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Running with machine learning

A study on running technique using foot placed IMUs and multinomial logistic regression

Master's thesis in Systems control and Mechatronics

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Master's thesis 2018

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Abstract

This master thesis investigates whether it is possible to distinguish good and bad running technique using machine learning and no more sensors than two IMUs, one attached to each foot. The long term vision is to create a real-time running coach application that can help to improve the running technique while running. The chosen machine learning model is called multinomial logistic regression and was trained using known sets of features and classes. Aktivitus, a company located in Gothenburg helped classifying 18 runners at 4 different velocities as bad, good and very good while sampling data. The acceleration and angular velocity data from the sensors was used to extract some of the features, namely ground contact time (GCT), air time (AT), step frequency (f_{step}) and a modified version of the direction of the acceleration at foot strike (a_{FS}). The validation of the features was done with the help from another company in Gothenburg called Qualisys. The other features used were speed, fitness level, body mass index (BMI) and gender. Various combinations of input features were tested and the highest success rate of 67% was obtained in two cases. The first case used all features obtained from the sensors divided by BMI together with gender and speed. The second case used only (a_{FS}), BMI, fitness level and gender. It was considered that 67% is a relatively good result considering the small amount of data.

Keywords: Machine Learning, Signal Processing, Track and Field, Running Technique, Multinomial Logistic Regression, IMU.

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Finally but not last, we would like to embrace our families for supporting us during our years of studies, thank you for always being there.

Therese Damberg & Linnéa Sjöberg, Gothenburg, December 20, 2018

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1 Introduction

1.1 Background

Human activity recognition (HAR) are increasing in their popularity within research and consumer-based usage. For runners that compete, e.g. track and field runners or marathon runners, running technique improvement is important. The knowledge regarding the gait analysis of an athlete can make the difference between winning or losing, which is why spatial - temporal parameters are useful information for the runners. The correlation between the parameters and performance have been studied previously [1] and this have shown the importance of the parameters for coaches and athletes. From an elite performer perspective, the objective feedback can be crucial for a higher qualitative training. Pure observation from the coach can sometimes be restricted because of the parameters being difficult to observe with the eye. Sometimes athletes must be able to generate speed quickly and the movement easily becomes too subtle for a human eye. [2].

Today there exists applications which provide runners with data during their run but most applications provide data only after the run. It can however be difficult to know how to improve the technique when only getting feedback afterwards and not directly. If for example someone tells you that you should increase the step frequency, it can be difficult to know if the frequency or only the speed is increasing, using only intuition. Force platforms, contact mats, opto-electronics and motion capture systems are such devices that collect data which can be analysed. However, these systems are limited within the field of use because the non-mobility of the systems [3]. Previous studies have brought to notice that it is not necessarily devices with more sensors that produces a better energy expenditure estimation [4]. Earlier distinguished generations with accelerometery-only devices seems to be able to produce similar accurate data than more advanced devices. This thesis will provide information regarding such a device which will only collect data from an accelerometer and a gyroscope.

A device that could provide instantaneous feedback makes it easier for the runner to improve their running technique. There are many practitioners within the world of running, both competitive athletes and those who run in their spare time. Many runners desire to improve their technique which makes it interesting to find patterns correlated to that specific running technique. CONSAT Engineering AB would like to join the field of running gait analysis to help athletes improve their technique and to aid them into keeping that defined technique even when experiencing fatigue. The system design within this report consists of sensors on both feet that can be attached to any type of running shoe. The sensors that will be used within the project is an Inertial measurement unit (IMU) that will measure the direction of the acceleration and angular rate. The knowledge gained within the gait analysis can be the base for many other applications such as problems related to human posture, patients with Parkinson, stroke, body injuries [5] and other medical condition which requires analytically data reports.

1.2 Purpose

The idea of this thesis is therefore to investigate how a machine learning algorithm can separate different techniques, given predefined classification on the training data. The thesis includes an investigation whether it is possible to distinguish spatial - temporal parameters within running techniques by only analysing data from IMUs attached to each foot of the user.

How to distinguish good and bad running technique is a difficult task to take on. This is due to the fact that every runner is an individual and it is consequently difficult to tell what the optimal way to run is.

1.3 Scope

Previous studies have shown that it does not exist a running technique that is optimal for all scenarios and individuals. The running technique depends on e.g. speed and body structure [6] but other studies, such as one made by Bushnell [7], also show that the running technique of short and long distance runners differs even when running at the same speed. This study will therefore use a restricted target group, which will be track and field runners.

When it comes to the classification of running techniques, machine learning does not work well using raw sensor data [8]. Instead, features correlated to good performance will be extracted and used for the machine learning part. A study by Folland et al. [6], showed that there are features that correlates to running economy and performance but not all can be extracted using a gyro and an accelerometer. The focus of this project will thus be on the extractable features mentioned in the article and features chosen after gaining insight from running coaches. The parts of interest within running technique will in this thesis be, step frequency, contact time and air time.

1.4 Delimitations

The focus of this thesis is on the data collection from track and field runners, without any known medical injuries that would affect their running technique. The data is used for feature extraction of step frequency, air time and contact time. The number of test runners that have been used during this project is limited to a certain number because of the logistics behind the process. This will have an effect on the machine learning result because of the number of runners being so low.

The intention of the final product is to provide the runner with real-time coaching, using for example an application on the mobile phone that notifies the runner. Creating an eventual application and enabling real-time coaching is however not included in the scope of this project. A prototype for working with signal processing is to be built, although the final product is not included in this report.

1.5 Disposition

The thesis outline is divided into four parts. First, a section regarding the theories behind the thesis is presented. Secondly, the methodology is explained, this chapter includes all the necessary information regarding the progress of the thesis but also how it was formed. Thirdly, the result is presented of the collected data and the machine learning algorithm. Lastly, the conclusion of the project is made and further developments are discussed.

2

Theory

In this chapter, theory behind this master's thesis will be presented. The running cycle will be explained as well as some interesting features that are relevant for classifying running techniques. The chapter also includes the theories behind the communication, calibration as well as choosing the features for the machine learning algorithm.

2.1 Running technique

According to Nicholas Romanov and Graham Fletcher [9], there are four forces involved within running, namely gravity, ground reaction, muscle and potential strain energy. These forces increase the horizontal acceleration of the centre of mass during the ground contact time. Gravity generates torque from the moment of inertia when the runner's centre of mass moves forward. Ground contact is not a moving force, but it engages Newton's third law, therefore it pushes the runner forward, together with the combination of the muscle forces. During leg extension, the leg and hip muscles are restrained, muscle-tendon forces regains most of the centre of mass. This concludes that the only external force during ground contact is the gravity torque, causing the horizontal movement [9].

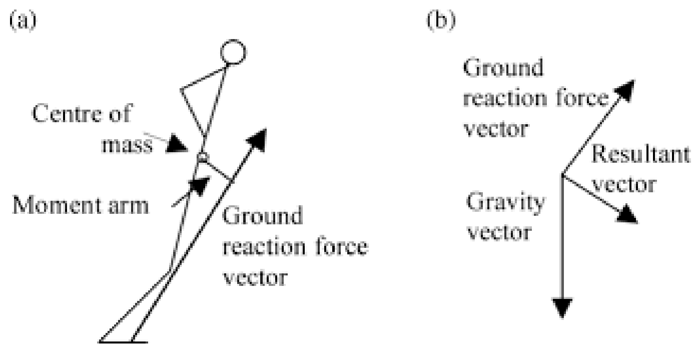


Figure 2.1: Gravity working on the centre of mass, figure adopted from `https://www.tandfonline.com/doi/abs/10.1080/14763140701491625?journalCode=rspb20`

The purposed running technique named Pose method, implies that the position of the ankle, hip and shoulders to be aligned. When the centre of mass moves away from the support surface of the foot, the body is exposed to a gravitational torque which moves the runner forward. Step frequency and step length are effects on the four forces influencing during running. The description within Pose method explains that the body falls forward without forcing the leg swing, this creates the step length. The step frequency is described from having to pull up the foot from the ground to keep up with the moving centre of mass.

Gravity makes the muscle system absorb body weight during landing that then creates elastic strain energy. Further on the centre of mass moves over the support surface and a gravitational torque occurs from extensor muscle activity. When the body falls forward the ground force decreases and the vertical forces that works against gravity reduces. The hamstring pulls back the foot and of the ground to catch up with the rest of the body moving forward. The ability to reach to these states and falling with gravity is what is named and described as the Pose method [9].

Furthermore, the foot placement is also an important factor to recognise when analysing running technique. The momentum arm will depend on the rotation of the placed foot. This means that less time is required for the centre of mass to pass the support point depending on how the foot is placed [9]. However, running on the toes is not recommended because it gives a higher risk of injuries pushing the body for this position. The recommended support point within Pose method is the ball of the foot, which causes less reduction in the horizontal velocity.

2.2 Gait cycle

The running motion can be described and characterised by different movement patterns. Each stride can be explained as the phase between the moment one foot hits the ground and the moment that same foot hits the ground again. This can also be called a running cycle, since it is equivalent to two steps. Each stride cycle contains a ground contact time and an air time of the corresponding left and right foot [10].

The movement patterns can be divided into different events, in fig 2.2 the green colour is illustrated with the purpose of looking at a stride of the left-foot. When the heel is in contact with ground, the foot strike event (FS) is initialized and the running cycle can begin. The leg moves along the horizontal axis with a continued velocity until the foot flat (FF) event on the ground, the velocity is then zero. Further on, the foot off (FO) event occurs which will initialise acceleration on the horizontal axis again. The air time stops when the foot is back on the ground [10]. This section describes the walking gait well but the cycle for running will differ depending on technique. For example, if the runner lands on the toes, the FF event will never occur. FS and FO is however always defined as the moment when the foot strikes the ground and when it takes off.

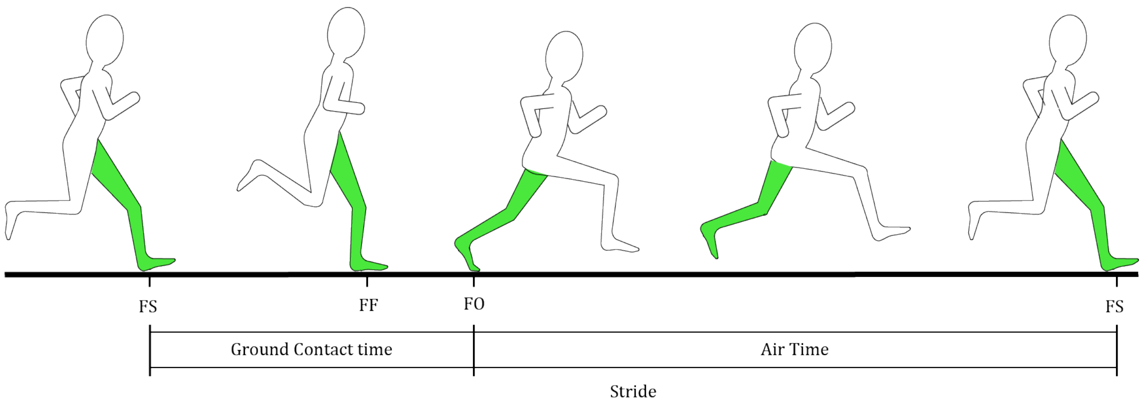


Figure 2.2: The running cycle picturing the different phases

2.2.1 Contact time and Air time

Ground contact time correlates with running performance. It can be concluded from literature regarding running techniques that less contact time is equivalent to faster and a better running economy [11]. High performance runners tend to spend a shorter time on the ground and more in the air. Although, the vertical movement of the body is to be kept neutral [11].

2.3 Inertial measurement unit

In this project an Inertial measurement unit (IMU) have been used, it is a combination of an accelerometer and a gyroscope, which is shown in figure 2.3.

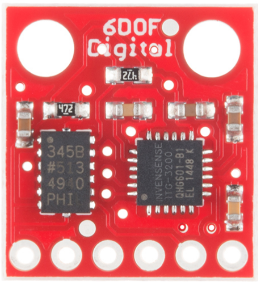


Figure 2.3: IMU Digital Combo Board – 6 DOF ITG3200/ADXL345. Figure adopted from `https://www.sparkfun.com/products/retired/10121`

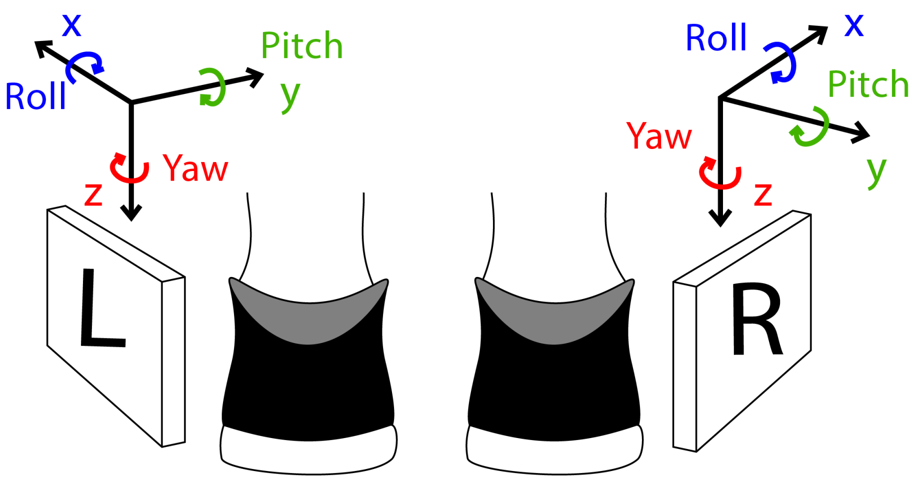


Figure 2.4: Axes of both sensors when mounted on the feet. The sensors in the picture are rotated out from the feet to illustrate the x-axis but in reality, the sensors are tightly attached which results in both x-axes pointing forward in the running direction

The accelerometer measures the gravitational vector and the gyroscope measures the angular velocity. A common use of this sensor is position estimation. The desired output from using these two together is to get the Euler-angles of the foot orientation. The Euler-angles can be described as roll, pitch and yaw, which is the rotation around the x-axis, y-axis and z-axis respectively, see fig 2.4.

The rotation of the Euler-angles can be obtained by integrating the gyroscope, although this is not enough because small measuring errors will add up over time, i.e. the angle estimation will drift. If only a small time frame is used, the integrated gyroscope readings are accurate. Further downsides on the gyroscope is the sensitivity for disturbances acting on the prototype. Roll and pitch can also be estimated from the accelerometer since it measures the gravitational vector. They can be calculated from,

$$\text{roll} = \theta = \arctan\left(\frac{a_y}{a_z}\right), \tag{2.1}$$

$$\text{pitch} = \phi = \arctan\left(\frac{-a_x}{\sqrt{a_y^2 + a_z^2}}\right). \tag{2.2}$$

The yaw rate is not possible to calculate with the accelerometer since it rotates around the gravitational vector, the z-axis. The disadvantage with the accelerometer is that during movement of the object, the sensor will sens not only the gravitational force but the acceleration of the object itself as well. The drawbacks of the two sensors are usually compensated for by using a complimentary filter which combines the readings by using a high-pass filter on the angles from the gyroscope and a low-pass filter on the angles from the accelerometer.

2.4 Calibration

The raw data from the sensors needs to be calibrated in order to provide readings with the desired unit. This is done by calculating an offset and a sensitivity scale factor. The offset is the reading that represents zero, i.e. the value that needs to be subtracted in order to get a zero reading. The sensitivity scale factor indicates how much the output changes when the input does, i.e. a scale factor to get the desired unit. The calibrated data is obtained from the raw data as

$$\texttt{data}_{cal} = \frac{\texttt{data}_{raw} - \texttt{offset}}{\texttt{sensitivity}}. \tag{2.3}$$

2.4.1 Accelerometer

The offset and sensitivity scale factor for the accelerometer can be calculated in different ways. One way is to use the fact that the acceleration should always have the magnitude of $1g$ when it lays still on a surface. The magnitude is calculated as

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2}, \tag{2.4}$$

where a_x is the acceleration in the x-direction etc. This can be written in terms of raw data as

$$|a| = \sqrt{\left(\frac{a_{x,raw} - o_x}{s_x}\right)^2 + \left(\frac{a_{y,raw} - o_y}{s_y}\right)^2 + \left(\frac{a_{z,raw} - o_z}{s_z}\right)^2} \tag{2.5}$$

where o and s is the offset and sensitivity scale factor respectively. The problem of finding o and s can then be solved by first placing the accelerometer still in an arbitrary position, collect the readings for some time, calculate the mean and repeat that six times. It needs to be done six times since there are six unknown parameters. Since $|a|$ is supposed to be 1, the error from each reading i is

$$\epsilon = \left(\frac{a_{x,raw} - o_x}{s_x}\right)^2 + \left(\frac{a_{y,raw} - o_y}{s_y}\right)^2 + \left(\frac{a_{z,raw} - o_z}{s_z}\right)^2 - 1. \tag{2.6}$$

The problem can then be considered as a non-linear least square error problem that is to find o and s that minimises the function,

$$\sum_{i=1}^{6} \epsilon^2. \tag{2.7}$$

2.4.2 Gyroscope

The offset of the gyroscope can be found by placing it still and collect the readings from various positions and calculate the mean. The mean represents the offset since the gyroscope measures angular velocity which of course is zero when the sensor is fixed. Gyroscopes readings are generally temperature dependent which should be considered when calibrating.

2.5 Communication Simulink

The communication bus I^{2}C was used in this thesis, it consists of a Serial Clock Line (SCL) and a Serial Data Line (SDL). SDA is the line for the master and slave to send and receive data, SCL is the line that caries the clock time. The data is transferred bit by bit over the line of communication, SDA.

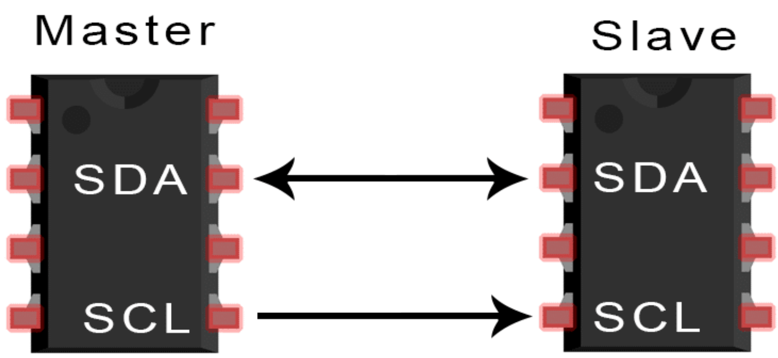


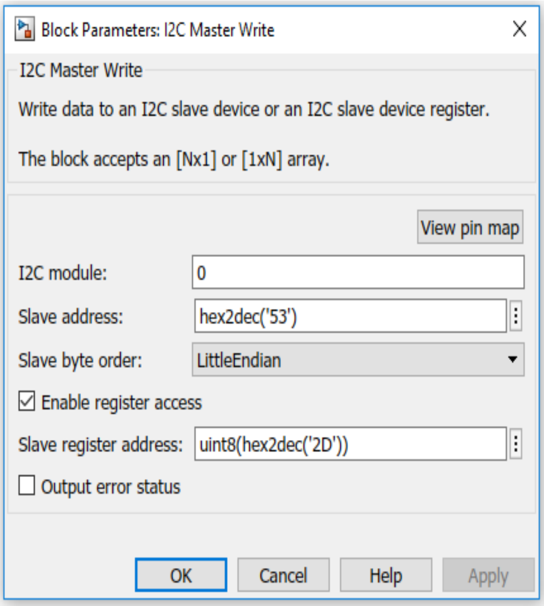
Figure 2.5: I2C Master and Slave. Figure adopted from `http://fab.academany.org/2018/labs/fablabkochi/students/salman-faris/week14.html`

2.5.1 I2C Master Write

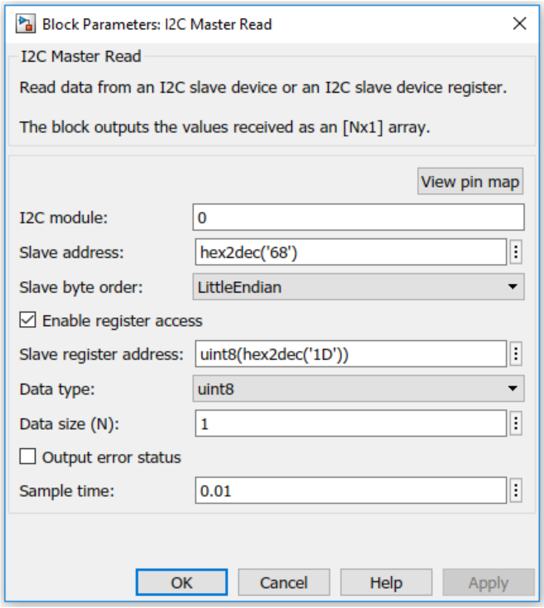
The I^{2}C Master Write block writes a decimal to a specific address of a device. An example with a device with internal register addresses is illustrated in figure 2.6a. The device is connected to the pins associated with I^{2}C module 0. The address of the device is 0x53 and the address of the internal register address is 0x2D. More information about the parameter settings can be found on Mathwork's web page [12].

2.5.2 I2C Master Read

The I^{2}C Master read block reads information from a specific address of a device. The example illustrated in figure 2.6b shows a case where data is transmitted from a device with internal register addresses. The I^{2}C module has the same purpose as that of the I^{2}C Master Write block. The address of the device is 0x68 and the internal register address is 0x1D. More information about the parameter settings can be found on Mathwork's web page [13].



(a) I2C Master Write block parameters dialog box



(b) I^{2}C Master Read block parameters dialog box

Figure 2.6: Examples of parameter settings for the I^{2}C Master Write and Read blocks respectively

2.5.3 SCI Write

The SCI Write block sends data to a selected universal asynchronous receiver transmitter (UART). It can be used in combination with an I^{2}C Master Read block where the I^{2}C Master Read block specifies which device the data is transmitted from and is in turn connected with the SCI Write block that specifies which UART the data is sent to. More information about SCI Write block can be found on Mathwork's web page [14].

2.6 Multinomial logistic regression

This method is a classification method derived from logistic regression which is a classification method with binary output. Since three classes are used in this project, the modified model multinomial logistic regression which can handle multiple classes were used. What characterises a classification model is a model that is trained to classify something based on features. For example, if it is desirable to classify people as hungry or not, then possible features could be the time elapsed since the last meal, body weight, etc. The more varieties that affect the classification, the more features are needed. Generally, the features are used as input to the system, which then are multiplied with weights and then the product is often modified using different kinds of transfer functions to yield the class as an output. The model is trained using known data sets of classes corresponding to certain features and the weights are updated until all outputs are as similar to the desired class as possible. When the model has been trained and the weights are obtained, it is often validated using other known data sets. This is to investigate if the model works good for data other than the data the model was trained with.

2.7 Bland & Altman analysis

The B&A plot presents the agreement of two quantitative measurements. The statistical method constructs limits of agreement from calculating the mean and the standard deviation of the difference between the measured variables [15]. To check for normality of differences, a scattered plot is created, it consists of the difference (A - B) between the two measurement methods on the y axis, and the average of these values (2.8) on the x axis.

The paired methods differences are plotted against the mean of both measurement methods and the Limit of Agreement (LoA)is set to 95% within ± 2s.

$$\mathrm{mean} = \mu = \frac{\mathrm{A} + \mathrm{B}}{2} \tag{2.8}$$

$$\mathrm{X} = (\mathrm{A} - \mathrm{B})_i \tag{2.9}$$

$$\mathrm{variance} = \sigma^2 = \frac{\Sigma X^2}{N-1} - \mu^2 \tag{2.10}$$

$$\mathrm{standarddeviation} = \mathrm{s} = \sqrt{\sigma^2} \tag{2.11}$$

$$\mathrm{LoA}(+) = \mathrm{mean}(\mathrm{X}) + 1.96 * \mathrm{s} \tag{2.12}$$

$$\mathrm{LoA}(-) = \mathrm{mean}(\mathrm{X}) - 1.96 * \mathrm{s} \tag{2.13}$$

3

Method

In this chapter, the method used in the thesis is described. It includes the work with the hardware, signal processing, data collection, feature extraction and the machine learning process. MATLAB Simulink®was used within this thesis and the toolbox Stateflow®enabled the feature extraction method.

The purpose of the project was to distinguish good running technique from bad using a machine learning method and the chosen method was multinomial logistic regression (MLR). To fulfil this goal, the MLR-model must know how to make the distinction, i.e. a requirement is to train the model. If the training phase is successful, the model can classify the runner as bad, good or very good given relevant features such as step frequency and ground contact time. Such a machine learning model is usually trained using sets of features and classes that are known to correlate. More about this method is described in Section 2.6.

Some of the features were extracted using previously known methods that involves an accelerometer and a gyroscope attached to each foot [16, 17, 18, 19]. Those methods were validated with the help of Qualisys, which is a company that specialises in motion capture systems. The next step was to obtain the sets of correlated classes and features for the training phase. An employee at Aktivitus, which is a company that provides e.g. running technique coaching, classified the runners while data was collected to obtain the training sets. The final step was to train and validate the model. All parts of the project are more thoroughly described in the sections below.

3.1 System design

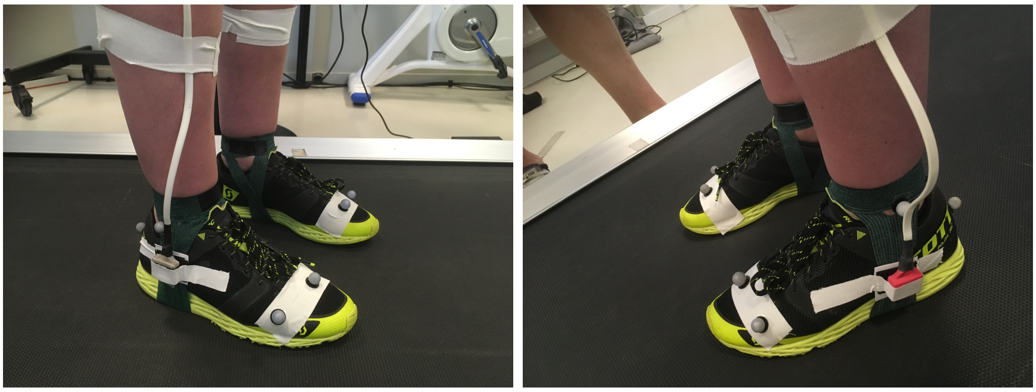
The purpose of the prototype was to measure acceleration and angular velocity of the foot placement, with the desire to perform signal processing and create a machine learning algorithm for that data. The designed prototype consists of

- one single-board microcontroller, STM F401RE,
- two accelerometers, ADXL345,
- two gyroscopes, ITG-3200,
- one laptop with Matlab Simulink and Simulink Coder Support Package for STMicroelectronics Nucleo Boards,
- one USB type A to Mini-B cable to connect the board with the computer
- wires to connect the sensors with the board.

3.1.1 Assembly system design - hardware

It was important to construct a system that would not interfere with the runner nor the data collection. The sensors were placed between two plates and secured with shrink tubing for the purpose of keeping the sensors protected, the microcontroller was secured inside a plastic case. The IMUs were attached to the outstep of each foot with elastic bandages and Velcro which generated a simple solution that made the prototype easy enough to mount and remove. The IMU was also secured with sports tape on the outside of the foot to attach it tightly. The white wire attached from the IMU to the microcontroller, was taped on the runner's leg and the microcontroller was placed inside a bum bag.

The system design setup can be seen in fig 3.10b. The picture includes two silver reflection balls, but these are to be ignored in the system design since they are components of Qualisys' measurement system. Figure 3.2 shows the axes of the sensors when mounted on the feet and the Euler-angles described in Section 2.3.



(a) Right foot IMU **(b)** Left foot IMU

Figure 3.1: The assembly of the prototype's system design, disregard Qualisys silver reflection balls on the toes

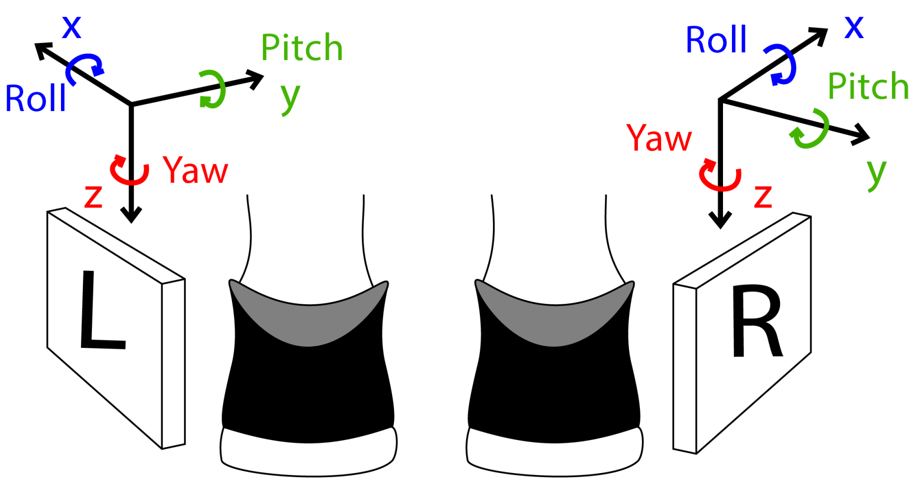


Figure 3.2: Axes of both sensors when mounted on the feet. The sensors in the picture are rotated out from the feet to illustrate the x-axis but in reality, the sensors are tightly attached which results in both x-axes pointing forward in the running direction

3.1.2 Microcontroller

STMicroelectronics F401RE, see appendix. B.1, was chosen for the project, this because it was compatible with Matlab and the signal processing could be done with Simulink. The Simulink Coder Support Package for STMicroelectronics Nucleo Boards was used as a toolbox for working with the board. The board was also considered powerful enough with 64 pins, 32.768 kHz LSE crystal oscillator and the 512 kB flash memory size.

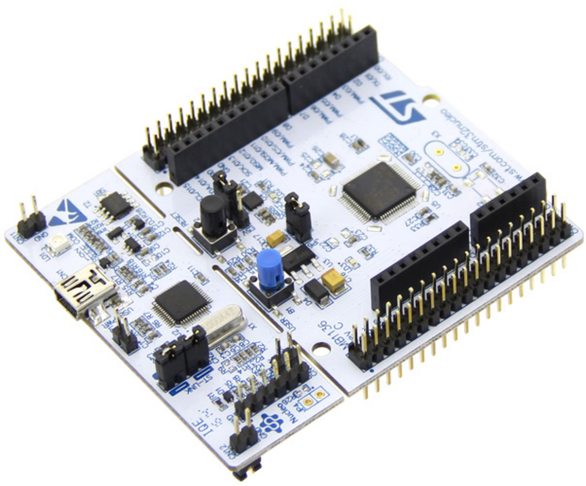


Figure 3.3: STMicroelectronics F401RE. Figure adopted from: `https://docs.zerynth.com/latest/official/board.zerynth.st_nucleof401re/docs/index.html`

3.1.3 Accelerometer

The 3-axis accelerometer ADXL345 sensor, were set to have full resolution, which in this case were a 13-bit resolution at $\pm$ 16 g. The output sensor data rate was varied for different data collections. The settings within the board were changed by writing decimals to specific addresses, this was done in order to set up the communication between the board and the sensors. Information about the addresses and what decimals to write can be found in the data sheet [20] and how to write to the addresses is described in Section 2.5.1.

3.1.4 Gyroscope

The ITG-3200 gyroscope was also set to have a a full-scale range of $\pm$ 2000 deg/s with an internal sampling rate set to 1000 Hz. The output data rate again varied for different data collections. An internal low pass filter with cutoff frequency of 42Hz was also used. More information about the addresses and what decimals to write can be found in the data sheet [21].

3.2 Communication Simulink

MATLAB Simulink was used as communication with the board and sensors and for these two Simulink models were created. One of the models, `sensor2board_SCI_together`, see figure. 3.4, was deployed on the board to set up the communication, e.g. specify which port that was used for each signal and specify settings. The other model, `read_SCI_together` was then executed to read the data that was sent from the sensors to the microcontroller.

The overall layout of the model, `sensor2board_SCI_together` consists of two subsystems, namely *Initialization* and *Communication*. The blocks outside of the subsystems, together with the enable blocks inside the subsystems, makes sure that the subsystem *Initialization* is only enabled during the first time step. They also make sure that the subsystem *Communication* is disabled during initialization and enabled for the subsequent time steps.

The subsystem *Initialization* is shown in Figure 3.5 and the purpose of that model is to adjust the settings of the sensors. In the top left corner of the figure, the decimal 8 is written to a register called Power_CTL which among other things places the accelerometer into measurement mode. The subsystem *Communication* specifies which addresses to read from, which in this case are addresses that outputs the data from the accelerometer and gyroscope. More about communication using Simulink can be found in Section 2.5.

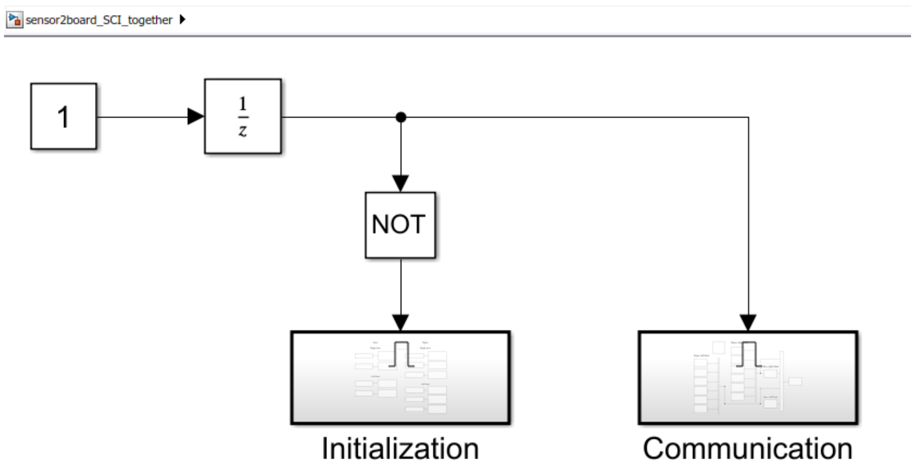


Figure 3.4: The overall layout of the Simulink file `sensor2board_together_SCI`

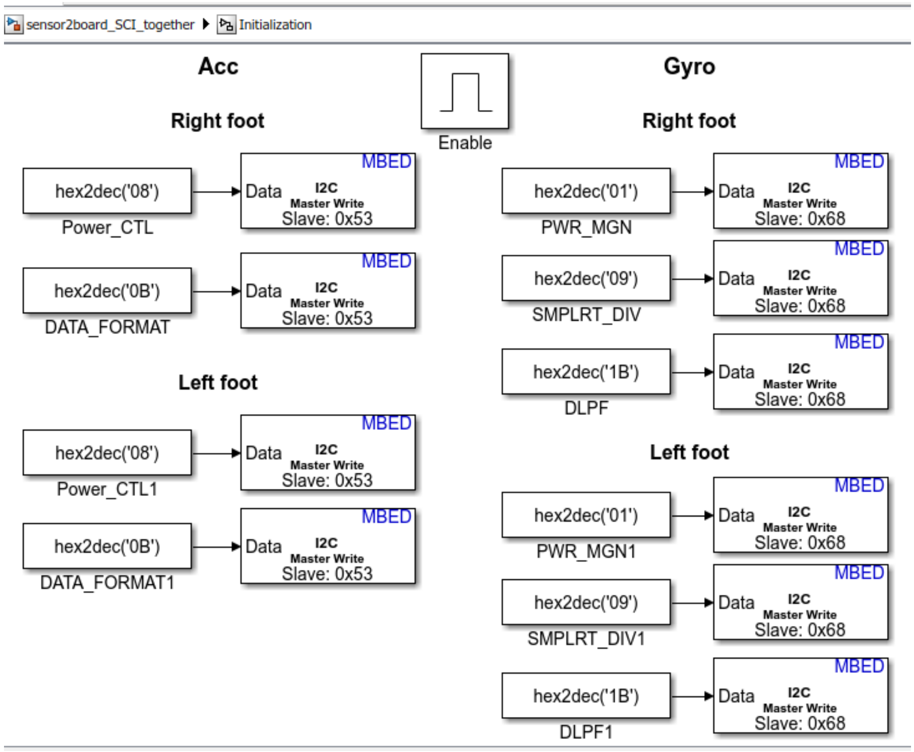


Figure 3.5: The subsystem *Initialization* within the Simulink file `sensor2board_together_SCI`

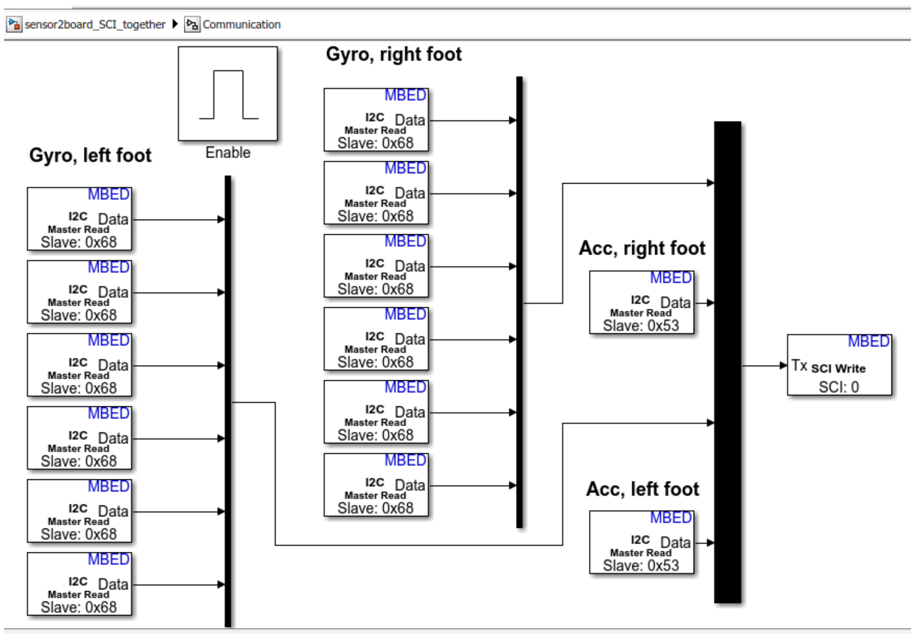


Figure 3.6: The subsystem *Communication* within the Simulink file `sensor2board_together_SCI`

3.3 Choosing features

It is important that the features are relevant to train the model. For example, it is of course not helpful to use a persons favourite food as a feature to determine if that person has a good running technique or not. The pose method described in Section 2.1 were used and various running technique coaches were consulted with to get an impression of which features to include.

Some features that appeared relevant were ground contact time (GCT) and air time (AT). GCT and AT are related to each other and a longer AT and shorter GCT means spending more time moving forward and less time standing still on the ground. It was also said that a combination between step length and step frequency (f_{step}) is important as described in Section 2.1. The angle between the foot and the ground at foot strike is something that could be obtained using an IMU but it was told that there is no optimal range. It was however told that the foot placement at landing is important (toe, midfoot or heel landing), which is in a way correlated with the angle. To calculate the step length and the angle, a complementary filter described in Section 2.3 is used. The step length and angle was never used though because there was not enough time to tune such a filter and to solve problems that appeared in Simulink.

Another interesting feature is the direction of the acceleration at foot strike which was suggested by CONSAT. If the runner pushes off in a direction that is not optimal, force will be wasted. The complimentary filter mentioned above is needed to obtain this feature as well since the location of the foot at foot strike must be known.

Personal fitness and body structure also matters when it comes to running technique. As mentioned in the introduction, there is no running technique that fits everyone. A running technique that fits a track and field runner might cause injuries for a person that lacks the muscle capacity. Therefore it is necessary to take that into account and use features that correlates with fitness and body structure. It is also important to consider the velocity of the runner since it will affect the way of running.

All involved running technique coaches mentioned the importance of the pelvis. For example one coach within middle distance running explained that if the pelvis is pushed forward and the body is not placed in a sitting position, a rubber band effect occurs that will aid the leg to move forward after take off, which saves a lot of energy. The importance of the pelvis is also mentioned in Section 2.1. If the pelvis and thus the body centre of mass is located in front of the feet during ground contact, gravity will create a torque, that together with muscle activity, increases horizontal acceleration. It is not intuitive to measure the movement of the pelvis by using an IMU attached to the foot but it was desirable to investigate possible correlations between the sensor data and the pelvis. The plan was to use the data collected at Qualisys for the investigation but there was not enough time unfortunately.

3.3.1 Resulting features

All of the desired features could not be extracted, for example the direction of the acceleration at foot strike and the angle between the foot and the ground at foot strike. A combination of the two was used instead. The position of the sensor when the foot was flat with respect to the world frame was known. The world frame in this thesis is when the x-axis is parallel to the ground and the y-axis is orthogonal to the ground. The rotation from the world frame was then removed from the accelerometer reading at foot strike to obtain the modified feature. Note however that the gravitational force is not removed. This feature is further on denoted as a_{FS}.

It was difficult to come up with features that represent fitness and body structure that could be obtained relatively easy. The percentage of fat and muscles in the body was considered for example but due to simplicity, the features that ended up being used was level, BMI and gender. The level is how many minutes it generally takes for the participant to run 5 km and is a way to represent fitness. The resulting features are presented in the table below.

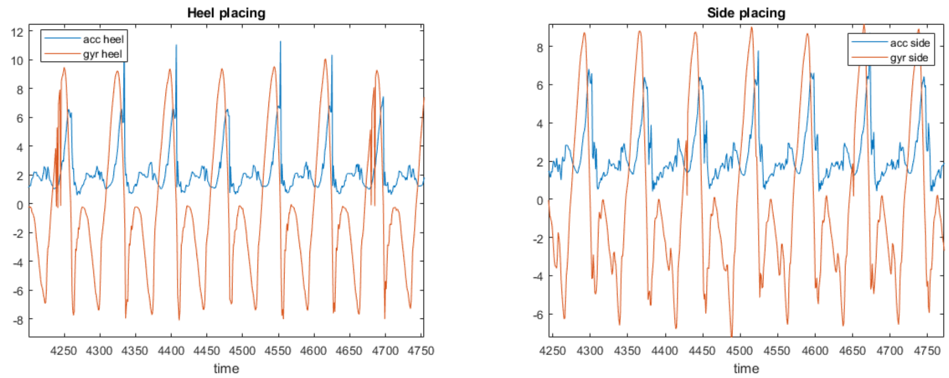
Table 3.1: Features used in this project

Feature	Description	Abbreviation
Ground contact time (s)	The mean value of how long time each foot is in contact with the ground	GCT
Air time (s)	The mean value of how long time both feet are in the air between two consecutive steps	AT
Step frequency ($steps/min$)	The amount of steps per minute	f_{step}
Modified accelerometer readings at foot strike (m/s^2)	Initial position removed and normalized	a_{FS}
Speed (km/h)	Velocity of the runner	
Level (min)	Fitness level in terms of amount of minutes it generally takes to run 5 km	
BMI (kg/m^2)	Weight divided by lenght squared	
Gender		

3.4 Choosing the sampling frequency and sensor placement

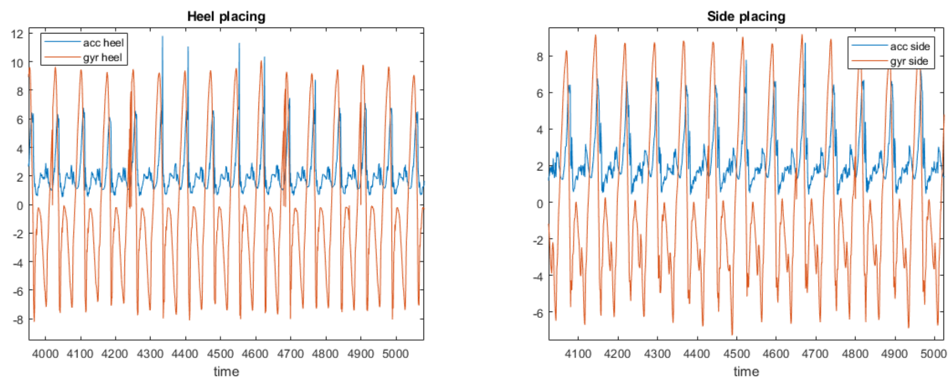
A problem occurred that was never solved and remained throughout the project. At first, it was most likely associated with the sampling frequency. There seemed to be a mismatch between the output data rate from the sensors to the microcontroller and the sampling rate in Simulink. This assumption was made because when the sampling started, it worked well up to a point when the data did not make sense anymore and the higher the frequency, the faster the error occurred. It seemed like the sampling rate from the board to Simulink was lower than the output data rate from the sensors to the board, causing a memory overflow on the board. Both frequencies were the same though and the problem was not solved by increasing the ratio between the sampling frequency and the output data rate. Later on it was discovered that the sampling worked for a longer time when reducing the amount of scopes in Simulink. The extent of the problem still varied though. It could be due to lack of knowledge about combining the hardware and software but it remains a mystery.

Before collecting data at Qualisys, tests were held at the nearby gym Fysiken, where different sampling frequencies were tested to choose the most suitable one but also to decide the placement of the sensor. Studies have shown that placing the IMU directly on the skin could overestimate the amplitude of the accelerometer [22], which was one of the criteria when choosing to place it on the shoes. Two placement tests were held to find the optimal placing of the IMU in this thesis. The tests were made by placing the sensor on the heel and on the side of the foot, to see which placement would be most beneficial. The tests also investigated the duration of sampling acceptable data to choose the sampling frequency. The test runner ran consequently for 15 minutes while data was sampled and several 15 minutes tests were held until a conclusion could be made. The results are presented in Figures 3.7, 3.8, 3.9 and 3.10.



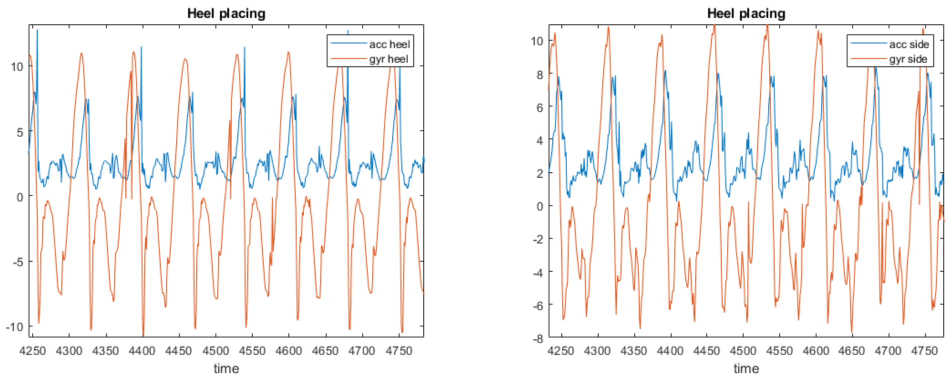
(a) Heel placing on the runner at 7 km/h **(b)** Side placing on the runner at 7 km/h

Figure 3.7: Sampling frequency of 100 Hz



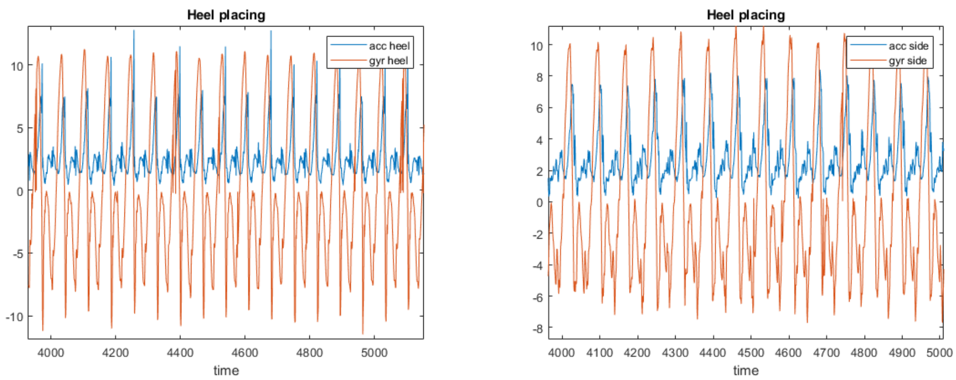
(a) Heel placing on the runner at 7 km/h **(b)** Side placing on the runner at 7 km/h

Figure 3.8: Sampling frequency of 167 Hz



(a) Heel placing on the runner at 9 km/h **(b)** Side placing on the runner at 9 km/h

Figure 3.9: Sampling frequency of 100 Hz



(a) Heel placing on the runner at 9 km/h **(b)** Side placing on the runner at 9 km/h

Figure 3.10: Sampling frequency 167 Hz

The result from the tests showed that the data acted similarly regardless of the placement, except for placing it on the heel would yield a smoother measurement. However, it was difficult to place the IMU on the heel because of the mounting system, thus the outstep was considered the most optimal system design for this thesis. A difference between sampling with 100 Hz and 167 Hz that is not visible in the figures is that the system responded slower with 167 Hz and therefore 100 Hz was chosen. It was however difficult to draw a complete conclusion of what frequency to choose because the intention from the beginning was to extract the features before collecting data but that was not possible because the prototype took longer to build than expected.

After the data collection at Qualisys, the will of having a higher sampling frequency emerged. More data points needed to be collected to simplify the feature extraction. Therefore, the frequency of 167 Hz was chosen.

3.4.1 Calibrating the accelerometer

The first calibration was done prior to the data acquisition at Qualisys and it was done as described in Section 2.4.1. Data was collected for two minutes before calculating the mean. The non-linear least squared error problem was solved using a built-in Matlab function called `lsqnonlin`. Another sampling frequency was used at Aktivitus and therefor the accelerometer needed to be re-calibrated, but the same procedure was used. The calibration values for both data collections are presented in the table. 3.2.

Table 3.2: Calibration values for the three axis accelerometers for both data acquisitions. The values are presented in the order $(Z, X, -Y)$ for the right foot and $(Z, -X, Y)$ for the left foot because the calibration was done before the axis adjustment. The unit is g

Qualisys						
	Offset			Sensitivity		
Axes	Z	X	-Y	Z	X	-Y
Acc. right	7.90	0.55	-17.37	259.66	259.55	261.24
Axes	Z	-X	Y	Z	-X	Y
Acc. left	10.47	2.97	-16.11	253.27	260.33	251.63
Aktivitus						
	Offset			Sensitivity		
Axes	Z	X	-Y	Z	X	-Y
Acc. right	17.32	4.13	-5.83	245.19	250.88	251.59
Axes	Z	-X	Y	Z	-X	Y
Acc. left	8.90	1.72	-15.96	261.66	258.63	249.96

3.4.2 Calibrating the gyroscope

Prior to the data acquisition at Qualisys, the calibration of the gyroscope, namely finding the offset, was done as described in Section 2.4.2. As mentioned in that section, gyroscopes are temperature depended. The prototype was calibrated in room temperature at the office for six different drift temperatures, from when the device was switched on to when the drift temperature had stabilised. This was considered enough because the data collection took place indoors and the room temperature at the office and at Qualisys where the data collection took place were similar. The data was collected for two minutes before calculating the mean and the sensitivity factor of the gyroscope was given from the data sheet [21].

At Aktivitus, another sampling rate was used and as for the accelerometer, the gyroscope needed to be re-calibrated. The procedure was slightly different. The initial intention was to calibrate the sensors in the room where the data collection took place because the room temperature was higher than at the office. Due to some difficulties however, the calibration could not be done there. The data collection began with a static acquisition where the runners were instructed to stand still in order to gather the initial position. That static data was used for the calibration instead. It is of course not optimal because the sensor can be more fixed using for example a clamp, rather than being attached to a person trying to stand still. The data was gathered in three rounds. The mean value of all rounds was used at first, but the accuracy was not satisfying enough due to differences in drift temperature. Three different sets of offsets were therefore calculated which accounted for the differences. Runner 1-3 was in the first round, runner 4-17 in the second and runner 18 in the last. The calibration values for both data collections are presented in Table. 3.3

Table 3.3: Calibration values for the three axis gyroscope for both data acquisitions. The values are presented in the order $(-Z, -X, Y)$ for the right foot and $(-Z, X, -Y)$ for the left foot because the calibration was done before the axis adjustment. The unit is $°/s$

Qualisys				
	Offset			Sensitivity
Axes	-Z	-X	Y	-Z, -X, Y
Gyr. right	-21.08	-5.52	17.06	14.38
Gyr. left	1.87	-11.10	2.82	14.38
Aktivitus				
	Offset			Sensitivity
Axes	-Z	-X	Y	-Z, -X, Y
Gyr. (1-3)	-20.39	-4.40	14.58	14.38
Gyr. (18)	-18.71	-0.31	12.58	14.38
Gyr. (rest)	-19.66	-2.19	13.77	14.38

3.4.3 Data collection at Qualisys

Qualisys is a company specialised in motion capture systems within the field of engineering, entertainment and sports. The motion capture system for gait analysis measures the position of various body parts to analyse the running technique. Features such as step length, step frequency and air time are also extracted to get an impression of the runner. The main purpose of this data collection was to validate the event and feature extraction method. The accuracy of the method could be validated by comparing the extracted features with Qualisys measurements. The purpose in the beginning was also to investigate possible correlations between data from Qualisys and sensor data from the IMUs. If any of Qualisys' features that are known to have an impact on running technique correlates with our sensor data, that data is useful to have as an input to the machine learning algorithm. This was never done due to lack of time.

Four people were analysed in this test, two experienced runners and two people without any running technique practice. One of the two experienced runners compete in track and field, middle distance, and the other one in ultra-marathon. The first measurement was static to gather the initial position of the sensor. Data was then sampled for 10 seconds for different velocities. The velocity range differed between the analysed runners but overall the velocities ranged between 8km/h to 24km/h.

Figure 3.11: Trials at Qualisys from one of the athletes

3.4.4 Data collection at Aktivitus

For a machine learning algorithm to work, a lot of data needs to be collected. It was not possible to collect as much data as desired for a machine learning algorithm to work perfectly within the scope of this project. That is one of the reason why a narrow target group of middle distance runners within track and field was chosen from the beginning. If the target group is broad, i.e the running techniques differs, more data is needed which is described in Section 2.6.

During the project though, it was considered to choose another target group, namely runners that do not compete but run in their spare time due to a broader market. When a final decision had to be made however, a target group of track and field runners was not an option anymore since it was not possible to gather enough participants within that group. A few track and field runners participated along with colleagues and friends. To compromise for the broad target group, restrictions were made. The runners could not have any injuries that would affect the running technique and they needed to be on a certain athletic level, namely to be able to run consecutively for at least 5 km. The later because if a certain technique is good or not varies depending on physical capability.

A velocity range was chosen between 10 and 16 km/h because the running technique is velocity dependent. A flat surface on a treadmill indoors was used as well for simplification.

The data collection was conducted at Aktivitus in Gothenburg. Data was sampled from 18 runners (6 females, 12 males) while an employee with a sports medicine degree classified the runners. Prior to the data collection, the runners age, weight, height and personal best on the distance 5 km was gathered to use as a feature within the machine learning algorithm. These features are presented in Table 4.10

Figure 3.12: Trials at Aktivitus from one of the athletes

The runner was first instructed to stand still on the treadmill to gather the initial position. The data collection and evaluation of the runner was then done simultaneously for 30 seconds for each speed. The runner stood still between the different speeds to gather a new initial position to investigate the validity of the sensor attachment. The chosen speeds were 10km/h, 12km/h, 14km/h and 16km/h.

The runners where divided into the following three classes:

1. Very good technique,
2. Good technique,
3. Bad technique.

The evaluation was based on an overall impression of the runner. If the runner did not seem uncomfortable for any speed, the runner was classified as very good. The runner was classified as good if uncomfortable at 16km/h and bad if uncomfortable at both 14 km/h and 16km/h. If the runner looked comfortable or not was based on looking at the position of the foot at foot strike (heel, middle foot or toe landing), step length, posture and arm swing. The result from the trials is presented in Section 4.2.

3.5 Event detection and feature extraction

Two important events for finding the features are the foot-strike (FS) and the foot-off (FO) event. Finding these two events is a challenging task but when the events are detected, the features are relatively easy to extract. If the stride starts with FS of the right foot, $\mathrm{f_{step}}$, AT and GCT for both the right and left foot are calculated as

$$\mathrm{f_{step}} = \frac{\mathrm{n_{FS,R}} + \mathrm{n_{FS,L}}}{\Delta \mathrm{t}}, \tag{3.1}$$

$$\mathrm{AT_{RL}} = \mathrm{TS_L} - \mathrm{TO_R}, \tag{3.2}$$

$$\mathrm{AT_{LR}} = \mathrm{TS_R} - \mathrm{TO_L}, \tag{3.3}$$

$$\mathrm{GCT_R} = \mathrm{TO_R} - \mathrm{TS_R}, \tag{3.4}$$

$$\mathrm{GCT_L} = \mathrm{TO_L} - \mathrm{TS_L} \tag{3.5}$$

where $\mathrm{n_{FS,R}}$ and $\mathrm{n_{FS,L}}$ are the amount of times the right and left foot strikes the ground respectively during the time interval Δt and TS and TO denotes the time for when FS and FO happens.

The feature $\mathrm{a_{FS}}$ that is a modified version of the direction of the acceleration at foot strike requires more calculations. First the roll and pitch angle between the initial position of the sensor and the world frame was calculating using Equation (2.1)-(2.2). The world frame in this thesis is when the x-axis is parallel to the ground and the y-axis is orthogonal to the ground. The roll and pitch angle where then removed from the accelerometer readings at foot strike as follows:

$$\mathrm{a_{FS}}' = \mathbf{R}_\theta \mathbf{R}_\phi \mathrm{a_{FS,read}} \tag{3.6}$$

where θ denotes roll, ϕ denotes pitch,

$$\mathbf{R}_\theta = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\theta & -sin\theta \\ 0 & sin\theta & cos\theta \end{bmatrix} \tag{3.7}$$

$$\mathbf{R}_\phi = \begin{bmatrix} cos\phi & 0 & sin\phi \\ 0 & 1 & 0 \\ -sin\phi & 0 & cos\phi \end{bmatrix} \tag{3.8}$$

and $\mathrm{a_{FS,read}}$ is the accelerometer readings at foot strike. $\mathrm{a_{FS}}$ is then obtained by normalising $\mathrm{a_{FS}}'$ with the following equation:

$$\mathrm{a_{FS}} = \frac{\mathrm{a_{FS}}'}{|\mathrm{a_{FS}}'|}. \tag{3.9}$$

There are some existing methods for finding these events using a foot-placed IMU. Two methods were tried and Stateflow, a MATLAB environment inside Simulink, was used for both methods. Stateflow is good for modelling decision logic based on flow charts and state machines.

3.5.1 Method 1

When the foot strikes the ground, the sudden deceleration of the foot will result in a peak on the total acceleration curve. Studies have shown that this peak can be used to find FS [16, 17]. During ground contact time, the foot is relatively still, thus FO can be found by using a threshold $\dot{\theta}_{FS}$. The FO event happens when the pitch angular velocity exceeds $\dot{\theta}_{FS}$ [18]. In this thesis the pitch angular velocity has opposite sign so FO happens when it is below the threshold. The variables for describing the methodology are `acc`, `gyr` and `acc_der` which are the acceleration, angular velocity and velocity.

At first, the total acceleration and pitch angular velocity were graphically examined briefly to get an intuition of where FS and FO occurs. This was done by comparing time intervals between where FS and FO should occur according to previous literature with the estimated GCT from Qualisys. However, the validation data was at first misinterpreted, GCT was interpreted as the combined value for both feet but it was only for one foot. The following methodology is based on that incorrect assumption. FS is represented by the highest peak but it was noticed that for some people, multiple peaks appeared, which can be seen in Figure 3.13. The acceleration was at first smoothed to obtain a single peak for FS but in that case, for GCT to be close to the validation data, a threshold `FO_delay` that was used for finding FO had to be adjusted for each runner. That was not desirable since there is no validation data from the data collection at Aktivitus, i.e `FO_delay` must be fixed to the same value for every runner. The smoothing was consequently reduced and further investigation showed that best result was obtained by choosing the last of the multiple peaks

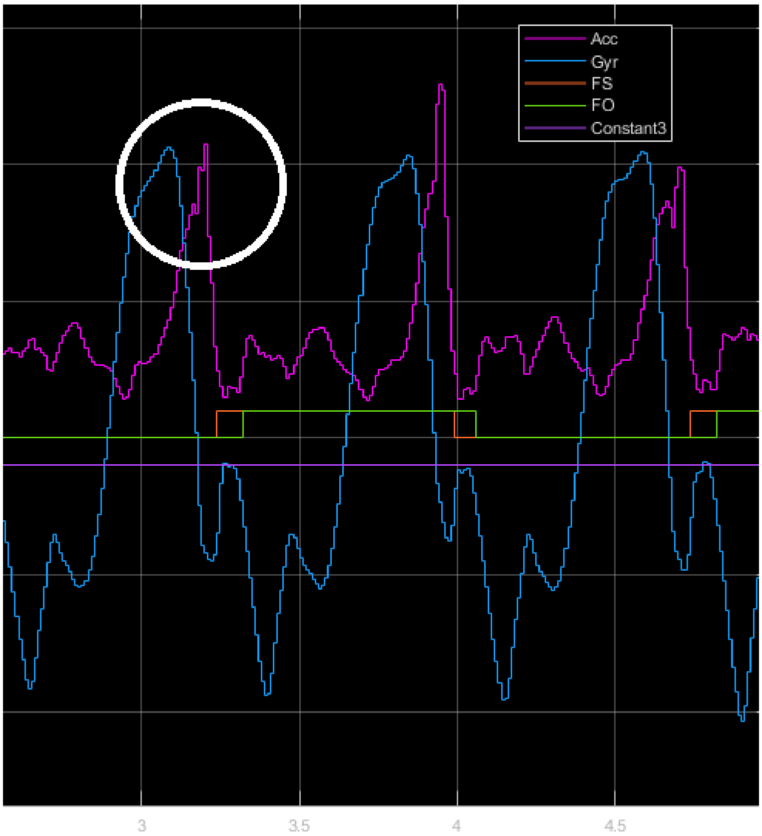


Figure 3.13: Illustrates multiple peaks on the acceleration curve where FS occurs, which can be seen inside the white circle

The original proposition that FO occurs when `gyr` is below a certain threshold turned out to be a bad approach. The amplitude of `gyr` where FO should occur varied and no common threshold could be found. It was however noticed that it occurred shortly after the broad peak which is illustrated in Figure 3.14. The angular velocity was also smoothed because it simplified the algorithm.

Most of the algorithm was built using state machines modelled in Stateflow. The flow chart takes acceleration and angular velocity as input and outputs the features. The algorithm starts by searching for the interval where FS can be found. FS is represented by the highest peak on `acc` which occurs after a lower and broader peak which can be seen in Figure 3.14. The search interval includes the lower unwanted peak since occasionally, that peak is higher than the desired one, which in this case is true for the first, third and fifth FS. The algorithm finds the interval by using a threshold `start_FS` with a value lower than the first peak but higher than all other peaks outside the interval. After that, `acc_der` is used because a derivative less than zero indicates that a peak has been found. The next part of the algorithm has within this thesis been denoted the "Multiple-Peak-Method" which updates TS each time a new peak has been found until `acc` exceeds `stop_FS`. The search interval for FO is then found using the threshold `no_low_peaks` on `gyr`. The name here does not make sense, but this constant already existed for another purpose and was at the time used because of its convenient value to reduce parameters. Occasionally, a couple of unwanted peaks before the broad peak associated with FO was included in the search interval but this was solved by again using the Multiple-peak-method which updated TO until `gyr` was below `no_low_peaks`. The algorithm is then repeated for each step.

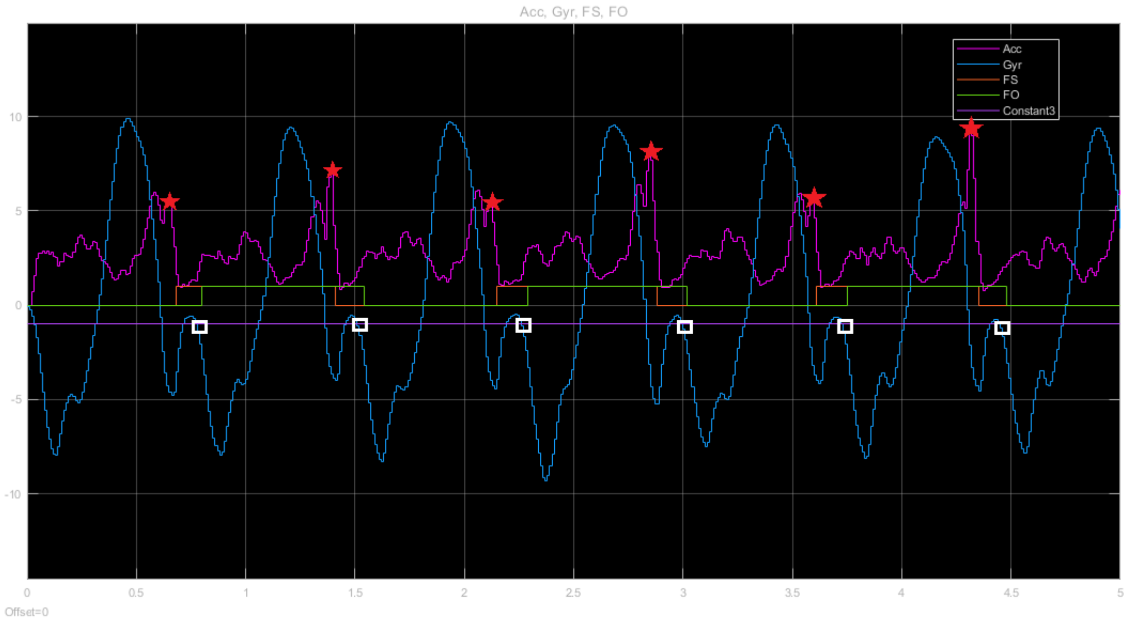


Figure 3.14: Shows method 1 for finding FS and FO, where the stars indicate FS and the squares indicate FO

3.5.1.1 Validation

At first, the result looked promising but that was before the misinterpretation was noticed. A quick overview like the first one indicated that FO occurred somewhere on the graph between the previous FO and the subsequent local minima. This made it difficult to find a common threshold for all runners and thus method 2 was proposed.

3.5.2 Method 2

Studies have found that FS and FO can be found using only one of the three components of the acceleration. That is the x-axis in this thesis, the axis that points in the running direction when the feet are placed flat on the ground [19]. The events FS and FO are equivalent to the global and a local minimum respectively of the acceleration in the x-direction which can be seen in Figure 3.15.

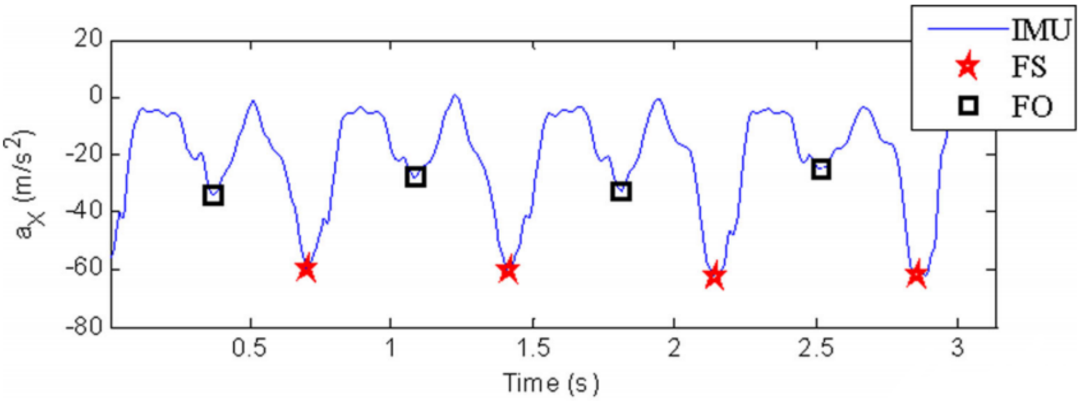


Figure 3.15: A method of finding FS and FO by using the acceleration in the x-direction, adopted from [19]

Notice that the sensor in that article [19] was placed on top of the foot instead of the outstep of the foot as in this project. In both cases though, the x-axis of the sensor pointed along the running direction when the foot was flat and the movement of the top and outstep of the foot were considered similar enough to try the method.

At first, a similar pre-examination was done. Similarly to method 1, the local minimum related to FS and FO was surrounded by multiple local minima. The investigation indicated that the last one for FS and the lowest for FO should be chosen. It was also noticed that for some runners, a couple of unwanted minima occurred between FS and FO that were lower than the one related to FO. This had to be considered when writing the algorithm.

The algorithm starts in a similar way as method 1, that is by looking for the search interval for FS. It is also found by a threshold `start_FS` and its value lays between the minima corresponding to FS and all other unwanted local minima. A similar method as the Multiple-peak-method but for minima instead of maxima was then used to find FS. When `acc` exceeds the threshold `stop_FS`, a delay `FO_delay` was implemented to ignore the unwanted local minima. The search interval for FO begun after the delay and the lowest local minima were then chosen by updating TO for each local minima that was lower than the previous ones until `acc` exceeded the threshold `stop_FO`. Figure 3.16 illustrates where FS and FO occur.

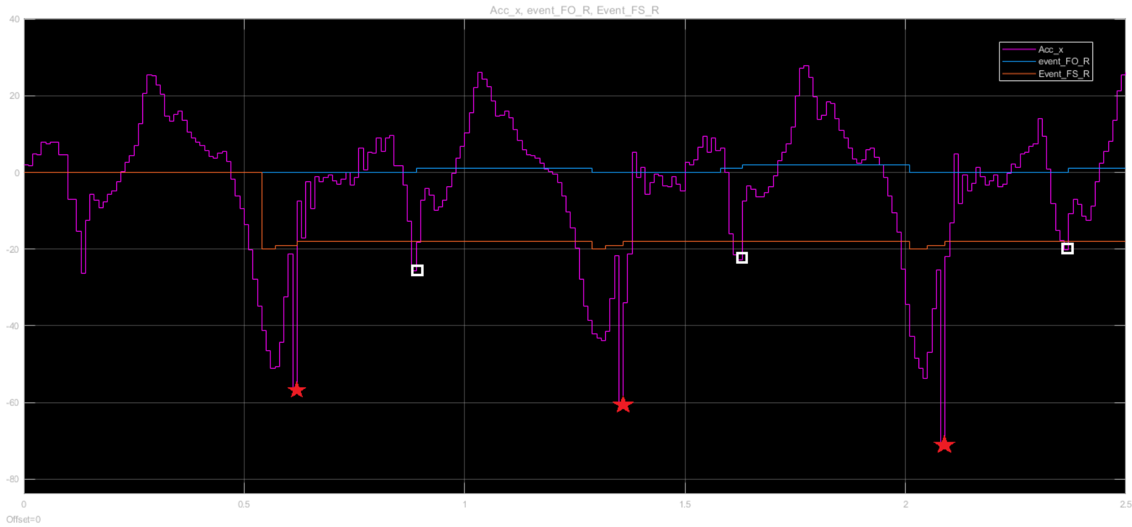


Figure 3.16: Shows method 2 for finding FS and FO, where the stars indicate FS and the squares indicate FO

3.5.2.1 Validation

The method was as mentioned validated using the estimated GCT, AT and f_step from Qualisys. The thresholds were adjusted until the features were close to the validation data for all runners. Only validation data between 10 and 16 km/h was used however since these were the velocities used at Aktivitus. This is because exactly how the data collection at Aktivitus would be carried out was not yet established when collecting data at Qualisys. Also, only data from the right foot could be used from runner number 4, due to measurement disturbances because of the unstable mounting of the sensor. It could be seen from the gyroscope being insignificant and not following any related pattern.

The thresholds were as mentioned varied to obtain the desired features but there was only one feature that was used to fine tune the values of the features. The thresholds `start_FS`, `stop_FO` och `FO_delay` varied for different runners and could be adjusted from observing the graph with the resulting events, similar to the graph in Figure 3.16 except for the stars and squares. The functions event_FS_R and event_FO_R increase one step when a new TS and TO have been found respectively, which makes it easy to visualise if there is something wrong with the algorithm. The thresholds `start_FS`, `stop_FO` and `FO_delay` can thus be adjusted if the algorithm makes mistakes. For example if the algorithm misses one or several steps, `start_FS` might be to low. In that case, FS has already occurred when when the algorithm starts to search. Another example is if the algorithm starts to search for FO to soon and an unwanted minimum is chosen instead, `FO_delay` is too short and needs to be increased.

When the validation was done, the first step was to adjust the three thresholds above until the algorithm found the FS and FO events. After that, the threshold `stop_FS` was adjusted to obtain features as close as possible to the validation features. Different values for `stop_FS` were tried and a threshold that yielded the smallest sum of errors from every participant.

3.6 Feature extraction method

As mentioned in the section above, `start_FS`, `FO_delay` and `stop_FO` were in a sense not obtained during the validation phase. The first step in the extraction phase was to adjust those three thresholds until the algorithm could find all events, which is explained in the section above. After that, the times for the events, TO and TS, could be extracted where the value for `stop_FS` that was obtained from the validation phase was used. The features f_{step}, GCT, AT and a_{FS} were then extracted by using Equation (3.1)-(3.9) and averaging over all steps for each runner and velocity.

3.7 Statistical data analysis

Numerous of statistical methods can be applied to the objectives within the thesis, e.g. correlation analysis and regression analysis. These methods are various approaches for evaluating the agreement between two different measurement equipment's [23] measuring the same object. However, degrees of errors are always occurring when measuring variables and therefore comparing two different methods do not provide a certainly correct measurement data without having one of them as the ideal. Qualisys was chosen to be the reference for the analysis in the thesis and the thesis system design were then compared with Qualisys data. Other studies [15] claim that the correct statistical approach is not obvious when comparing two measurement devices. It concludes that correlation analysis, studies the relationship between variables, but for assessing the comparability between two different systems a Bland Altman (B&A) plot can be used. Correlation can describe a linear relationship between the measurement methods but not their agreement to one another. The result of the analysis is shown in Section 4.1.1.

3.8 Multinomial logistic regression

For this project, Aktivitus made the classification for 18 runners. The data was divided into two sets where the data for 9 people were used as training data and the other 9 where used as validation data. About 20 cases were tried where the input features varied. For example, for one case, all features were used as the input while for another case, only GCT and fixed personal features such as length and weight where used. A built-in function in MATLAB called `mnrfit` were used to train the model. The validation phase used the weights from the training phase and the output of the model is stochastic. This means that three outputs where obtained from each feature set, namely the probability for each class. The validation was done by choosing the output with the highest probability and compare it with the class that should be the output to calculate the success percentage.

4

Results

The result of the thesis is presented in this chapter. Section 4.1 presents the result from the data collection at Qualisys and section 4.2 refers to the results from Aktivitus. The four participants at Qualisys are denoted as runner A-D while the 18 participants from Aktivitus are denoted as runner 1-18.

4.1 Validation of the feature extraction method

The data collection was successful for three runners but for one runner, the gyroscope measurements from the right foot was compromised. This since the mounting of the prototype was not enough and it came loose, which unfortunately was not noticed until the day after. It was because of the running speed being that high, that it was not well fitted for the mounting system. Despite that, the data collection overall was considered successful. As mentioned in Section 3.5.2.1, three of the thresholds were implemented in order for the algorithm to work. Those thresholds are presented in Table 4.1. The threshold `start_FS` was the most insensitive threshold which is why an interval for the parameter is presented. The lower and upper limits of the intervals were rounded up and down respectively to the nearest multiple of 5. The result shows similar thresholds for each runner.

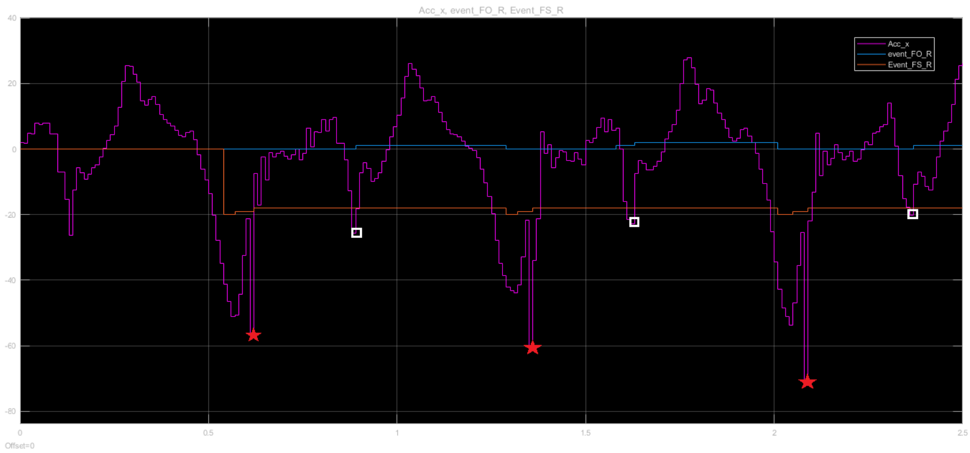
Table 4.1: Thresholds for extracting features to validate the feature extraction method, where F and M stand for female and male

	Gender	Speed (km/h)	start_FS (m/s^2)	stop_FO (m/s^2)	FO_delay (s)
A	M	10	$\in [-15 - 60]$	13	0.18
		12	$\in [-40 - 80]$	13	0.18
		14	$\in [-40 - 80]$	13	0.18
		16	$\in [-45 - 100]$	13	0.18
B	F	10	$\in [-30 - 60]$	13	0.18
		12	$\in [-40 - 60]$	13	0.18
		14	$\in [-40 - 60]$	13	0.18
C	F	10	$\in [-40 - 50]$	13	0.18
		14	$\in [-50 - 60]$	13	0.18
		16	$\in [-50 - 60]$	13	0.18
D	M	16	$\in [-45 - 80]$	17	0.15

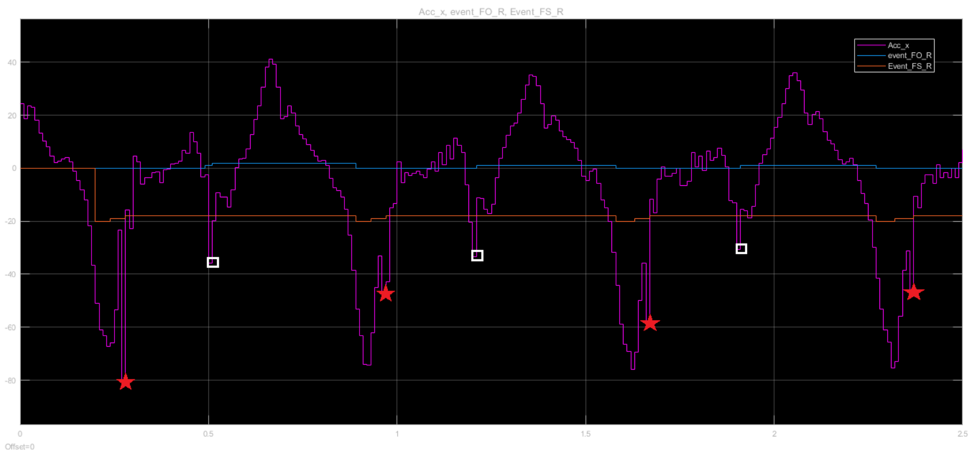
Figure 4.1a-4.1c shows data from runner A and B running at the same speed and data from runner B running at a different speed. The graphs show similarities between different

runners and velocities within the velocity range. The amplitude and pattern varied a bit depending on e.g technique and velocity but the minima for FS and FO existed for all data and could be found using the same algorithm.

(a) Data from participant B at 10 km/h



(b) Data from a participant C at 10 km/h



(c) Data from participant C at 16 km/h

Figure 4.1: Shows where FS (star) and FO (square) occurs when using method 2 on data from two different runners and different velocities. The participants are denoted by B and C only for this figure

The validation was done by comparing GCT and f_{step} with the values from Qualisys. AT was not compared due to the strong relation between GCT and AT when f_{step} is known. The result is presented in Table 4.2-4.5. It can be seen that the errors are consistent, for example the value for GCT for runner A is always too low while GCT for runner B is always too high and the error for runner C is small for all velocities. The error is smaller for runner A but the fact still remains. Since there could be only one value for `stop_FS`, the one that was overall best suited for all runners was chosen which was $-20m/s^2$.

Table 4.2: Validation of features, 10 km/h

	Runner A			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.253	0.27	182.3	183
-20	**0.255**		**182.3**	
-30	0.258		182.3	
-40	0.266		182.3	
-50	0.281		182.3	
	Runner B			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.300	0.28	168.6	170
-20	**0.300**		**168.6**	
-30	0.300		168.6	
-40	0.304		168.6	
-50	0.314		168.5	
	Runner C			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-20	**0.265**	0.26	**163.4**	163
-30	0.275		163.2	
-40	0.281		163.3	
-50	0.287		163.3	

Table 4.3: Validation of features, 12 km/h

	Runner A			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.245	0.25	187.1	187
-20	**0.247**		**187.1**	
-30	0.252		187.1	
-40	0.262		187.0	
-50	0.276		187.0	
	Runner B			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.287	0.25	171.7	172
-20	**0.287**		**171.7**	
-30	0.287		171.7	
-40	0.289		171.7	
-50	0.293		171.7	

Table 4.4: Validation of features, 14 km/h

	Runner A			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.228	0.23	196.0	196
-20	**0.229**		**196.0**	
-30	0.234		196.0	
-40	0.244		195.8	
-50	0.251		195.8	
	Runner B			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.275	0.24	178.6	179
-20	**0.275**		**178.6**	
-30	0.275		178.6	
-40	0.275		178.6	
-50	0.275		178.6	
	Runner C			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.223	0.22	170.7	172
-20	**0.228**		**170.7**	
-30	0.245		170.7	
-40	0.257		170.7	
-50	0.264		170.6	

Table 4.5: Validation of features, 16 km/h

	Runner A			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.214	0.21	203.4	206
-20	**0.214**		**203.4**	
-30	0.220		203.4	
-40	0.224		203.4	
-50	0.231		203.4	
	Runner C			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.219	0.22	160.7	162
-20	**0.219**		**160.7**	
-30	0.219		160.7	
-40	0.222		160.7	
-50	0.229		160.7	
	Runner D			
`stop_FS` (m/s^2)	GCT	GCT Qualisys	f_{step}	f_{step} Qualisys
-10	0.213	0.21	176.5	179
-20	**0.227**		**176.4**	
-30	0.242		176.3	
-40	0.254		176.4	
-50	0.258		176.4	

A comparison between the calculated features for each velocity and the values from Qualisys are presented in Table 4.6-4.9. The following abbreviations are characterised as: **P** = Participant, **M** = Male, **F** = Female, **R** = Right, **L** = Left.

Table 4.6: Feature comparison, 10 km/h

Data set	P	Gender	GCT IMU	GCT Qualisys	AT IMU	AT Qualisys	f_{step} IMU	f_{step} Qualisys
1	A	M	0.255	0.27	0.074	0.05	182.3	183
2	B	F	0.300	0.28	0.056	0.07	168.6	170
3	C	F	0.265	0.26	0.100	0.11	163.4	163

Table 4.7: Feature comparison, 12 km/h

Data set	Nr	Gender	GCT IMU	GCT Qualisys	AT IMU	AT Qualisys	Step freq. IMU	Step freq. Qualisys
4	A	M	0.247	0.25	0.074	0.07	187.1	187
5	B	F	0.287	0.25	0.063	0.09	171.7	172

Table 4.8: Feature comparison, 14 km/h

Data set	Nr	Gender	GCT IMU	GCT Qualisys	AT IMU	AT Qualisys	Step freq. IMU	Step freq. Qualisys
6	A	M	0.229	0.23	0.077	0.08	196.0	196
7	B	F	0.275	0.24	0.061	0.10	178.6	179
8	C	F	0.228	0.22	0.123	0.12	170.7	172

Table 4.9: Feature comparison, 16 km/h

Data set	Nr	Gender	GCT IMU	GCT Qualisys	AT IMU	AT Qualisys	Step freq. IMU	Step freq. Qualisys
9	A	M	0.215	0.21	0.080	0.08	203.4	206
10	C	F	0.227	0.21	0.113	0.13	176.5	179
11	D	M	0.219	0.22	0.155	0.15	160.7	162

4.1.1 Statistical analysis

Because of the thresholds being designed from the validation against Qualisys, a comparison between the two methods outputs were made. Assumptions must be met before a linear regression analysis could be used on the data set collected from the trials. Normal distribution needed to be ascertained prior to make conclusions regarding the data sets. However, for reason of having a limited number of runners in the test group, the data was not normally distributed. Insufficient data reveals a skewed distribution of the data collected from the trials. Although, when the aim is to compare the two methods agreement, the behaviour of the differences between them can be studied.

From plotting the 11 data sets analysed from each method, the data from the IMU and Qualisys were generating analogous step count per minute, see fig 4.2.

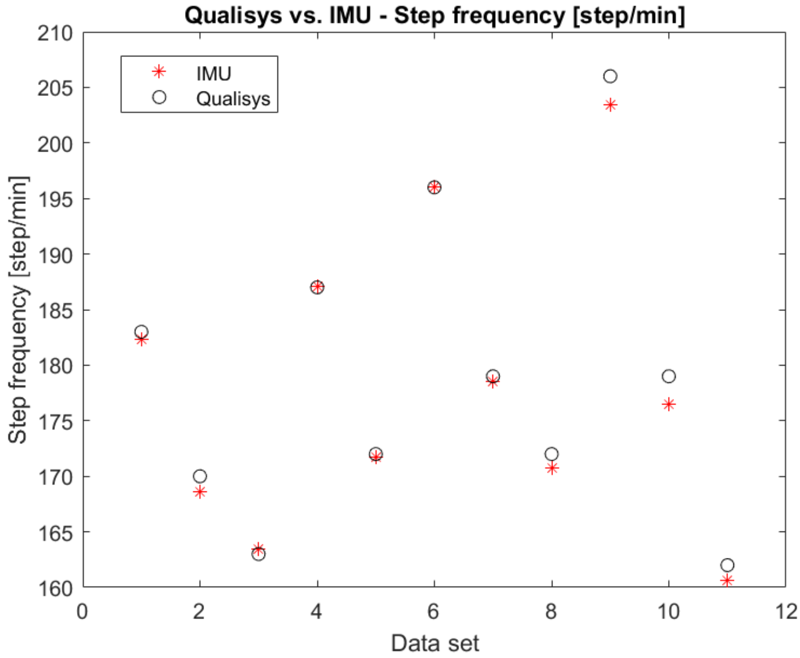


Figure 4.2: A comparison of the data set Step frequency, from Qualisys and the IMU. Given the 11 data points shown at the x-axis and the frequency on the y-axis

The step frequency is found from counting the peaks within the sampled data. This feature is persistent to find since it is not dependent on a specific time frame only on the event count. The point of picking the event FS will be consistent through the data sample and is only depended on the start_FS threshold.

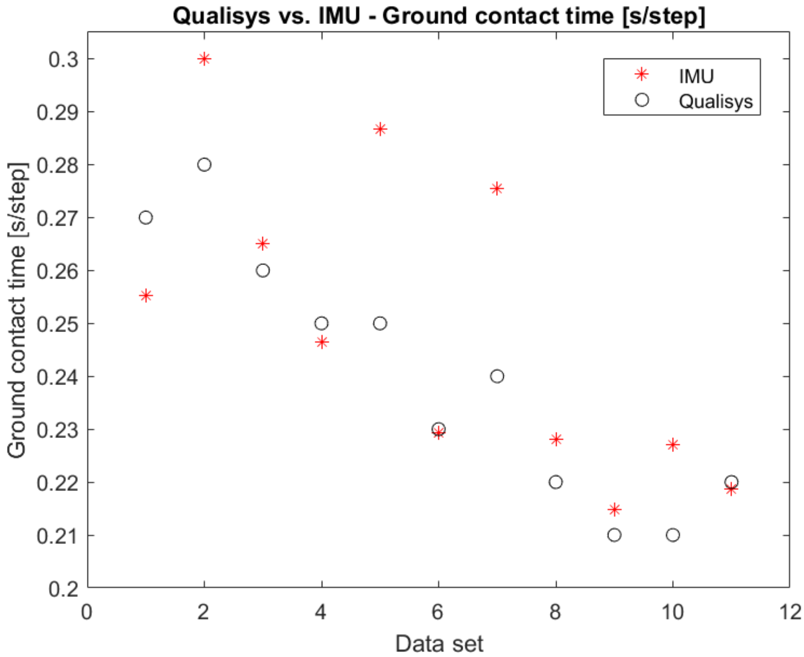


Figure 4.3: A comparison of the data set Ground Contact Time, from Qualisys and the IMU. Given the 11 data points shown at the x-axis and the frequency on the y-axis

Moreover, the ground contact time and air time features are more complex to observe, since they are sensitive to the time interval. A comparison between the two different methods gave a relatively connected output 4.3.

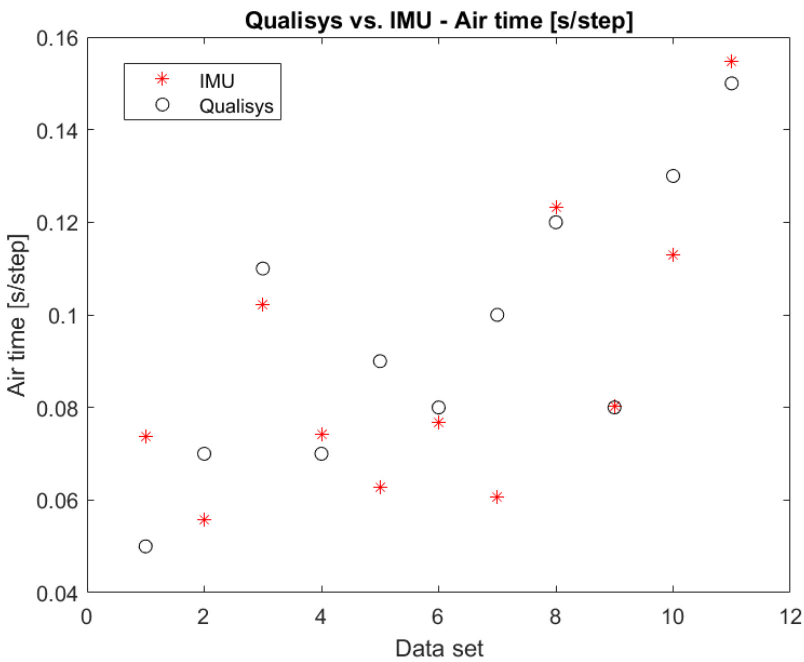


Figure 4.4: A comparison of the data set Air Time, from Qualisys and the IMU. Given the 11 data points shown at the x-axis and the frequency on the y-axis

More data would have been needed for making it possible to conclude any further statistics on the IMUs measurement capacity. Despite this, a Bland & Altman, described in Section 2.7, method was applied to the data to show further results of the differences behaviour.

The scattered plot consists of the difference between the IMU and Qualisys measurements ($IMU - Qualisys$) on the Y-axis, and the average of these values ($\frac{IMU-Qualisys}{2}$) on the X-axis.

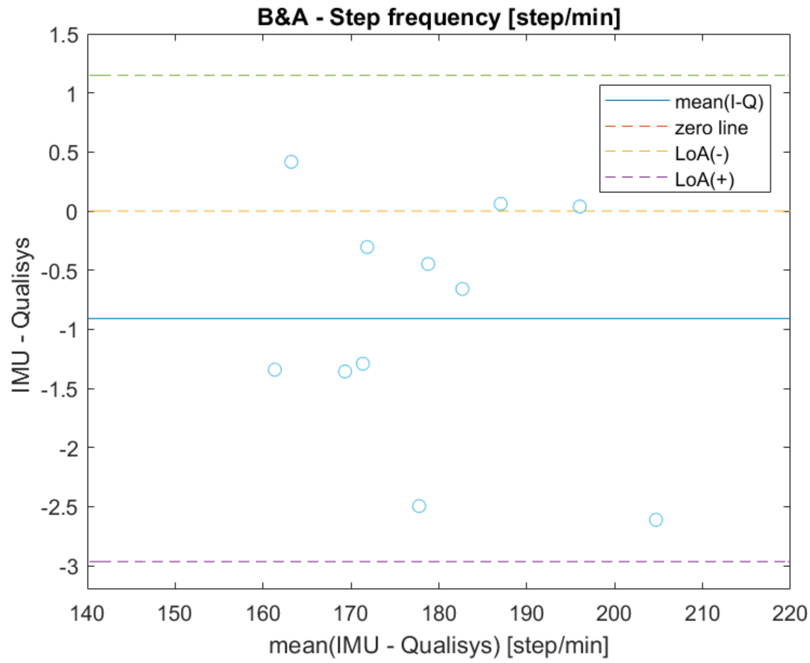


Figure 4.5: Bland Altman plot of the Step frequency

From the step frequency, the average between the two methods was, -0.9079 [step/min]. This implies that Qualisys method measures 0.9079 [step/min] more than the IMU, corresponding to zero differences between them two.

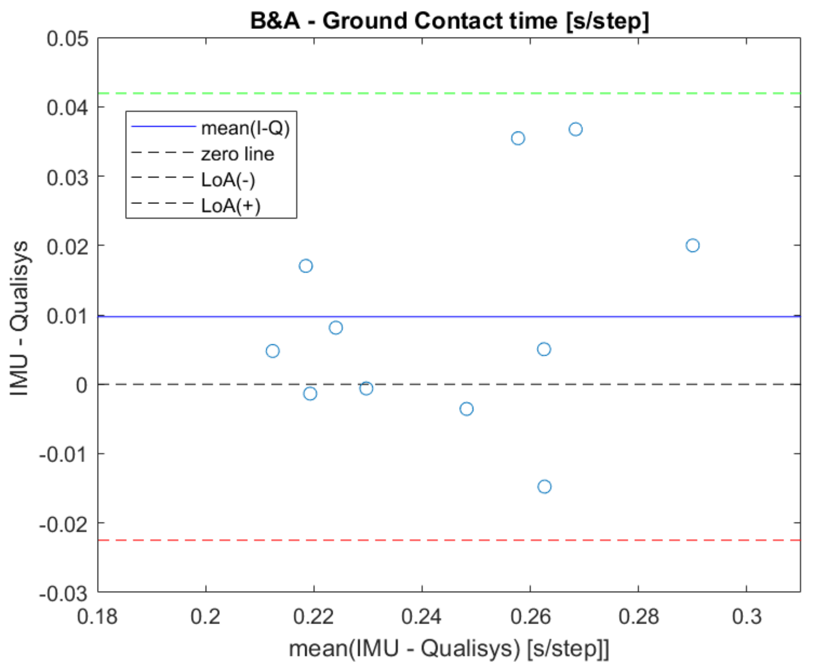


Figure 4.6: Bland Altman plot of the Ground Contact Time

The ground contact time B&A analysis reveals that a average of 0.0097 [s/step] is given. Which means that Qualisys measures -0.0097 [s/step] less of ground contact time then the IMU does.

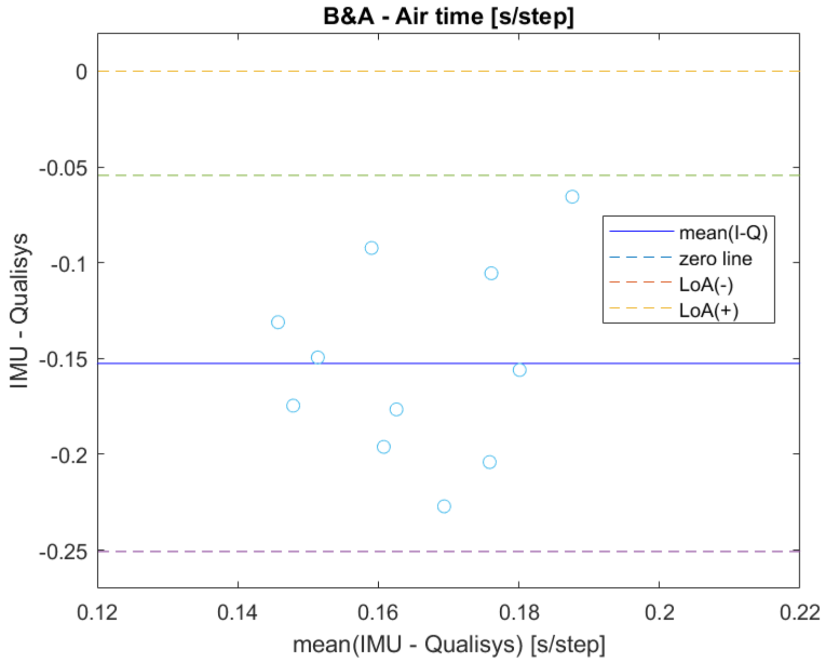


Figure 4.7: Bland Altman plot of the Air Time

The air time B&A analysis gives a average of -0.1526 [s/step]. It means that Qualisys measures 0.1525 [s/step] more than the IMU does.

4.2 Feature extraction

The data acquisition at Aktivitus was less successful than at Qualisys. Two prototypes were used and one of the prototype stopped working and the other one did not work as supposed. The latter suffered from the problem explained in Section 3.4, that the data became incomprehensive after sampling for a while. This only happened for the gyroscope on the left foot and since method 2 only uses the acceleration, the features could be obtained despite the problem. A problem that seemed to follow though was that a time lag seemed to occur for some runners, which changed the time scale, i.e one second was no longer one second. This problem was noticed at the end when there was no time to investigate it and the time might have been scaled differently for different runners. This was only something that was thought of, thus the large uncertainty. One minor investigation was also made at Aktivitus regarding the sensor attachment. The participants stood still between sampling at different speeds and the data showed that the sensor attachment made the sensor stable even when running. Table 4.10 shows the features that was gathered from the runners and their resulting classification.

Table 4.10: Information that was gathered from the runners prior to the data collection and the resulting classification for each runner

	Gender	Age	Weight (kg)	Length (cm)	Class
1	Female	28	72	174	3
2	Female	26	52	168	3
3	Man	25	70	171	1
4	Man	17	71	189	1
5	Man	16	57	175	1
6	Man	20	74	188	1
7	Female	50	60	173	2
8	Man	52	82	185	3
9	Man	33	80	177	2
10	Man	36	92	180	2
11	Man	44	60	170	2
12	Man	45	70	189	1
13	Female	24	82	178	2
14	Man	46	77	177	1
15	Man	49	80	190	1
16	Man	24	65	174	2
17	Female	26	58	161	3
18	Female	22	78	177	2

The thresholds needed to be found in order to extract the features. The threshold `stop_FS` was obtained in the previous validation phase and was set to -20 m/s^2. The threshold `stop_FO` could be set to 13 m/s^2 for all runners and the rest of the thresholds are presented in Table 4.11.

Table 4.11: Thresholds used for extracting training data, where `stop_FO` was 13 m/s^2 and `stop_FS` was -20 m/s^2 for all runners

Runner	Speed (km/h)	start_FS (m/s^2)	FO_delay (s)
		Default values	
		-50	0.07
1	10		
	12		
	14		
	16		
2	10		
	12		
	14		0.08
	16		
3	10		0.06
	12		
	14		
	16		

Table 4.11: (continued)

Runner	Speed (km/h)	start_FS (m/s_2)	FO_delay (s)
4	10	-40	
	12		
	14		
	16		0.08
5	10	-40	
	12		
	14		
	16		
6	10		
	12		
	14		
	16		
7	10		
	12	-60	
	14	-60	
	16		
8	10		
	12		
	14		
	16		
9	10		
	12		
	14		
	16		
10	10		
	12		
	14	-60	
	16		
11	10		
	12		
	14		
	16		
12	10	-40	
	12		
	14		
	16		
13	10	-40	
	12		
	14		
	16		
14	10		
	12		

Table 4.11: (continued)

Runner	Speed (km/h)	start_FS (m/s_2)	FO_delay (s)
	14		
	16		
15	10		
	12		
	14		
	16		0.05
16	10		
	12		
	14		
	16		
17	10	-40	
	12		
	14		0.08
	16		
18	10		
	12		
	14		
	16		0.04

4.3 Analysis and multinomial logistic regression

Figure 4.8-4.10 shows the correlation between class and GCT, AT and f_{step} respectively for all speeds. According to the people proficient in running techniques who have been consulted throughout this project, a lower GCT is beneficial since the runner spends more time in the air. This means that class 1 should have lower GCT than class 3 but figure 4.8 shows no obvious indication of that. For 10 km/h a slightly noticeable trend in the right direction can be seen but the data for different classes overlaps too much to be clustered.

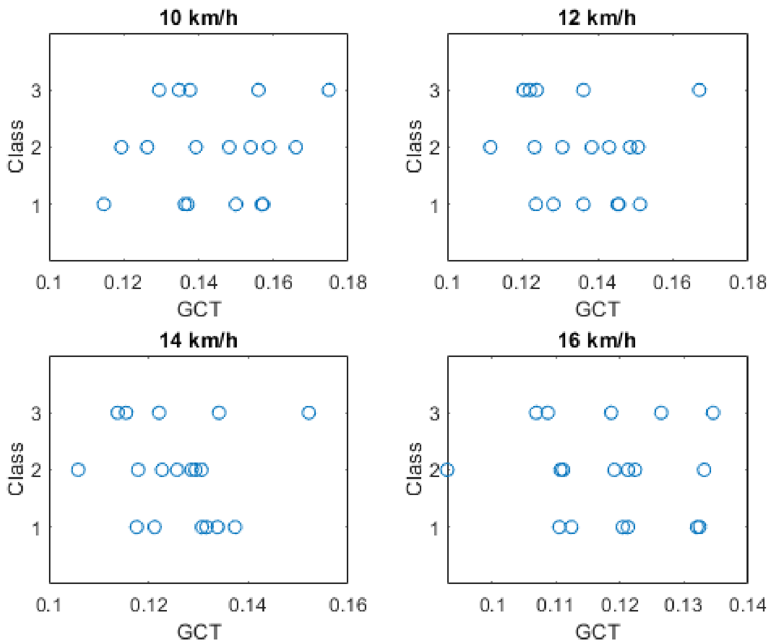


Figure 4.8: Correlation between class and ground contact time for all speeds

The correlation between class and AT is the same as for GCT but reversed. As for GCT, a slightly noticeable trend in that direction can be seen for 12 km/h, 14km/h and 16km/h but the data can again not be clustered.

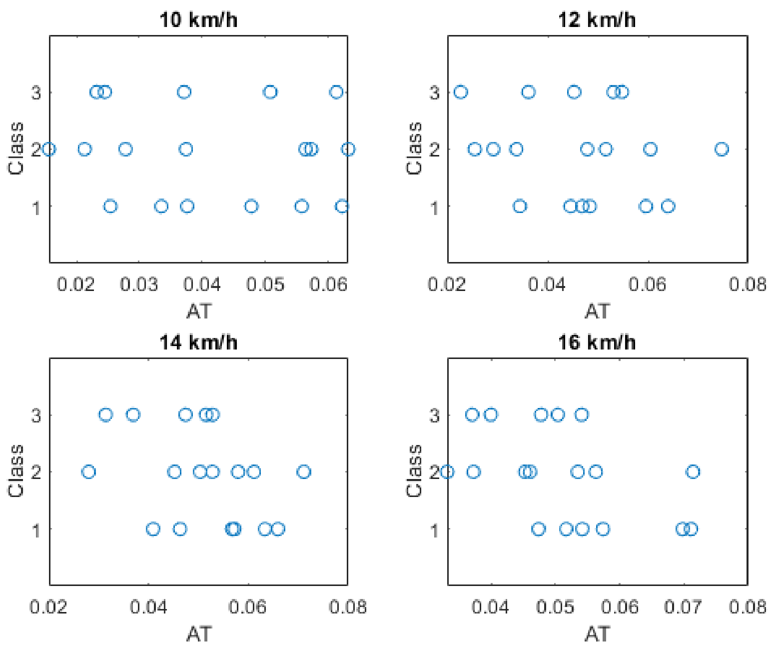


Figure 4.9: Correlation between class and air time for all speeds

Figure 4.10 that shows the correlation between class and step frequency shows no correlation either by just looking at it.

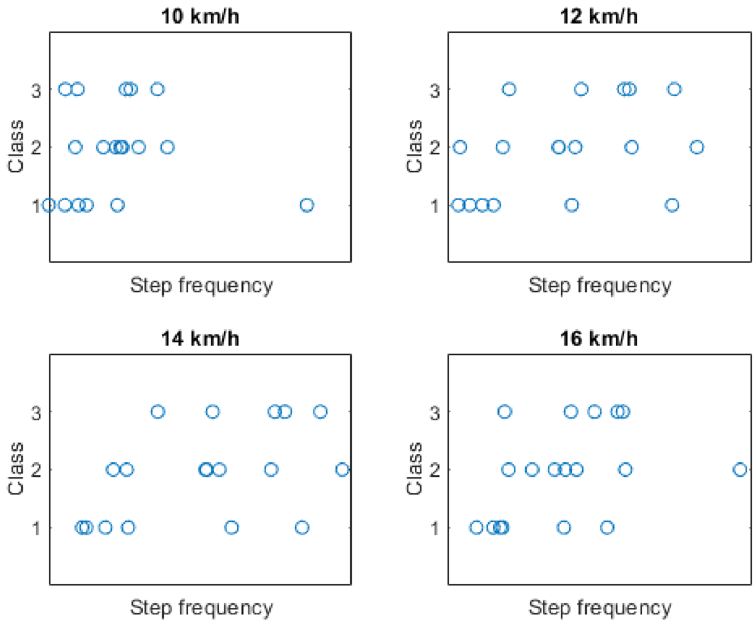


Figure 4.10: Correlation between class and step frequency for all speeds

The highest achieved success percentage from the multinomial logistic regression model was 67%, calculated from the validation data. This was achieved for two cases. One case included GCT, AT, a_{FS} and f_{step}, all divided by BMI together with Speed and Gender as features. The other case included a_{FS}, BMI, Level and Gender which is surprising since a lot of the features are not used. When different cases were examined there was no clear pattern, for example in some cases when the speed was added as a feature, the result got better and sometimes it got worse. All cases that were tried and the respective success rates are presented in Table 4.12. More cases could have been tried but the randomness of the result made it too uninteresting to continue.

Table 4.12: Machine learning cases that were tried

Case	Input features	Success rate
1	All features	64 %
2	All features except a_{FS}	44 %
3	All features except Gender	47 %
4	GCT, AT, f_{step}, a_{FS} and Speed	58 %
5	GCT/BMI, AT/BMI, a_{FS}/BMI, f_{step}/BMI, Speed and Gender	**67 %**
6	GCT/BMI, AT/BMI, a_{FS}/BMI, f_{step}/BMI, Speed, Gender and Level	64 %
7	GCT/BMI, AT/BMI, f_{step}/BMI, a_{FS}, Speed and Gender	64 %
8	GCT/BMI, AT/BMI, a_{FS}/BMI, f_{step}/BMI and Speed	50 %
9	(GCT/AT)/BMI, f_{step}/BMI, a_{FS}, Speed and Gender	61 %
10	(GCT/AT)/BMI, f_{step}/BMI, a_{FS} and Speed	42 %
11	(GCT/AT)/BMI, f_{step}/BMI, a_{FS} and Gender	42%
12	a_{FS}, BMI, Level and Gender	**67 %**
13	a_{FS}, BMI and Level	53%
14	a_{FS} and Speed	47 %
15	a_{FS} and BMI	44 %

5

Conclusion

During this thesis, the question has been weather or not it is possible to distinguish good or bad running technique by using machine learning and only two IMUs attached to the feet. The authors have gained knowledge within the field of running and were able to adapt this into a multinomial regression algorithm. Based on the fact that the features that were extracted yielded a success rate of 67 % and there are improvements that can be done, a conclusion was drawn that the two IMUs together with a machine learning algorithm are most likely enough for the purpose of this project. More research is needed to fully be able to answer the question though. One reason why more research is needed is because the event detection was more complex than predicted. Another reason is that the prototype took over six weeks to create, which was more time than intended from the beginning. This meant that time was taken from other parts of the project, especially the machine learning, therefore compromises had to be made. The sections below include an interpretation of the result, possible improvements, things that preferably should have been done differently and further developments.

5.1 System design

Working with hardware parallel with software can sometimes be complex. Searching for errors is difficult due to the many areas that can be covered in booth system designs. However, the overall knowledge towards the system design can increase when working with all the components of the system. Building a system model and simulating with hardware in the loop is a good way when wanting to analyse the signal process throughout the model. Although, working with code rather than modelling blocks could be an easier way of debugging, because it was more difficult to find information and examples about combining the microcontroller and Simulink than using other code based programs. This would be less time consuming which would have given more time to other parts of the project.

Another reason why the software design of the prototype took a long time, was due to the fact that the wrong format was being written to the registers on the Nucleo board. Within Simulink the communication block assigns the constant of the controller when writing to the specific register. The constant can have different formats and in this case, the issue was not found directly.

5.2 Trials and Data collection

The protocol at Qualisys were not fully premeditated. It was not yet known that the data would be used for finding the thresholds manually for the algorithm generated further on. Therefore, the runners got to choose their own speed and the data was then collected from different speeds. Luckily, the runners ran most of the same speeds anyway, which was why these speeds still could be used in the end to find thresholds. It would however be preferable to sample data for 10, 12, 14 and 16 km/h for all runners because that might have shown that another value for the threshold `stop_FS` would be more suitable. Another reason is that the pattern noticed for `stop_FS` and GCT would be easier to investigate. It could be possible to find some correlation to be able to set different values for `stop_FS` depending on the runner.

There are a couple of things to take into account regarding the validation. One is that Qualisys' features are also approximations of the real values. The other is that the interval for calculating the mean differed because the systems were not synced. The difference is that the sampling started a couple of seconds before Qualisys' system was started and the sampling ended a couple of seconds after Qualisys' system was stopped. It was not considered to be worth the effort but it is still a source of error.

A lot more data needs to be collected to improve the machine learning model. This project would have required more runners participating during the Aktivitus trials, and especially more runners within the discipline of track and field since the intention was to focus on middle distance runners. To include more participants was however not an option at this point because it would have gone over the budget at Aktivitus. Some of the requested runners before the trials expressed the shortage of information regarding the trials. The time used for administration and further structure of the trial, also took time from the preparations with the software design. This was unfortunate since there was no time to investigate the performance of the prototype enough. The prototype was confirmed to be working but that turned out to be incorrect. It was indirectly due to changing the sampling frequency from 100 to 167 Hz since the prototype was working for 100 Hz. This should not have been done and it was noticed that more time was needed but the date for the trial was given before the summer vacations, which was why it could not have been held later. The problem that followed about the time scaling mentioned in Section 4.2 would not occurred if the sampling frequency was change. And even though the result is considered good, it could have been improved and it could explain the outliers in Figure 4.8-4.10.

5.3 Event detection methods

If the dates for the trials at Qualisys and Aktivitus would not have been fixed, more time for testing the algorithms before the trials would have been given. A few tests were held at Fysiken, but more tests should have been done before the trials at the two companies. Method 1 could have worked better with placing the IMU on the heel instead of the outstep of the foot. Again, time was not enough to fix a stable system design that would be mobile enough to attach on the heel. To find the events also turned out to be more difficult than expected so the method used in this thesis could be improved.

5.4 Multinomial logistic regression

The highest achieved success rate of the algorithm was 67 % and was obtained for two cases. It was not very surprising that the case that included GCT, AT, a_{FS} and f_{step}, all divided by BMI together with Speed and Gender as features was one of the cases to yield the best result since it included almost all of the features. As mentioned above in Section 5.2, to add more features would probably improve the result. It was however surprising that the other case that only included a_{FS}, BMI, Level and Gender yielded such a high success rate. One explanation could be that there might be a strong correlation between level and technique. The purpose of including the level was because the recommended running technique depends on fitness, not the other way around but it is likely since training often yields both fitness and technique. This would be interesting to investigate but to do that, data from unfit runners with good technique and data from fit runners with bad technique is needed. The result also contradict the theory however. In table 4.12 it can be seen that when level is added from case 5 to 6, the success rate decreases. The result also indicates that gender is an important factor despite the uneven distribution between men and women. This could be an incorrect indication because of the uneven distribution though since for example half of the women belonged to category 3 while only 1/6 of the men did. The purpose of trying different cases was to compare the relevance of the features and to investigate if an optimal combination of features could be found. The randomness of the result however made it difficult to draw any conclusion. This is most likely due to the insufficient data size but could also be due to lack of features. Since there were three options, bad, good and very good, anything over 33 % is better than random. It is difficult to tell how good 67 % is but it can be argued that it is acceptable considering the amount of data.

5.5 Further development

Even though the prototype is constructed to fit for gait analysis of a runner, the technology behind it can be used for other purposes. The idea is to collect data from track and field runners, but it can also track data from various other type of runners or even people with medical problems such as e.g. gait difficulties. The objectives of the thesis could therefore be used in many areas within bio-mechanics which makes it even more interesting to work with.

Aside from being able to adapt the thesis into different fields, the knowledge and outcome of the prototype can be used as a training tool for coaches and athletes within the field of running. As the project is today, it has the opportunity to fulfil the enquires from the beginning.

5.5.1 Improvements of the system design

When the prototype was discussed in the beginning of the project, it was to be created without possible disturbances and interruptions for the runners. Throughout the project, problems have been found with the prototype. The Velcro attached on the sensor and on the runners, lacked stable support towards each other. Therefore, tape was used on the outside of the sensor to keep it attached to the runner's shoe. However, this did not seem to be enough in some cases where the sensor came loose from the surface. A robust mounting system needs to be created to gain a reliable data collection, as the one today need improvements. Another improvement is to make the prototype wireless. There was not enough time for that but it would definitely be beneficial for both the runners and to yield better data since the wires on the current prototype disturbs the runner.

There is not yet a user friendly interface since it is within Matlab and Simulink the data is received. An improvement that is included in the long-term vision of this project is to create an application that for examples through a headset can coach the runner in real time.

5.5.2 Features

Some of the features that were recommended to be analysed within running, given from the Pose method and running coaches were step frequency, ground contact time, air time, step length and the movement of the pelvis. In this thesis, the first three were found but the step length and pelvis movement could be included as features to improve the performance. The angle between the foot and the ground at impact, or probably better, the foot area that strikes the ground (toe, middlefoot or heel landing) could also be included. A complimentary filter that is described in Section 2.3 can be used to calculate the step length and angle. The optimal running technique also depends on the fitness level of the runner. In this thesis, the personal best for running 5 km and BMI were used but there are other features that can be added to better represent the fitness level, for example body fat and muscle percentage. The dimension of various body parts could also improve the performance since it had been told that one of the reasons why runners have different techniques is due to the body structure. It would be interesting to include the length of the legs, the ratio between the shin and the thigh and the length of the upper body for example.

The thresholds for finding the features are manually implemented, a possible development could be to create an algorithm that automatically calculates the features. One idea to set `start_FS` for example is to write an initiation algorithm that analyses the minima and calculates the threshold using that information. To be able to set the features automatically is something that has to be done if a commercial product is to be created.

When it comes to the event detection method, there are a lot of work that can be done to develop the method and to come up with a better one. One way to improve the model is to gather more validation data. There is also of course possible to use an entirely different method and there is probably enough work that can be done withing event detection to spend a whole master's thesis project on this alone.

5.5.3 Classification

Multinomial logistic regression is one of many machine learning algorithm and there exists a lot of algorithms that are more advanced. It would be interesting to try an artificial neural network for example, the first step however is to collect more data, especially if a neural network is to be tried. For example data sets from only 6 women were used while data sets from 12 men were included and a more even distribution is preferred. To include more features would probably also improve the performance as mentioned.

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A

Appendix

A.1 Specification of requirements

Table A.1: Specification of requirements on System design and Prototype

R1 = Requirements R2 = Request

	Function	**R1/R2**	**Specifier**
1. Software			
	Readings from acc.	R1	Authors
	Reading from Gyroscope and temp.	R1	Authors
	Being able to sample data from board	R1	Authors
	Known sampling frequency	R1	Authors
2. Hardware			
	Protective box for STMicroelectronic board	R1	Authors
	Soldered longer cable attachment for IMU	R1	Authors
	Closed box for IMU	R1	Authors
3. Additional			
	No interference with collecting data	R1	Authors
	Wireless	R2	Authors
	Wireless - Direct transmission	R2	Authors
	Battery	R2	Authors
	Power time approx. 6 hours	R2	Authors
4. Time schedule			
	6 weeks	R1	Authors

B

Appendix

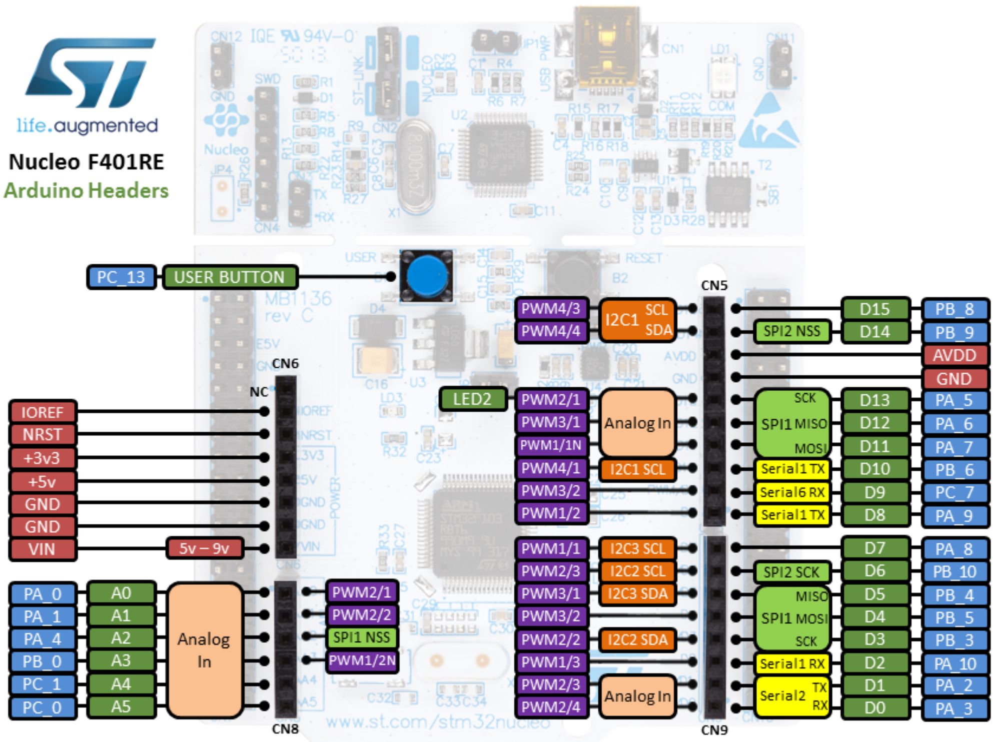

Figure B.1: Nucleo - Arduino headers

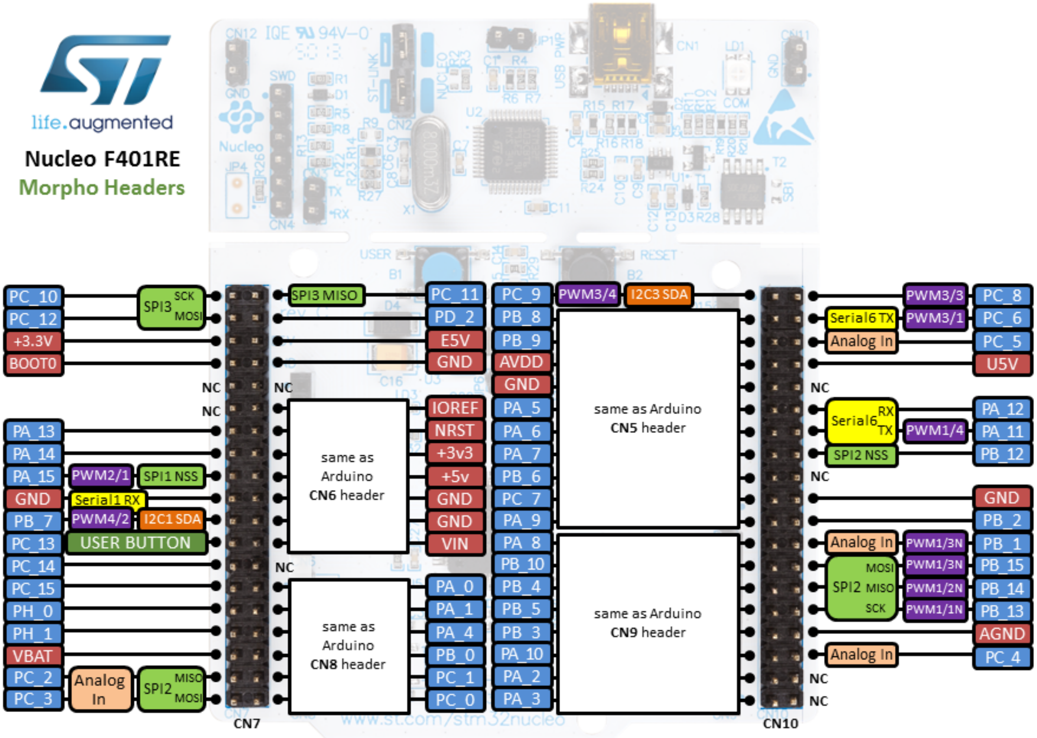

Figure B.2: Nucleo - Morpho headers