0.7952744	0.7629307
12	0.7951298	0.7627607
13	0.7953998	0.7630618
14	0.7952842	0.7629168
15	0.7957472	0.7634474
16	0.7955350	0.7631946
17	0.7954578	0.7630993
18	0.7956507	0.7633182
19	0.7953903	0.7630109
20	0.7945413	0.7620194
21	0.7946860	0.7621840
22	0.7938177	0.7611725
23	0.7930845	0.7603196
24	0.7931424	0.7603831
25	0.7927275	0.7599004

26	0.7922258	0.7593155
27	0.7918785	0.7589099
28	0.7919074	0.7589438
29	0.7913576	0.7583028
30	0.7908752	0.7577443

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 15.

Results of Bootstrapped for KNN

k-Nearest Neighbors

103651 samples
4 predictor
8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Bootstrapped (10 reps)
Summary of sample sizes: 103651, 103651, 103651, 103651, 103651, 103651, ...
Resampling results across tuning parameters:

k	Accuracy	Kappa
1	0.7723853	0.7368168
2	0.7636323	0.7266867
3	0.7649699	0.7281837
4	0.7683848	0.7320824
5	0.7724783	0.7367622
6	0.7758138	0.7405772
7	0.7786721	0.7438483
8	0.7804625	0.7458829
9	0.7824659	0.7481758
10	0.7839644	0.7498857
11	0.7849117	0.7509658
12	0.7852560	0.7513505
13	0.7861557	0.7523789
14	0.7865103	0.7527794
15	0.7868806	0.7531984
16	0.7871612	0.7535149
17	0.7872874	0.7536510
18	0.7878778	0.7543264
19	0.7884002	0.7549253
20	0.7884236	0.7549468

```
  21  0.7873133  0.7536420
  22  0.7873340  0.7536565
  23  0.7874155  0.7537429
  24  0.7875662  0.7539149
  25  0.7871745  0.7534596
  26  0.7869455  0.7531890
  27  0.7870240  0.7532828
  28  0.7867123  0.7529159
  29  0.7866233  0.7528092
  30  0.7866624  0.7528527
```

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 20.

Results of k-fold CV for Random Forest

Random Forest

103651 samples
    4 predictor
    8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 93286, 93290, 93284, 93288, 93285, 93285, ...
Resampling results:

```
  Accuracy   Kappa
  0.8073728  0.7768298
```

Tuning parameter 'mtry' was held constant at a value of 2

Results of Bootstrapped for Random Forest

Random Forest

103651 samples
    4 predictor
    8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Bootstrapped (10 reps)
Summary of sample sizes: 103651, 103651, 103651, 103651, 103651, 103651, ...

Resampling results:

Accuracy	Kappa
0.8044371	0.7734344

Tuning parameter 'mtry' was held constant at a value of 2

Grid Search Results for ntree Values in Random Forest

	mtry	ntree	Accuracy	Kappa	AccuracySD	KappaSD
1	2	1000	0.8062536	0.7755378	0.003502089	0.004058681
2	2	1500	0.8065720	0.7759101	0.003334618	0.003878400
3	2	2000	0.8062921	0.7755824	0.003431506	0.003990353
4	3	1000	0.8459927	0.8217767	0.002244179	0.002612695
5	3	1500	0.8464655	0.8223209	0.002373885	0.002763047
6	3	2000	0.8461663	0.8219756	0.002549960	0.002961088
7	4	1000	0.8453174	0.8210102	0.002379773	0.002767184
8	4	1500	0.8454717	0.8211913	0.002161149	0.002515023
9	4	2000	0.8451244	0.8207880	0.002630166	0.003057772

Results of k-fold CV for Gradient Boosted Trees

Stochastic Gradient Boosting

103651 samples
4 predictor
8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Cross-Validated (2 fold)
Summary of sample sizes: 51825, 51826
Resampling results across tuning parameters:

shrinkage	Accuracy	Kappa
0.002	0.6302206	0.5704896
0.003	0.6756712	0.6234866
0.004	0.6946581	0.6456764
0.005	0.7107891	0.6644517
0.006	0.7204658	0.6757422
0.007	0.7304705	0.6874107
0.008	0.7364328	0.6943531
0.009	0.7424627	0.7013754
0.010	0.7478558	0.7076317

0.020	0.7811888	0.7464363
0.050	0.8204841	0.7921134

Tuning parameter 'n.trees' was held constant at a value of 1000
Tuning parameter 'interaction.depth' was held constant at
a value of 4
Tuning parameter 'n.minobsinnode' was held constant at a value of 1
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 1000, interaction.depth = 4, shrinkage = 0.05
and n.minobsinnode = 1.

Results of k-fold CV for Gradient Boosted Trees (n.trees = 2000)

Stochastic Gradient Boosting

103651 samples
4 predictor
8 classes: 'Sit', 'All 4s', 'Crawl Hands & Knees', 'Fall', 'Lie', 'Run', 'Stand', 'Walk'

No pre-processing
Resampling: Cross-Validated (2 fold)
Summary of sample sizes: 51826, 51825
Resampling results:

Accuracy	Kappa
0.6301627	0.5704409

Tuning parameter 'n.trees' was held constant at a value of 2000
Tuning parameter 'interaction.depth'
was held constant at a value of 4
Tuning parameter 'shrinkage' was held constant at a value of 0.001

Tuning parameter 'n.minobsinnode' was held constant at a value of 1