Engineering Degree Project

Slip Detection For Robotic Lawn Mowers Using Loop Signals

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Abstract

Husqvarna AB is one of the leading producers of outdoor products such as autonomous lawn mowers. One important feature of these products is the ability to quickly respond to environmental factors such as slippy areas. A reliable slip detector is needed for this mission and many different technologies exists for detecting slip events. A common technique is to check the wheel motor current, which clearly deviates when the lawn mower is subjected to slipping. The on-board sensors opens up for an alternative solution which utilizes the loop sensors as the main slip detector. This thesis covers the construction of a slip detection prototype which is based on the loop sensors. In the end, Husqvarna AB was provided with a new alternative solution, which was successfully compared to the exiting solution. It proved to be a reliable slip detector for manually induced slipping indoors, outdoor performance were not investigated. Ultimately, the implemented prototype outperformed the existing solution in the intended environment of indoor testing.

Keywords: autonomous lawn mower, loop signals, slip detection

Preface

First of all we would like to thank Husqvarna AB for the opportunity to perform this thesis. We would also like to thank our supervisor at LNU, Morgan Ericsson, for being very helpful and providing guidance. Finally, we would like to thank our friends and family for being such a support when needed during this final course.

Contents

1 Introduction

Robotic lawn mowers are one of the steps towards outdoor home automation. Lawn mowing is an essential activity which can be repetitive and time consuming, perfect for automation. It is important to have reliable and robust autonomous robots for this task. It is even a fundamental assumption made from the consumers of these products, any deviation from the expected performance means waste of time, money and decreasing prospects of the involved technology. Assurance that a robotic lawn mower can handle the problems it faces, such as knowing when it slips, is of vital importance to the development of related technologies within the outdoor home automation domain. The work is also very relevant for the involved company Husqvarna AB, which is looking to find a new alternative to the slip detection problem on their robotic lawn mowers.

1.1 Background

Husqvarna AB was founded in 1689 and was at first a rifle factory. Later, they also started producing sewing machines, kitchen equipment, bicycles, motorcycles, garden equipment and lawn mowers that later became robotic [1]. Husqvarna AB are the leaders in sustainable, user-centered solutions and their passion for innovation is what defines them [2].

Automatic mowers have on-board electromagnetic loop sensors which senses the electromagnetic field that emanates from a wired loop in the ground. The wired loop which is called the boundary wire, encloses the cutting area and the loop sensors senses if the magnetic field is positive or negative. Inside the perimeter, loop signals are positive, while they are negative on the outside. The sensor interval is in the range of ± 15000. According to the curled right-hand rule, the moving charges generates a magnetic field that moves in the direction in which the fingers encircle the wire [3].

The focus is on one autonomous lawn mower called Husqvarna Automower 405X, which has four electromagnetic field sensors in total, three in the front and one in the back. Together, these sensors forms the basis of a new alternative slip detection module. When a robotic lawn mower detects a problematic area that causes slipping, this triggers a slip event that stems from the slip detection module and the next course of action is a small maneuver to move around it. The particular problem to solve is thus slip detection in autonomous lawn mowers using loop signals. The current solution that is being used to detect slip is checking the wheel motor current.

1.2 Related work

There are not so many publications specifically on robotic lawn mowers and especially slip detection, that is related to the problem. In the master thesis [4] the author Edward Joseph Kreinar describes a filter-based slip detection using an Extended Kalman Filter. The author defines slip as where the measured wheel velocity does not equal to the true wheel velocity. The author also describes different alternatives to wheel-slip detection.

In the article [5] the authors A.S. Belyaev, O.A. Brylev and E.A. Ivanov does a research of dependencies between motor current across different types of surfaces, such as dirt, snow, sand and grass, as well as the difficulties surrounding slip-detection. The authors explain that the algorithms used in different types of slip-detection, often starts to gain errors which leads to negative effects.

The data analysis in the research shows that a correlation between the motor currents and the type of surface is very clear, and provides information about the type of the underlying surface. However, in the experiments that were carried out, they discovered that placing the robots wheels on different types of surfaces, the mutual influence affected the data. The conclusion drawn from this was that the difference between wheels' currents are too small on highly differing surfaces. In their research the used robot has a ArUco marker on its top side, for determination of the robots position using computer vision algorithms.

1.3 Problem formulation

The problem is to find out if loop changes in software based on sensor input can be used to detect slip-events and compare this potential solution to already existing solutions, which heavily uses the wheel motor current. This includes creating a new slip event module that adheres to the design principles and standards at the company. A solution that evaluates the slip detector using different performance metrics also needs to be implemented. There is currently no existing solution that uses these loop changes or a way to compare alternative modules. The problem will be limited to only one automatic lawn mower, the Husqvarna Automower 405X, and the results that are expected is a prototype implementation fulfilling the criteria of detecting slip. The module must be implemented according to the software standards of Husqvarna AB. The reliability of detecting slip using the wheel motor current (during controlled testing inside) may be affected by different types of surfaces, which is discussed in [5]. The reliability of indoor testing may increase when using loop signals instead. The current main methods of detecting slip which is covered in the mentioned papers [4, 5] may become challenged by using an alternative method.

1.4 Motivation

Slip detection in autonomous lawn mowers most likely expands into other areas, such as smart vacuum cleaners, robotic snow-mowers and basically everything that is autonomous and runs on wheels. If there is no viable slip detection then these robots run the risk of getting stuck and running out of battery. How these robots handles the detected slip varies, but the common denominator is that a reliable slip detection is vital to the overall functionality and service provided.

1.5 Milestones

M1	Finish Introduction
M2	Visualize loop sensor output
M3	Upload simple program to lawn mower
M4	Analyze slip scenarios
M5	Minimal viable slip detection module
M6	Final implementation
M7	Test implementation
M8	Create test method for module
M9	Compare new implementation against existing one
M10	Finish Report

1.6 Scope/Limitation

This project will be limited to only one autonomous lawn mower, the Husqvarna Automower 405X illustrated in Figure 1.1, which has four loop-sensors, three in the front and one in the back. The controlled experiments will be performed on only one type of lawn, that is located indoors. The size of the lawn is approximately 35 square meters. The implementation will be compared to only one of the existing solutions, the wheel motor current. The slip detection module must be built in the C programming language and only use the internal libraries provided by the company. In addition to this, a Non-disclosure Agreement (NDA) limits the information that can be shared in this thesis. Sensitive details can be rewritten in the best case or in the worst case, get discarded entirely.

Figure 1.1: Illustrates the Husqvarna Automower 405X [6].

1.7 Target group

This project targets Husqvarna AB and other companies that develop autonomous robots that use a boundary wire. The project might also interest software engineers similar to those working in the software department at the company. Basically embedded software programmers that constructs the logical behaviour of autonomous robots within the outdoor domain.

1.8 Outline

The outline of the report is as follows. Chapter 2 covers the theory needed to understand the work. Chapter 3 covers the methods and how they are applied. Chapter 4 covers the implementation of the prototype. Chapter 5 covers the experimental setup, the results, and the analysis. Chapter 6 contains a thorough discussion, and finally Chapter 7 is a concluding section.

2 Theory

This section includes information about theoretical areas and important concepts that are related to the problem and solution.

2.1 The Physics Behind Slipping

The force of static friction is the force between two surfaces that stops them from sliding or slipping over each other. Kinetic friction occurs when two surfaces are sliding past each other and it opposes the sliding motion and effectively reduces the speed. When there is relative motion between two surfaces and they slide with respect to each other, slipping is occurring. This also means that the relative motion has overcome the resisting frictional force between the two surfaces [7].

2.2 Automatic Mower Boundary Wire

Most robotic lawn mowers uses a perimeter wire. In the paper [8] which covers different brands, Husqvarna automatic mower is covered along with some general technical details regarding the boundary wire. The boundary wire is implanted at the border of the lawn and it is also laid out around trees and surfaces which will not be cut. The boundary loop wire foremost holds the lawn mower to the enclosed lawn and a search loop ensures that it can return to the docking station for battery recharging. The perimeter loop wire defines the robotic mower's cutting area while the guide loop wire directs the mower to the charging station. When the wire is electrified, it generates a magnetic field that emanates in all directions. This magnetic field creates a dynamic input for the on-board loop sensors, as the robotic lawn mower is moving around. The resulting signal is called the loop signal and it is especially important for autonomous movement.

2.3 Finite State Machine

To understand where the slip detection module comes in, it is important to cover the fact that a robotic lawn mower is functionally built according to a Finite State Machine (FSM) where different states are triggered from real-time events.

The concept of Finite State Machines can be described as a collection of states, input events, output events and transitions. A state describes what the status of a system is, input events may be arrival of data to the Finite State Machine. Output events occur after an input event has arrived and is triggered by a transition, when the Finite State Machine is changing state [9, 10].

In the article [11], important features and advantages of using Finite State Machines were presented. The advantages are simplification, model verification, derivation and testing. By dividing a complex problem into different states, and include the actions of changing states - the transactions, one can achieve clarity and precise specifications. It is also possible to define various rules for the Finite State Machine model.

According to the article, defining rules and verifying the model against those rules can help uncover errors and omissions. The Finite State Machine model can also be used to make the transition from requirements to design easier, help with implementation, and also simplify the verification process by using the model to generate various test case scenarios.

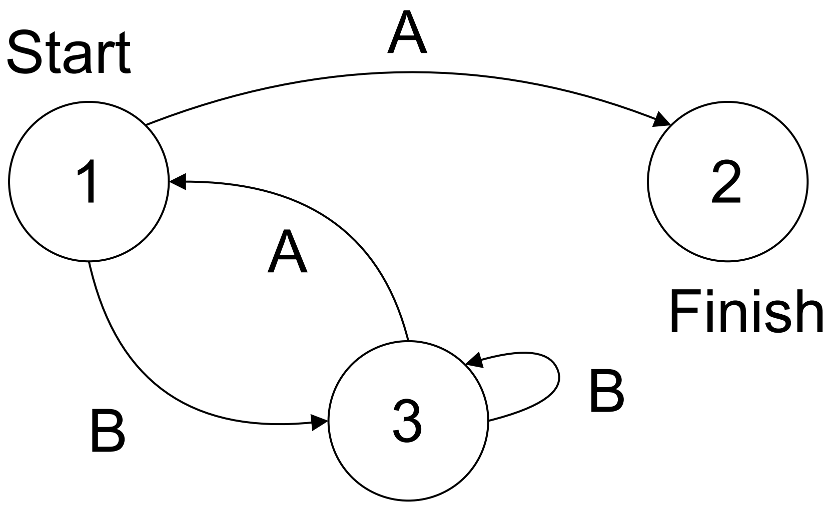

Figure 2.1: An example of a graphical Finite State Machine.

2.4 Electromagnetic Sensor

An electromagnetic sensor detects the presence and magnitude of a magnetic field. The three most common sensors used to measure a magnetic field is search coils, fluxgate magnetometers and Hall-effect devices [12, 13]. These sensors adheres to the laws of physics and are susceptible to interference. Electromagnetic interference is a disruption caused by other magnetic fields generated by another electronic device. Anything that runs on electricity, give off electromagnetic interference. The interference can travel through different types of material, such as air, water and other solid materials [14].

In the context of the automatic lawn mower model, each individual loop sensor is essentially an electromagnetic sensor, which is usually in numerous quantities integrated in a Printed Circuit Board Assembly (PCBA). At the software level, the magnitude of the magnetic field measured by the sensor is translated into a number in the range of ± 15000. Whenever the lawn mower passes the boundary wire, the resulting signal is negative, while it is positive inside the perimeter.

2.5 Variability

This section covers the measures of variability that was used in this thesis. In the field of statistics, variability denote the width of the distribution, meaning how spread out the values are in a dataset.

2.5.1 Variance

The variance of a data set reveals how spread-out the data points are. Mathematically, the variance is the average of the square of observations deviated from the mean. The closer the variance is to zero, the more closely the data points are clustered together. When working with partial datasets where only a smaller sample of the data is available, the sample variance formula seen in Equation 1 is used [15].

$$
\begin{aligned}
s^2 &= \frac{\sum(x_i - \overline{x})}{n-1} \qquad (1)\\
s^2 &= \text{Variance}\\
x_i &= \text{Term in data set}\\
\overline{x} &= \text{Sample mean}\\
\sum &= \text{Sum}\\
n &= \text{Sample size}
\end{aligned}
$$

2.5.2 Range

The range is a simple measure of variability and it is calculated by taking the difference between the largest and smallest value in a given data set. A broader range means more variability, whereas a smaller range means the opposite, lower variability. In the context of the implementation, the largest value is the local maxima and the smallest value is the local minima. The range is given by calculating the delta between these two extreme values [16]. The capital letter delta (Δ) is used to symbolize change. Calculating the delta between two numbers represent the difference between them, and can be accomplished by subtracting the smaller number from the larger one [17].

2.6 Local Maxima and Minima

The local maxima and minima of a function are the maxima and minima in a particular interval. A value of a function is considered to be a maxima if all nearby values are smaller, whereas a minima has all nearby values to be larger. There can be multiple local maxima and minima across the entire domain of a function.

The highest and lowest points across the entire domain are known as the global maxima and minima. There can only be one global maxima and minima in a function. The global maxima or minima is the greatest or smallest value a function can achieve [18].

2.7 Evaluation Metrics

This section contains the evaluation metrics used to evaluate the slip detector. The metrics are classification accuracy, precision, recall, F2 score and average precision. Together, these metrics makes it possible to measure the performance of the slip detector.

2.7.1 Classification Accuracy

The metric that encapsulates the performance of a classification model as the number of correct predictions divided by the total number of predictions is called classification accuracy. It is intuitive to understand and easy to calculate, making it the most common metric used for evaluating models [19].

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

For binary classification problems, accuracy can also be expressed in terms of positives and negatives.

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP + TN + FP + FN}}$$

2.7.2 Precision and Recall

When a data set has a class-imbalanced problem, it is better to use another evaluation metric. Class imbalance means that the class ratio is skewed towards one class, the number of labels are not equal. In such cases, it is better to use precision and recall for evaluation. Precision shows the proportion of correct positive identifications, whereas recall shows the proportion of actual positives that was identified correctly. If a model has a precision of 0.5, it predicts correctly 50% of the time and if model has a recall of 0.10, it correctly predicts 10% of all positives. True positive (TP) and true negative (TN) means that the features was classified correctly. False positive (FP) and false negative (FN) means that the prediction was wrong [20, p. 92–93].

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \qquad\qquad \text{Recall} = \frac{\text{TP}}{\text{TP + FN}}$$

Since both precision and recall is equally important, there is a precision-recall curve that displays the trade-off between the precision and recall values for different thresholds. This curve helps to select the best threshold to maximize both metrics. The graph can be used to graphically decide the best point, meaning where both the precision and recall are high. However, if the graph is complex this can be difficult, so instead a metric called the F1 score can be used. The F1 score measures the balance between precision and recall. When the value of F1 is high, this means that both the precision and recall are also high. A lower F1 score means a greater imbalance between precision and recall [20, p. 93–96].

$$\text{F1 = 2} \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

The average precision (AP) is a method of summarizing the precision-recall curve into a single value which represents the average of all precisions.

$$\text{AP} = \sum_{k=0}^{k=n-1} [\text{Recalls(k)} - \text{Recalls(k+1)}] \times \text{Precisions(k)}$$

2.8 Clustering and Dimensionality Reduction

Clustering is an unsupervised machine learning task. The aim of a cluster analysis is to discover natural grouping in the data, meaning that the members of a group have similar but not identical values. In order to visualize the data in a comprehensible format, the dimension must be three or lower. This is where dimensionality reduction comes in. One of the main approaches of reducing dimensionality is projection. Principal Component Analysis (PCA) is a popular dimensionality reduction algorithm and it works by projecting data onto identified hyperplanes that lie closest to the data [20].

3 Method

This chapter is divided into four different subsections. Section 3.1 briefly describes which methods are going to be used to solve each problem. Section 3.2 will describe the methods thoroughly and how they will be applied to the problem. Section 3.3 contains a discussion about the reliability and validity of the thesis. Section 3.4 covers the ethical considerations in the thesis.

3.1 Research Project

The first method to be used to handle the initial phase of the problem is a literature review to gather the necessary information. The information gathering process includes related work, domain specific technical areas, and parts related to the final implementation. This is then followed by the second method, which is a controlled experiment where the slip detector is systematically tested in a controlled environment and measured quantitatively to assess its viability. The implementation of the testing methods is also a part of this stage.

3.2 Method

The method used in this thesis is presented here. Section 3.2.1 describes how the literature review was performed. Section 3.2.2 describes the controlled experiments performed in this thesis.

3.2.1 Literature Review

A literature review is performed to give an overview in a field of study and to gather necessary information regarding the problem. The literature review in this thesis was performed using the online tools Google Scholar, OneSearch, and Science Direct. To check for relevance, the abstract part of the articles were read before reading the remaining part of the article and at last the conclusion. Some keywords used to find relevant articles were: loop signals, autonomous mower slip detection, finite state machines, electromagnetic sensors in autonomous mowers. The Table 3.1 below displays the keywords as well as the search engines used and the number of results. No extended filtering was used beyond the default search parameters.

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Keyword	Search Engine	Results
Autonomous mower slip detection	Google Scholar	29
Autonomous mower slip detection	OneSearch	18
Autonomous mower slip detection using electromagnetic sensors	Google Scholar	8
Autonomous mower slip detection using electromagnetic sensors	Science Direct	2
Electromagnetic sensors in autonomous mowers	Science Direct	24
Electromagnetic sensors in autonomous mowers	OneSearch	38

Table 3.1: Table containing results of the literature review.

To summarize the findings in the literature review, there are not many publications about the problem that this thesis aims to solve. The final solution can be seen more as the creation of an innovative artifact that did not exist before. While there is previous knowledge about domain specific technical areas, designing a slip detector based on loop sensor signals requires new thinking and knowledge.

3.2.2 Controlled Experiment

A controlled experiment is a controlled test where a hypothesis can be evaluated and what the effects on a performance indicator could be when manipulating the test object. According to [21], clear and consistent task instructions in conjunction with the recording equipment functioning accurately, devotes that the experiment is robust. The article also mentions that the focus in controlled experiments is quantitative data and that it is necessary to investigate the phenomenon in more than one way by performing designed changes.

In the context of the thesis, the controlled experiment is the simulation of a slip-event. The slip-event can be manually generated in three different ways. The first approach is to slightly lift the rear part of the lawn mower so that there is still friction but no forward movement. The driving wheels will spin in an attempt to move but due to the manually applied backwards force, it will stay put. This physically simulates a standard slipping scenario.

The second approach is to lift the rear end entirely from the ground so that there is no friction. This simulates an extreme lack of friction, like a wet area. The third approach is to again slightly lift the rear part of the lawn mower so that there is still friction but instead of restricting movement, it is manually simulated by moving the lawn mower sideways. This effectively simulates the scenario where a lawn mower is slipping and changing position as a result, maybe due to a slope or initial speed.

The internal developer tools at the company allows data retrieval from the loop-sensors in real-time. The lawn mower pairs with the monitoring device via Bluetooth by using a specifically designed testing application. In the internal application, specific commands can be sent to the lawn mower and one can retrieve the data from the loop sensors, the current speed and the status of the lawn mower, and much more.

In the controlled experiments that were executed for the thesis, the data from the four different loop sensors were collected every 100ms in real-time. The collected data is presented in a graph and each corresponding point is stored into a CSV file.

The raw data in the CSV file had to be reformatted in order to be able to apply different algorithms such as dimensionality reduction and clustering for visualisation purposes. This included the removal of extra white space rows, the removal of the original time stamps column and finally the addition of labels and an adjustment of column titles. The Figure 3.2 below displays a sample of the reformatted data. The label of 0 in the slip-column means a non-slipping point, whereas the label of 1 means slipping.

Time	Front Right	Front Center	Front Left	Rear Center	Slip
1200	12 898	13 049	13 241	14 384	1
1300	12 942	13 103	13 225	14 026	1
1400	14 620	14 558	14 386	17 242	0
1500	14 502	14 349	14 102	16 428	0
1600	−14 165	−15 501	−15 619	16 701	0

Table 3.2: Table containing a sample of the reformatted data.

3.3 Reliability and Validity

This section covers the reliability and validity of this thesis.

3.3.1 Reliability

The data collection part relies heavily on controlled experiments indoors with many changing variables such as the size of the lawn, the surface, the surrounding interference and so on. The exact same data points that were collected by recording the loop sensor values in real-time would be hard to replicate due to the factor of randomness.

The data collection consisted of two types, slipping and normal operation. The slipping was simulated by manually lifting the driving wheels to the point where the lawn mower had less to no friction. While this procedure was done in a controlled manner to some extent, it is humanely hard to replicate the exact same movement. Changing factors such as pressure, movement and orientation will affect the collected data.

During normal operation the lawn mower is also moving around in a random pattern, so there is no predictable or repeatable pattern for generating loop sensor data in this case. However, since the main goal of the data collection is to differentiate between slipping and non-slipping, some level of noise is acceptable and even desired to simulate a real environment.

The human factor is a source of potential errors during data collection as slip is manually induced and the slip duration is also manually entered into the CSV file. This can either manifest itself in a delay for when the slip starts or ends, consequently effecting the final evaluation of the prototype.

As there were a lack of related works and no previous work for the general problem, there were no conventional technique of simulating a slipping event externally. The most optimal approach was chosen in accordance to what could be achieved with the given resources.

3.3.2 Validity

There are no direct validity threats, as any drawn conclusions would be backed by many test cases and direct field-analysis. As there are minimum requirements for a slip detector, any deviation from the expected outcome would be highly noticeable. For the external validity aspects, the evaluated performance of the slip detector prototype cannot be generalized beyond the scope/limitations of the solution.

3.4 Ethical considerations

The main method consists of a controlled experiment, so there are no direct ethical considerations. The collected data does not say anything about the position relative to the outer perimeter, so sharing of this data still complies to the NDA rules at the company.

4 Implementation

This chapter covers details regarding the implementation. Section 4.1 contains a general description and a schematic of the final implementation. Section 4.2, 4.3 and 4.4 describes the fundamental parts of the slip detector to solve.

4.1 Overview

The implemented software consisted of a stand-alone slip module which were integrated into the existing environment. Existing slip detection modules are easily switchable in the architecture, which is not shown here due to confidentiality reasons.

The overall structure of a general slip detection module is foremost an outer main function that returns a Boolean value of either true or false. Inside there is an evaluation function, where the most functional code resides. If a certain implementation evaluates to true, the slip module returns this value and the automatic mower responds to a slip-event. In the beginning of the module, all dependencies are imported, along with the necessary firmware interfaces that will be used in the implementation.

The implemented prototype uses the loop sensor values along with the wheel speed in order to differentiate between slipping and non-slipping. There were four loop sensors in total in the chosen automatic mower this thesis was limited to. Three in the front, positioned left, right and center and one in the back positioned at the center. The final implementation only uses three of these, discarding the rear center one.

Data analysis showed that the variability of a subset of samples over time were the best candidate for the utilization of the loop sensors as slip detection. The slip detection evaluation function essentially implements a sample variability algorithm in embedded C, along with other basic necessities such as conditional logic.
Figure 4.1 represents a flowchart of a general slip detection implementation. The first step is to check whether the automatic mower is moving or non-moving. Therefore, if the mower is moving, the values of the three loop sensors are retrieved until N number of samples exists. Otherwise, nothing will happen.

When N samples have been retrieved, the next step is to check if the autonomous mower is slipping X times in a row. If this condition is evaluated to true, the function returns true, which means slip, otherwise, it will return false, non-slip. The final implementation implements a slipping criteria based on the loop sensor values, which will determine the decision *Is slipping?*, represented in the flowchart. Retrieving N samples, X positive times introduces a delay D, as seen in Figure 4.2.

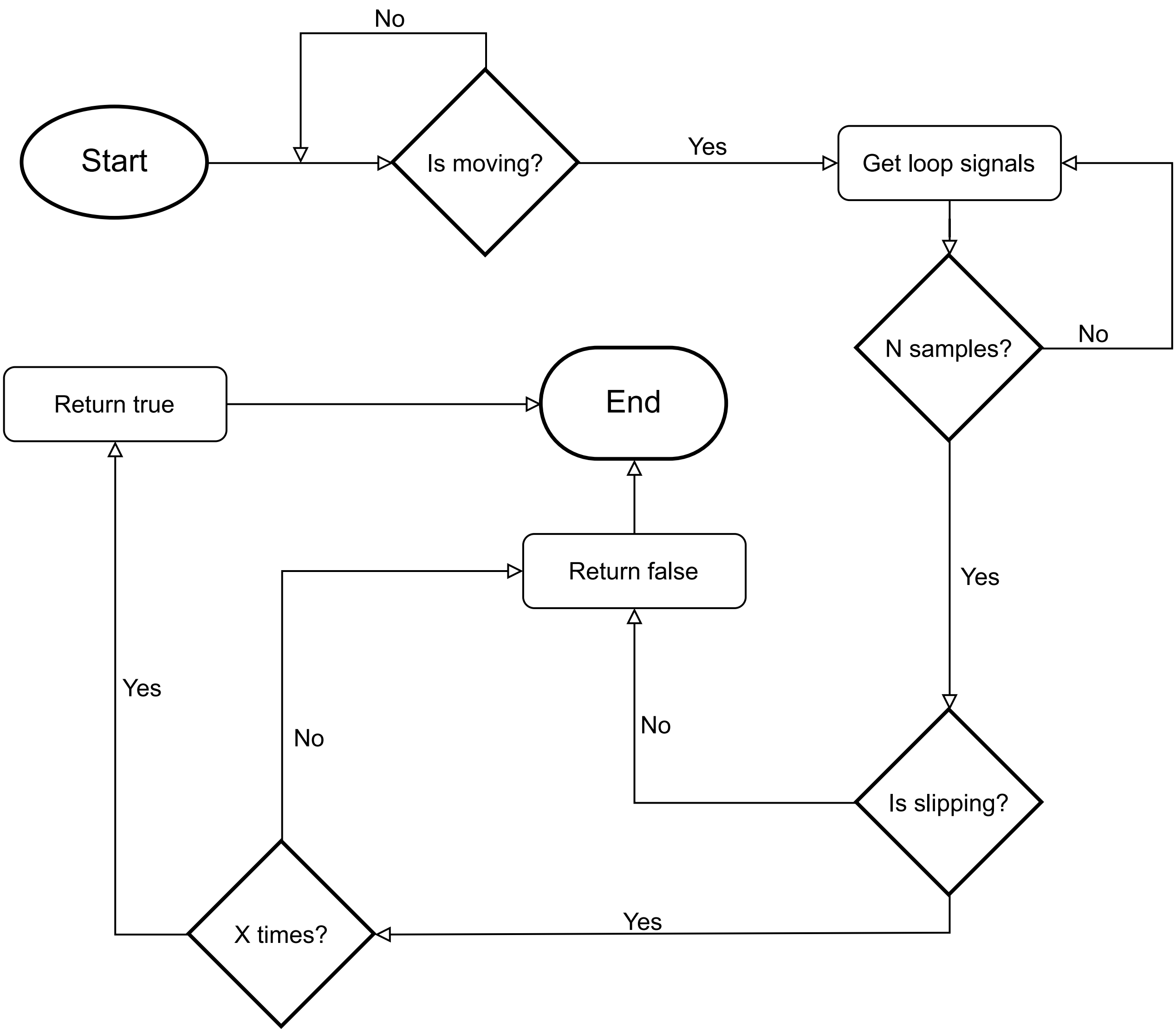

Figure 4.1: Flowchart of the implementation.

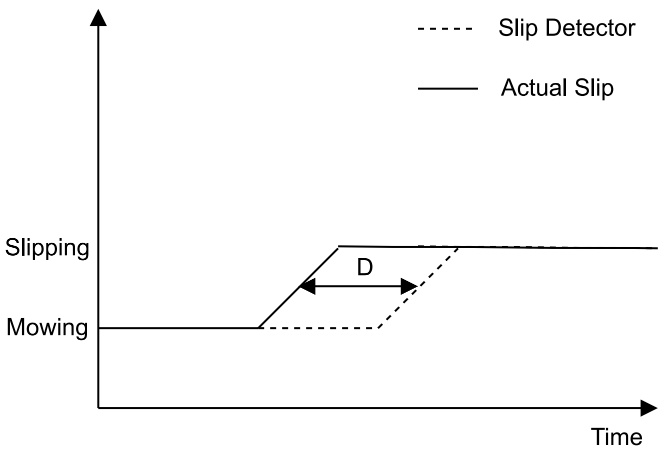

Figure 4.2: The delay between the slip detector and actual slipping.

4.2 Movement

According to Section 2.1 a check for relative motion is needed as a part of the physical slipping criteria. The first step is thus to check if the wheel speed is non-zero, this is achieved by using the wheel speed value inside a conditional statement. The motivation behind this is that during a typical slipping scenario, the wheels will spin but to no avail, as the actual mower is standing still. The non-zero speed check also covers driving backwards, as it is a negative value.

4.3 Sliding

The last physical slipping criteria according to Section 2.1 is to check if two surfaces are sliding, which occurs when there is relative motion but no general movement. The next step is thus to check if the mower actually is non-moving. This is achieved by measuring the variability in the loop sensor values over time. When the automatic mower is moving around normally, each individual loop sensor will have a greater variability compared to standing still, as witnessed in Figure 5.4.

4.4 Timing

The final step is to keep track of the time aspect, as a positive slipping event needs to occur continuously over a certain amount of time in order to become valid. Physical testing showed that the optimal duration was around 1.5 seconds, which corresponds to 15 positive variability calculations, as seen in Algorithm 1. The evaluation function is called every 100ms.

In order to prevent the mower from getting stuck in an infinity-loop of a slip event evaluating to true, a reset is needed. Inside this reset function, flag variables and counters are set to zero. This creates a cool-down corresponding to predefined duration value. A cool-down counter of 30 corresponds to 3 seconds, which is enough for the mower to initiate a responding maneuver to the slip.

5 Experimental Setup, Results, and Analysis

This chapter covers the experimental setup, the controlled experiments and their respective results and analysis. As there were several experiments conducted, the results of each individual experiment is directly analysed.

5.1 Setup

All data were collected in real-time when the lawn mower was operating autonomously inside the testing area and also when subjected to manually induced slipping. The data type of each column is numerical. The datasets which has the format of Table 3.2 contains all the required information to apply different algorithms. The processing of these algorithms were conducted using Python due to the simplicity and powerful libraries such as Matplotlib and Scikit-learn. All plots where plotted using Python expect for Figure 5.1, which was plotted using the internal developer application at the company.

5.2 Original plot

Figure 5.1 displays a linear graph of the real-time values of the four different loop sensors. Whenever the loop sensor value is negative, the lawn mower has passed the boundary wire. If only a subset of the loop sensor values are negative, it means that the remaining positive loop sensors never passed the boundary wire. This graph is always generated alongside the CSV file and foremost gives a direct visualization of the desired sensor output. It serves as a fundamental base which all other graphs are built from. In the early stages, the general behaviour of the loop sensor values where directly derived from the graph, such as variability changes and negative values. However, further processing and data extraction is required for a more detailed analysis. The x-axis represents the time with a 100 ms step, whereas the y-axis represent the loop sensor value. The values were collected in real-time using the internal application, which is covered in Section 3.2.2.

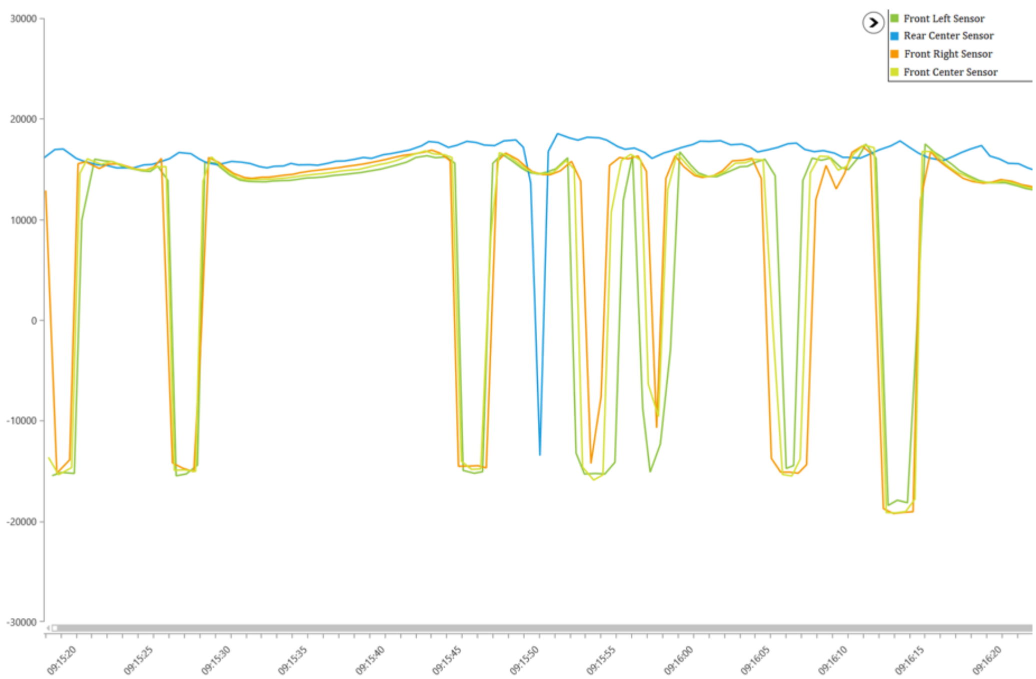

Figure 5.1: A linear plot of the loop sensor values in real-time.

5.3 Scatter Plot

Figure 5.2 shows a 3D scatter plot of the original data. A scatter plot was the first method of visualisation beyond what could be directly derived from the original graph. The goal is to differentiate between slipping and non-slipping, so it would be very desirable to achieve this directly on the basis of the formed clusters. A natural grouping of the members with a clear distinction would be visible in the visualized scatter plot. Since there were four loop sensors, dimensionality reduction was used to be able to visualize the data in 3D. PCA was the dimensionality reduction algorithm that was utilized, which is explained in Section 2.8.

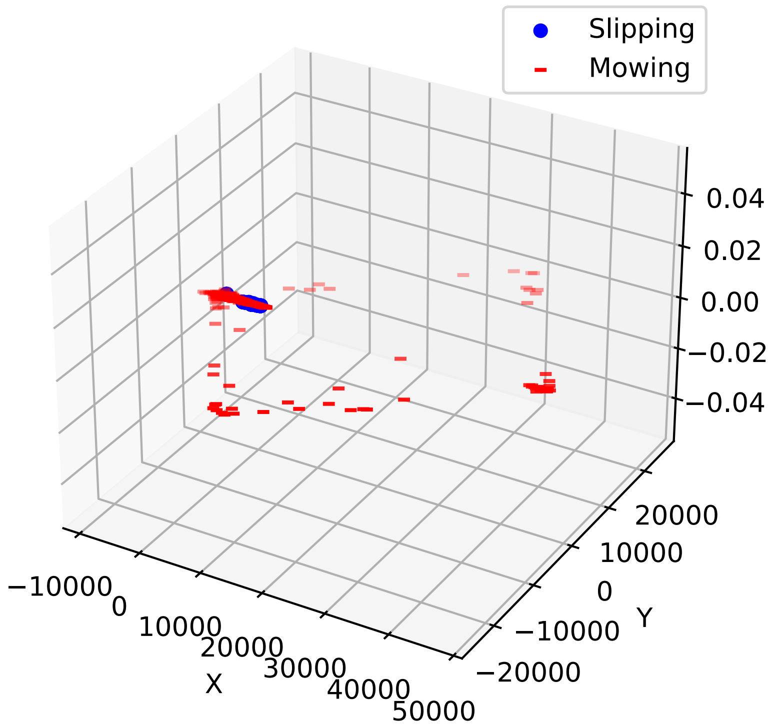

Figure 5.2: Scatter plot of slipping and non-slipping values.

In order to know if the loop sensor values were unique over a slipping period, the slipping values were plotted along with the non slipping values in a scatter plot. The data was labeled, so each class got its corresponding color. The results of the scatter plot in Figure 5.2 shows that the slipping cannot be differentiated from normal operation as the values were heavily overlapping. This means that the direct values cannot be used, leaving change over time as the only viable method of differentiation between slipping and non-slipping.

5.4 Sample Variance

Figure 5.3 displays a plot showing a sample variance of the front right loop sensor over time which is calculated using the formula explained in Section 2.5.1, where each point is the sample variance of 10 samples. Variance is the first measure of variability that was used in this thesis.

The aim of this graph is to visualize the difference between slipping and non-slipping on the basis of variance. A clear and consistent difference in the variance between slipping and non-slipping is desirable and would open up for a direct algorithmic implementation. The x-axis represents the time with a 5000 ms step, whereas the y-axis represents the variance. The blue circles represents slipping sample variance values whereas the red triangles represent the non-slipping sample variance values.

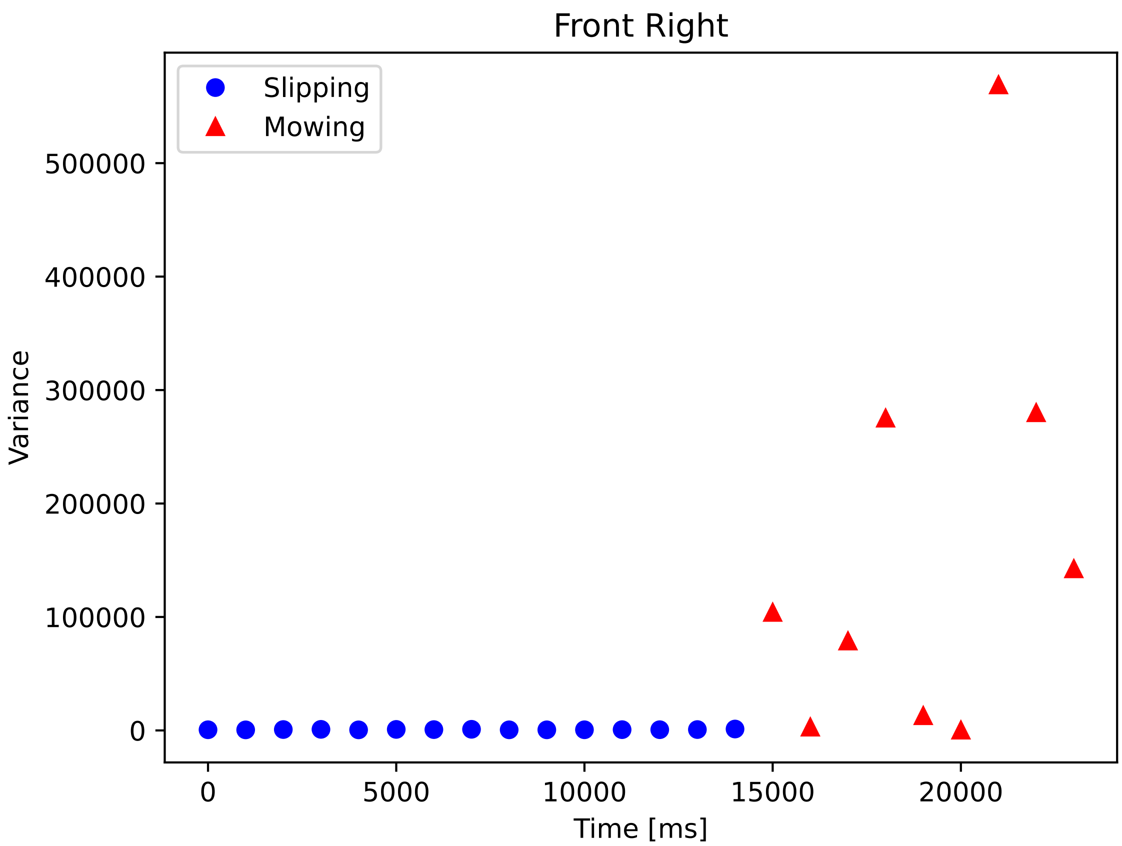

Figure 5.3: Sample variance over time, where each sample is of size 10.

While Figure 5.3 looks promising in a way that the sample variance over time undoubtedly deviates between slipping and non-slipping, it cannot be generalized due to the fact that the scale of the vertical axis is subjected to change. Loop signals can be of a different order of magnitude depending on the position of the lawn mower, which consequently translates into a higher value of the variance. The variance threshold would have to be dynamically updated according to the mowers physical position on the garden, which involves complex computations and many unknowns. Instead, range was used as the measure of variability as it is more simplistic and straightforward to implement. It also has the great benefit of having a static threshold.

5.5 Range

Figures 5.4, 5.5, 5.6 and 5.7 displays linear plots of the original loop sensor values. These graphs are not so different compared to the original plot as seen in Figure 5.1, the only difference is that each loop sensor is isolated and plotted individually. This gives a more distinct picture of how each loop sensor differs or if similar patterns are exhibited.

Range, which was the second measure of variability that was used in this thesis, can be directly applied and visually estimated for each individual loop sensor. The red regular line represents mowing values while the blue dotted line represents slipping values. The x-axis represents the time with a 5000 ms step, whereas the y-axis represents the loop sensor values.

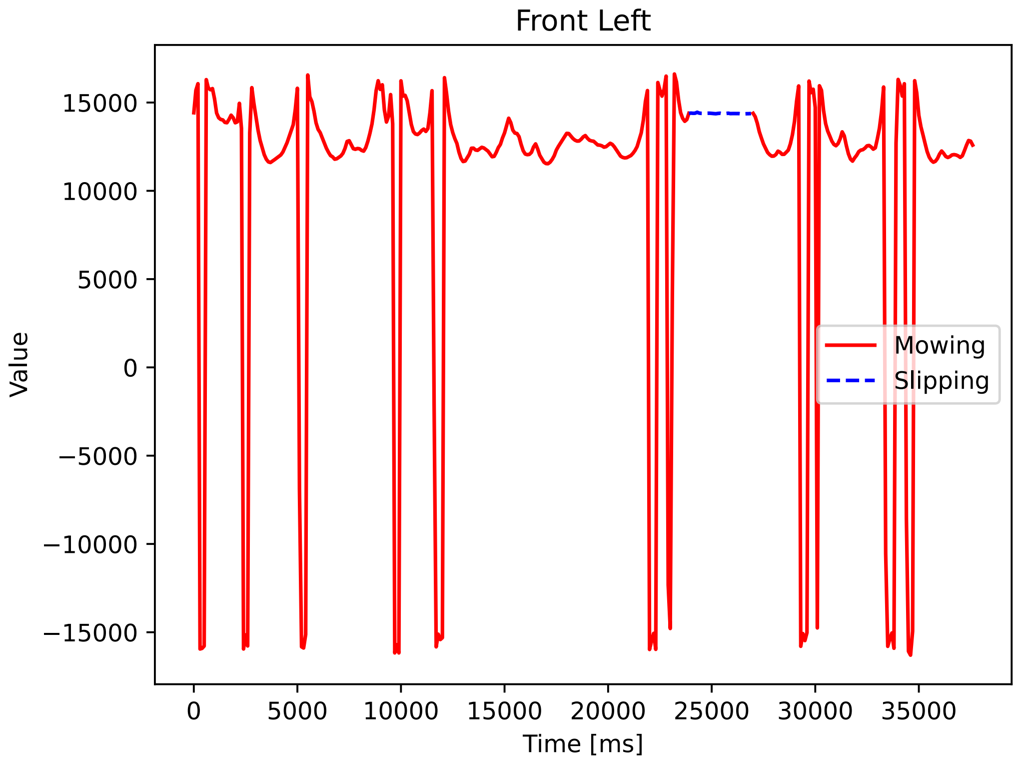

Figure 5.4: A linear plot of the loop sensor values of the front left sensor.

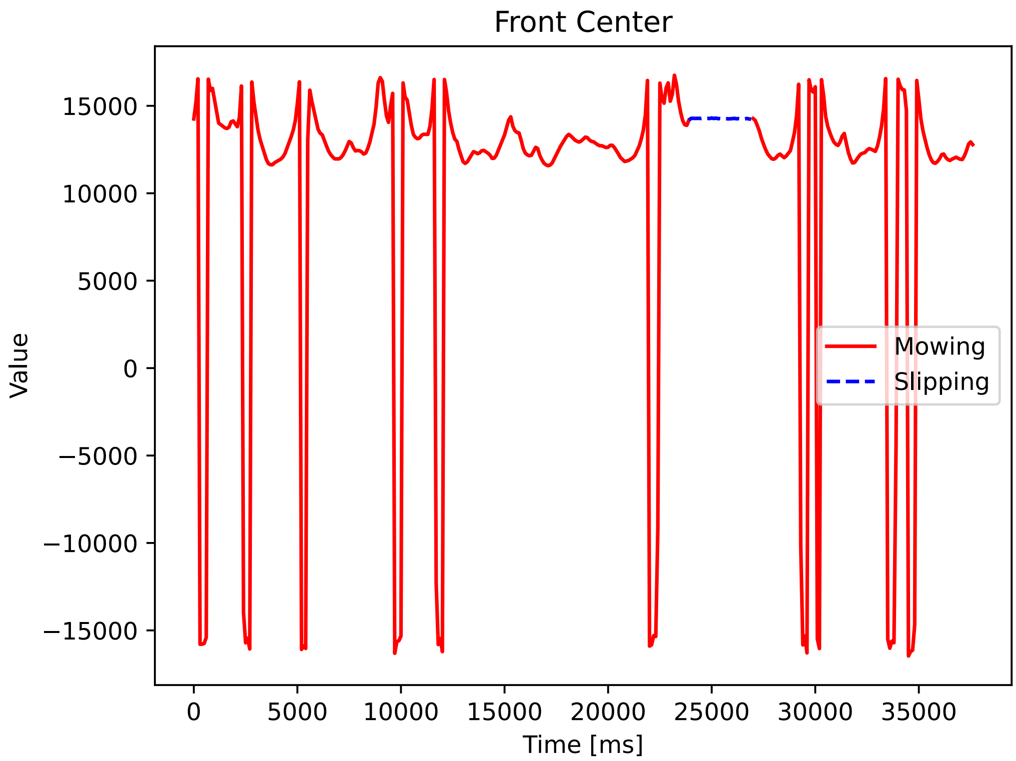

Figure 5.5: A linear plot of the loop sensor values of the front center sensor.

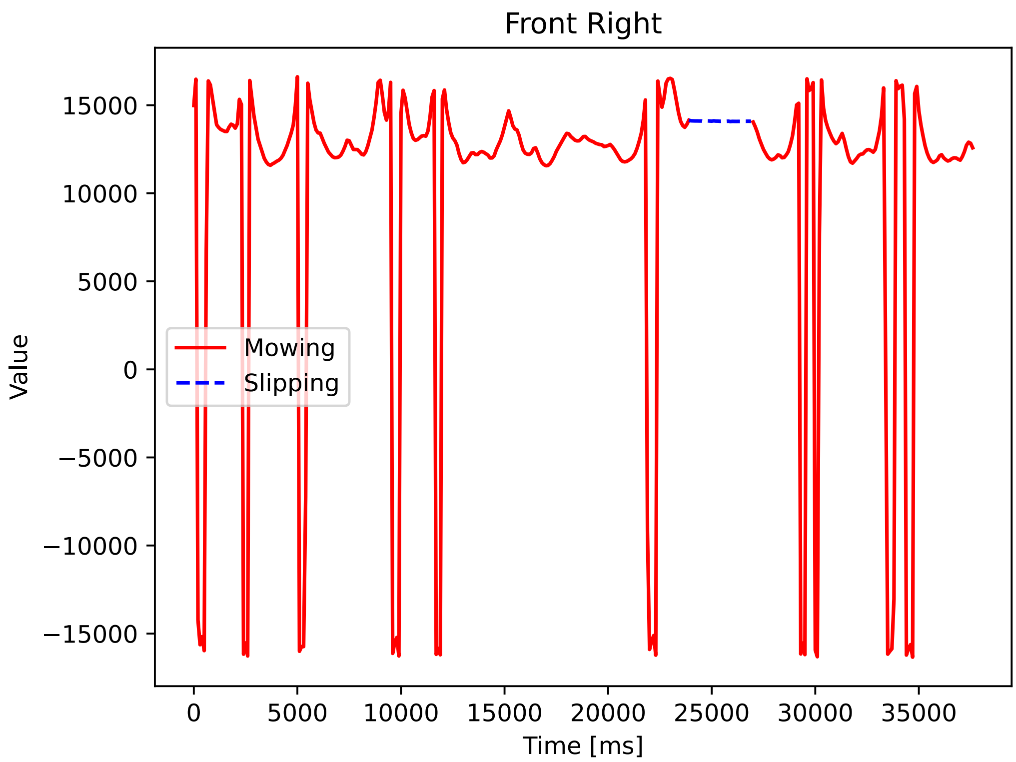

Figure 5.6: A linear plot of the loop sensor values of the front right sensor.

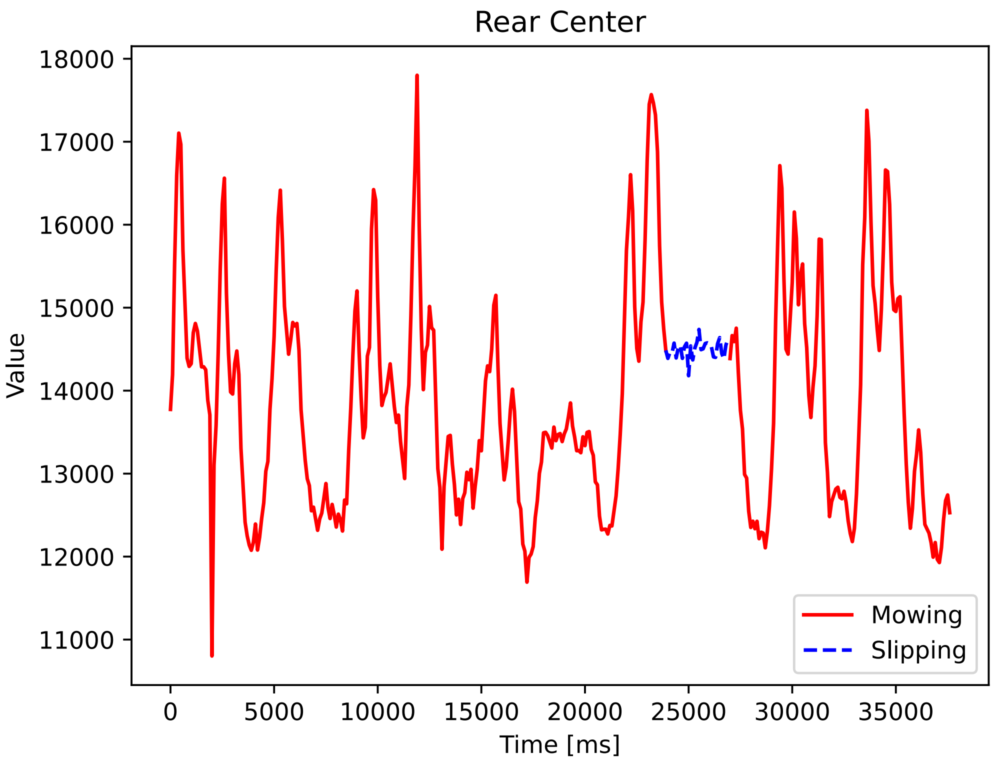

Figure 5.7: A linear plot of the loop sensor values of the rear center sensor.

The flatness of the slipping portion in Figures 5.4, 5.5 and 5.6, evidently stands out compared to the portions where the mower moves around normally. It is easy to visualize the delta of the loop signal, a flatter graph means a low and stable delta. However, the slipping portion in Figure 5.7 is less steady compared to slipping portion of the other figures. This is the reasoning why the rear center loop sensor was discarded from the final implementation. In addition to this, Table 5.2 shows that the rear sensor is a source of false predictions. The delta on the rear sensor is higher than the general threshold of 50, so to avoid having a unique threshold for the rear center loop sensor, it was removed from the prototype. The final motivation for this decision is that the absence of the rear center loop sensor showed no difference in the model accuracy, as seen in Table 5.3.

5.6 Calculating Threshold

Table 5.1 displays the average delta between the local minima and maxima for 10 continuous samples across the entire domain of each dataset. The first column in the table represents the numbers corresponding to the physical position on the garden, see Figure 5.8, where the data was collected. The other columns represent the average delta of each loop sensor, calculated on the respective dataset corresponding to each position. The size of each dataset contains at least 100 rows, which translates into at least 10 seconds of real-time data at each location. The mower was in a static position during all data collection. Using this table, a threshold for the variability can be statistically calculated. The threshold, which denotes the required range to differentiate between slip and non-slip, is used as a constant variable in the implementation.

Position	Front Left	Front Center	Front Right
0	54.78	50.1	46.97
1	50.97	44.2	56.0
2	40.8	43.47	40.76
3	34.24	33.53	32.6
4	35.53	37.26	38.88
5	45.65	54.1	58.55

Table 5.1: Table containing the average delta when the mower is non-moving at different positions.

The garden that was used to perform the controlled experiments is displayed in the Figure 5.8 below. The green outer line is the boundary wire, the yellow dotted line in the middle is the guide wire, and the black square on the bottom line is the charging station. The numbers represents the physical positions on the testing area. These are each corner and the middle, along with the middle up against the boundary wire.

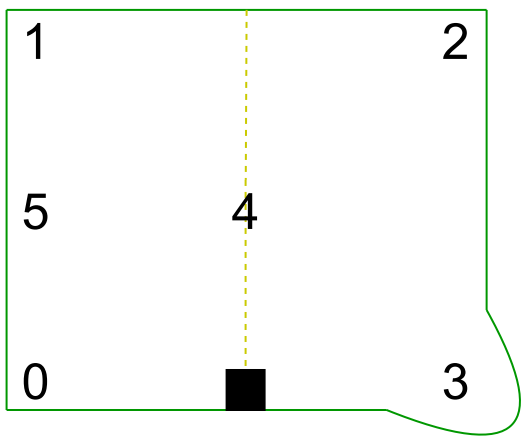

Figure 5.8: A digital visualization of the garden used in the experiments.

Table 5.1 shows that on average, the baseline delta of slipping or non-moving, is around 50. The average does not need to be below 50, as there are enough continuous samples that are well below the threshold. Outliers caused by interference covered in Section 2.4 explains why the total average climbs above the chosen threshold for some positions and loop sensors.

The threshold was statistically discovered by taking the average of the sample delta across the entire dataset where the loop sensor values corresponds to non-moving. This was repeated for different positions on the garden. Manual testing also showed that the delta reached below the set threshold for enough continuous samples that were needed to activate the slipping module.

In the digital visualization of the garden used in the experiments, see Figure 5.8, the positions for collecting data in real-time are numerically represented. The positions were foremost chosen to maximize the positional variability. In addition to this, some positions close to the boundary wire are also experiencing a greater interference due to the close proximity to the boundary wire. It is important to note that the orientation of the mower directly affects the electromagnetic sensor readings to some extent, as the individual sensors are placed at different positions on the mower. If the right side of the mower is facing the boundary loop, the right loop sensor will experience a higher magnetic magnitude and more interference compared to the left sensor. The position in the middle of the lawn (4) is inherently more stable, as seen in Table 5.1. This is explained by the simple fact that each loop sensor is far away from the boundary loop. This concludes the motivation behind choosing respective positions.

5.7 Evaluation Results

Table 5.2 displays a sample of the evaluation data where all four loop sensors are included, as well as the speed. The simulated model follows the same algorithmic implementation explained in Algorithm 1 and the computing environment is Python. In the final implementation, the rear center loop sensor is discarded. A model which contains the discarded loop sensor along with the same general variability threshold, would perform badly as seen in the contrast between the slip label and the predicted label by the model.

Negative speed represents the mower driving backwards and positive speed represents the mower driving forward. The first four columns represent the different values for each loop sensor, the column *Slip* represents if the mower is slipping and the column *Prediction* represents the predicted value, either slip (1) or non-slip (0).

Front Left	Front Center	Front Right	Rear Center	Speed	Slip	Prediction
34	38	39	392	−250	1	0
30	38	39	401	−250	1	0
30	48	39	558	−250	1	0
30	48	39	558	−250	1	0
30	48	39	558	−250	1	0
30	48	32	558	−250	1	0
31	53	32	558	−250	1	0
31	53	40	558	−250	1	0
31	47	40	368	−250	1	0
31	47	30	368	−250	1	0
25	31	30	331	−250	1	0
25	31	30	337	−250	1	0
37	31	30	337	−250	1	0
37	31	30	238	−250	1	0
37	31	23	238	−250	1	0
37	31	23	256	−250	1	0
18	36	19	256	250	1	0
18	44	14	256	250	1	0

Table 5.2: Table containing a sample of the evaluation data where all loop sensors are included. The faulty predictions are intentionally showcased.

Table 5.3 below displays the accuracy score explained in Section 2.7.1 for three different datasets, where each dataset consist of normal operation and slipping. The first two tests only had a binary split between the slip and non-slip portion, whereas the third test had two slipping portions in-between normal operation. The average accuracy score is 0.930, which can be derived from the table below.

Test	Total Samples	Correct Predictions	Accuracy Score
1	368	353	0.959
2	176	166	0.943
3	293	268	0.890

Table 5.3: Table containing the accuracy for three different datasets.

Table 5.4 below displays the TP, FP, TN, FN, the calculated precision and recall, explained in Section 2.7.2, but also F1 Score and average precision for three different datasets. The same datasets as in Table 5.3 where used for respective test.

Test	TP	FP	TN	FN	Precision	Recall	F1	AP
1	16	15	337	0	0.516	1.0	0.680	0.50
2	8	9	158	1	0.470	0.89	0.615	0.47
3	13	32	248	0	0.289	1.0	0.448	0.40

Table 5.4: Table containing the precision and recall for three different datasets.

Figure 5.9 below shows the precision-recall curve for the dataset with test number 1.

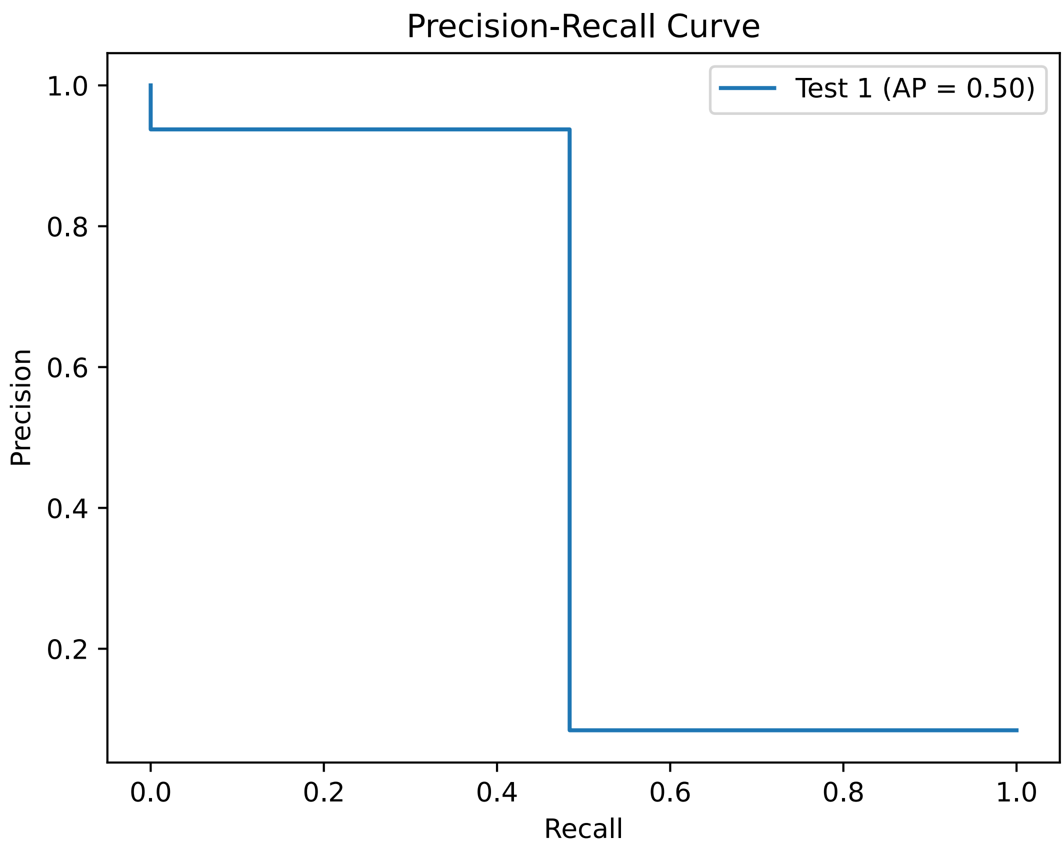

Figure 5.9: Precision-Recall Curve.

The evaluation of the slip detector using classification accuracy as the metric showed that the average accuracy score was 0.930, as seen in Table 5.3. An accuracy above 90% means that at least 9/10 slip identifications are correct, the slip detector is doing a great job at first glance. However, this metric alone is misleading if the dataset is class-imbalanced, meaning there is a significant disparity between the number of positive and negative labels. Another slip module that always detects slip would achieve the exact same accuracy if the class ratio of slip was equal to the accuracy, which means that the slip detector is no better than one that has zero predictive ability to distinguish non-slip from slip. A closer analysis using the improved metric explained in Section 2.7.2 reveals that the highest precision in the conducted tests are 0.516 and the recall is 1.0 for two datasets and 0.89 for another one, as seen in Table 5.4. The skewed scores for some tests can be explained by the factors covered in Section 3.3.1.

5.8 Algorithmic Implementation

The final algorithmic implementation can be seen in Algorithm 1. Ultimately, the results in Section 5.5 showed that the delta between the local minima and maxima in a subset of samples over time were the best candidate for the utilization of the loop sensors as slip detection. The final implementation thus implements a conditional sample range check which forms the basis of the slipping criteria, as seen in Figure 4.1.

In order to find the sample range or the delta between the local minima and maxima over time, N samples must first be retrieved. The the next step is to replace the oldest loop signal sample with a new one and calculate the local minima and maxima of the N latest samples. Using the local minima and maxima, the delta is calculated and checked if it is below the specified threshold, which could be derived from Table 5.1. If the delta has been below the threshold X times in a row, the function will return true, which means slip, otherwise, it will return false, non-slip.

Together with the threshold, there are some other constant variables defined before the slip evaluation procedure. These include the cool-down counter and the number of slip, along with the number of samples. The first two constants are explained in Section 4.4, whereas the motivation behind the number of slip is briefly covered in Section 5.6. The procedure contains all the necessary logic required for the general implementation, as shown in Figure 4.1, while rows 17-24 encapsulates the slipping criteria based on the loop sensor values, in pseudocode.

Algorithm 1 Evaluate Slip

```
NumberOfSamples ← 10
NumberOfSlips ← 15
Threshold ← 50
CoolDown ← 30
procedure EVALUATESLIP()
if CooldownCounter < CoolDown then
    CooldownCounder ← CooldownCounter + 1
end if
if CooldownCounter >= CoolDown then
    Slip ← False
    if Speed ≠ 0 then
        Loopsignals ← RetrieveLoopSignals
        ArrayIndexCounter ← ArrayIndexCounter + 1
        if ArrayIndexCounter >= NumberOfSamples then
            Shift all values to the left of the array and add a new value at index N-1
        end if
        Maxima ← Find maxima in array
        Minima ← Find minima in array
        Delta ← Maxima − Minima
        if Delta <= Threshold then
            Slipcounter ← Slipcounter + 1
        else
            Slipcounter ← 0
        end if
        if Slipcounter >= NumberOfSlips then
            Slip ← True
            Slipcounter ← 0
            CooldownCounter ← 0
        else
            Slip ← False
        end if
    end if
end if
return Slip
end procedure
```

6 Discussion

In comparison to the wheel motor current, the final implemented slip detector based on the loop signals could reliably detect slip indoors when slip was manually simulated. The already existing slip detector that was based on the wheel motor current could not be triggered manually in a reliable manner. This means that the implemented prototype outperforms the existing solution in the intended environment of indoor testing.

In the article [5] the authors A.S. Belyaev, O.A. Brylev and E.A. Ivanov concluded that even when the robots wheels were placed on highly differing surfaces, the difference between the wheels' currents were small. Using a slip detector based on the loop signal values, the underlying surface does not matter, which makes the solution more general in terms of surfaces.

During the development of the slip module and the analysis of the collected data, several different variability algorithms were tested. The derivative of each loop sensor value was plotted in a linear graph with different colors corresponding to slip and non-slip. The results was that there was no clear distinction. Others methods that succumbed to the same fate as the derivative were the difference between the previous and current loop sensor value, along with the delta between each combination of loop sensor pairs. Please refer to Appendix A for the graphs of these discarded measurements.

The lawn used in order to carry out the controlled experiments had several adjacent lawns, that had their own boundary wire. As explained in Section 2.4, the bordering lawns also generated their own magnetic field. As a result, this may have affected the values of the four loop sensors and thus the data collection. But the greatest source of errors of type I (false positives) and II (false negatives) where rooted in the human factor during data collection, as mentioned in Section 3.3.1.

The analysis of the results shows that accuracy score is on the higher end of the scale, which is desirable. Further inspection of the other metrics reveals that the model achieved a perfect recall score of 1.0 for two datasets and a lower precision score of 0.289 for the third dataset. This means that the model is good at classifying if the mower is actually non-moving. On the contrary, the score of precision was underwhelming, as having a precision below 0.5 means that slip is only predicted correct less than 50% of the time, which is not ideal. But less weight should be put on the precision as slip labels are not placed without fault. The delay mentioned in Figure 4.2 also adds further false labeling during the data processing phase. Finally, the F1 scores of 0.608 and 0.615 for the first two datasets means that both the precision and recall are above average. The last dataset is more unstable as there are two shorter slip portions among normal operation, instead of one clear and longer slip. The scores involved for the last dataset should thus be considered as more imprecise.

While these metrics gives a direct insight into the model performance of detecting slip and non-slip on paper, the general behaviour of a slip detection module does not fully resemble a classic binary classifier. The reason behind this is that only one initial slip needs to be detected, and after that any further classifications does not matter within the cool-down period. In addition to this, the delay showcased in Figure 4.2 means that the slip detector will always lag behind the actual slipping. This non-direct feedback is not compensated for during the data collection, further reinforcing the reason to not just analyze the numbers.

In other words, the evaluation scores cannot be directly translated into a fair model measurement, even if the sources of errors are minimized to the maximum. In the end, it is the physical testing that stands for the true evaluation.

7 Conclusion

The purpose of this thesis was to investigate if it is possible to implement a slip detector mainly based on electromagnetic sensors and compare the solution to an already existing solution.

This project has shown that it is possible to build a reliable slip detector that is mainly based on the loop signals. The results are definitely relevant for the company Husqvarna AB, as they wanted to investigate an alternative to their already existing solution, the wheel motor current. The generality of the solution is however limited to a specific lawn size indoors. No outdoor testing or testing on larger areas were conducted. As this thesis was constrained to a specific time window, there was not enough time to look into a broader use-case.

Other autonomous robots that runs on wheels and uses a boundary loop for navigation can greatly benefit from a slip detector based on the loop sensor signals. Even when the performance on larger areas remains uncharted, the development of slip response maneuvers can be easily tested physically on a robotic lawn mower, instead of having to rely on commands. This is an added benefit to the new slip detection alternative of loop based slip detection, which certainly challenges the existing solutions.

Some things could have been done differently to possibly get better results. One thing is to automate the data collection and remove the process of manual insertion of slip duration in the CSV files. This would reduce the errors in the data collection caused by the human factor and increase the reliability. Another thing that could have been done differently from the beginning, is to use a larger lawn for the data collection and the experiments from the start. This would help make the solution more general in terms of the size of the lawn, and also give insight into how the loop sensor values respond to a dynamically changing lawn size.

The validity can also be further improved by creating a simulation environment that more closely resembles the real world. The existing simulation tools at the company were at most only used as a check for code validity. The simulated loop sensor input were too perfect for the model, resulting in zero variability. An improved simulation environment would allow automated test cases and would rapidly build a large foundation for statistical analysis.

A method of comparison between different slip detector modules were devised. The method consisted of controlled tests indoors where slip was manually generated and the effects quantitatively measured. The automatic mower was allowed to operate freely and at fixed locations shown in Figure 5.8, the mower was subjected to slipping. The immediate results of the slip trigger was visualized using the internal developer application, as seen in the last figure at Appendix A.

7.1 Future work

A promising continuation of this project would have been to investigate all other available sensor options along with extended hardware monitoring except for the wheel motor current. The most optimal solution could then be investigated and extensive testing could make sure that it outperforms the presented prototype and the current solutions at the company.

This thesis only focused on finding a solution based on the loop sensors along with the wheel speed. Further additions of several sensors in conjunction with the main loop sensors may grant a more favorable end-result, or by replacing them entirely and ending the prospects of a solution mainly based on the loop sensors.

It would also be interesting to investigate the generality of the solution, by testing on larger lawns outdoors and emulate a real slipping situation instead of manually lifting the automatic mower. Another promising possibility is to reduce the number of required loop sensors in the loop based slip detection module. The rear center loop sensor could be removed without side effects and the remaining loop sensors showed a remarkable similarity.

This potentially means that only two loop sensors positioned symmetrically or just one loop sensor positioned in a central position, could be enough to satisfy the logical conditions in the implementation. If such an approach reduces the performance or not remains to be seen.

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A Appendix 1

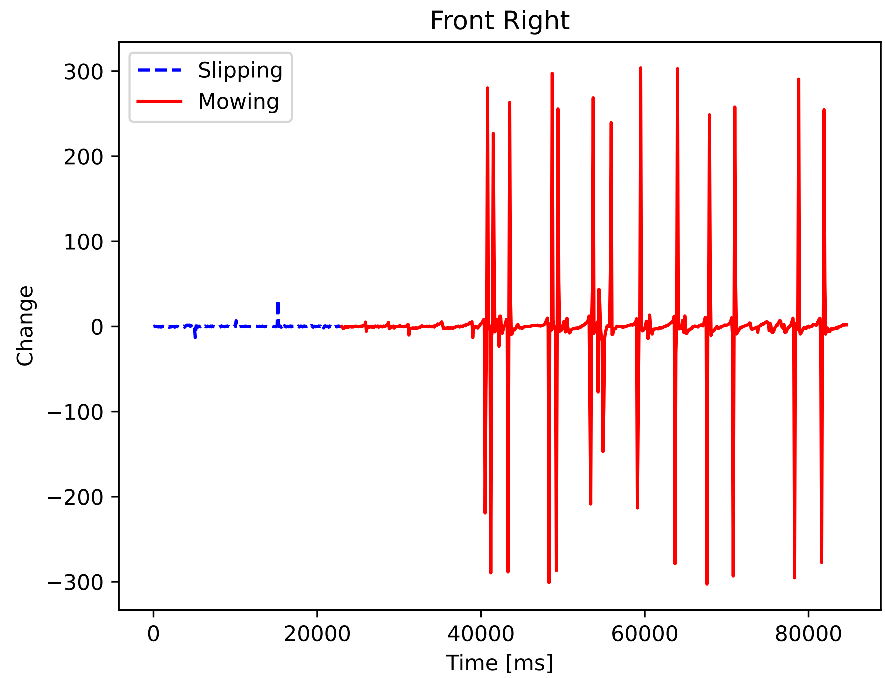

Figure A.1: Result of plotting the derivative for the front right loop sensor.

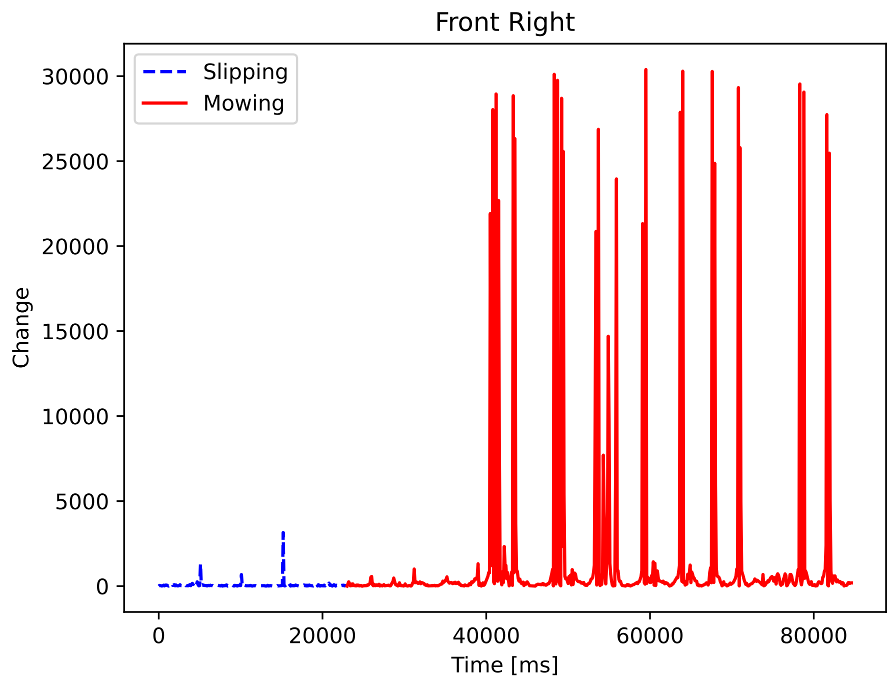

Figure A.2: The result of plotting the delta between the current and previous value in the front right loop sensor. A predecessor to the final implementation.

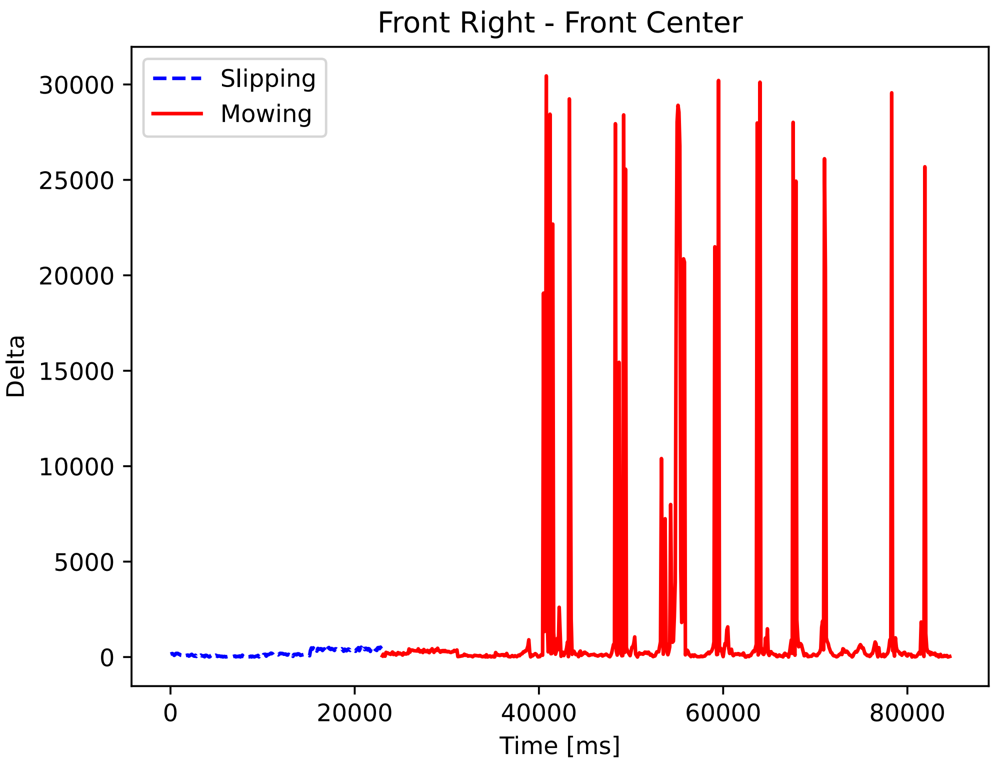

Figure A.3: The result of plotting the delta between the front right and front center loop sensor. There were six pairs in total, only one combination is shown here.

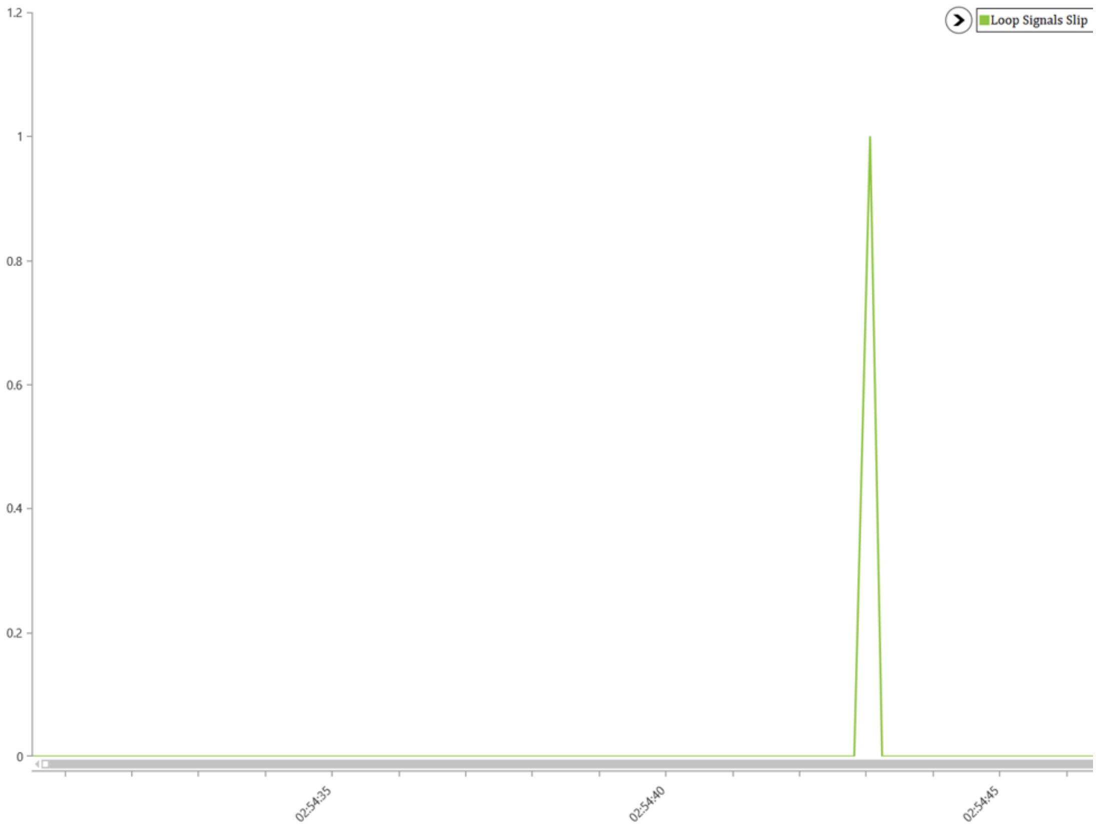

Figure A.4: Internal developer application graph of the triggered slip while using the loop sensor based slip detection module.