JÖNKÖPING UNIVERSITY
School of Engineering

Detection of motor skidding in autonomous lawn mowers

Detection of skidding in autonomous lawn mower using machine learning technique MLP with wheel motor currents and IMU.

PAPER WITHIN *Computer science*

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Abstract

Purpose – The purpose of the thesis is to evaluate the accuracy of two different approaches of how to detect skidding in autonomous lawn mowers. Using the motor currents and inertia sensors from the mower, a neural network is applied to predict if there was a skidding or not. The usefulness of knowing when a skid happens could be of value for future developments making better autonomous decision making.

Method – The thesis will adopt the methodology process of Design Science Research (DSR). The study begins with bringing awareness of the problem by previous knowledge and related works to skidding in wheeled robots. Thereafter an experiment is set up to generate data when the autonomous lawn mower is in conditions of skidding and non-skidding. The data collected will be processed with machine learning algorithm, multilayer perceptron.

Findings – The findings showed high accuracies in both techniques where adding an IMU sensor in addition to motor currents showed higher accuracy then only using motor currents. Both techniques showed low number of false detections and near zero missed detections which is a preferred feature, the behavior of the autonomous lawn mower benefits more from a false detection than not detecting any at all and get stuck.

Implications – The autonomous lawn mowers of today have a tendency of failing in the yard due to skidding in uneven or slippery terrain. The robot either reacts by assuming a collision has happened or gets no traction and gets stuck. A first step to solve this problem is by detecting such a skid to then be able to take action.

Limitations – The results will be limited to the autonomous lawn mower of Globe Group as the data collection is made with an autonomous lawn mower of Globe Group. The mower will run on a flat outdoor grass lawn to maintain the experiment on a reasonable level for a bachelor thesis.

Keywords – robot, autonomous, lawn mower, machine learning, detection, skidding

Contents

1 Introduction

1.1 Background

Skidding is a reoccurring problem in all wheel-driven vehicles, from electrical cars, trains, to Nasa's land rovers and there are different methods to detect these [1] – [8].

One common method to detect skidding is by reading motors' built-in encoders or wheel motor current [1], [2]. Another method is to use GPS-data to detect if the wheel-driven vehicle is slowing down compared to the velocity of the wheels [3], [4], [5].

Machine learning is used more frequently for wheel-driven vehicles, e.g. vision-handling [6] and immobilization detection [7]. In recent studies machine learning have been used to detect skidding and immobilization of robots, among them autonomous robots [9], [10] and a mars land rover [11].

In this bachelor thesis, two approaches to detect skidding will be implemented on an autonomous lawn mower. First, only the wheel motor currents will be processed with machine learning algorithm, Multilayer Perceptron (MLP). Second, sensor values from a built-in Inertial Measurement Unit (IMU) will be added and compared if the detection of skidding is improved.

The autonomous lawn mowers of today have a tendency of failing in the yard due to skidding in uneven or slippery terrain. The robot either reacts by assuming a collision has happened or gets no traction and gets stuck. A first step to solve this problem is by detecting such a skid to then be able to take action.

1.2 Purpose and research questions

The purpose of the thesis is to evaluate the accuracy of two different approaches of how to detect skidding in autonomous lawn mowers. Using the motor currents and inertia sensors from the mower, a neural network is applied to predict if there was a skidding or not. The usefulness of knowing when a skid happens could be of value for future developments of better autonomous decision making as well as extending the quality and lifetime of the autonomous lawn mower.

The first research question is as follows:

1. What accuracy of percentage in prediction can be achieved when using MLP with motor currents to detect skidding in autonomous lawn mowers?

The second research question is a follow-up to see how adding another sensor data affects the results in a positive or negative way, or if there is no significant difference. For this study, IMU data is added and the question is as follows:

2. How much is the detection of skidding affected in percentage when adding IMU readings?

1.3 Delimitations

The autonomous lawn mower can skid in an endless amount of ways and this study will not account all the endless ways of skidding. The mower will conduct on a flat outdoor grass lawn to maintain the experiment on a reasonable level for a bachelor thesis. The results will be limited to the autonomous lawn mower of Globe Group as the data collection is made with an autonomous lawn mower of Globe Group. The study will not involve other methods of machine learning but only focus on MLP. The study will not develop new methods but implement a known method for another application.

1.4 Outline

The report is organized in chapters in which chapter 1 and 2 provides background knowledge and purpose of the study. Chapter 3 describes the method and implementation of the study. The findings and analysis are shown in chapter 4, followed by discussions in chapter 5.

2 Theoretical background

2.1 Neural networks

An artificial neural network (ANN) is a model of connected neurons, much like the network of neurons in a biological brain. The neural network was designed with inspiration from the biological brain and is capable of learning patterns to solve less to more complex problems than a logic circuit can handle [12].

2.1.1 Multilayer perceptron (MLP)

A network consists of several neurons in three main layers. An input layer, a hidden layer and an output layer. As shown in figure 1, a network is often depicted with the input layer to the left, this is where all the input data goes. The input is then forwarded to the next layer, the hidden layers. The hidden layers is a group name for all layers in between the input layer and output layer which can be one to many, this is where all the computations happen.

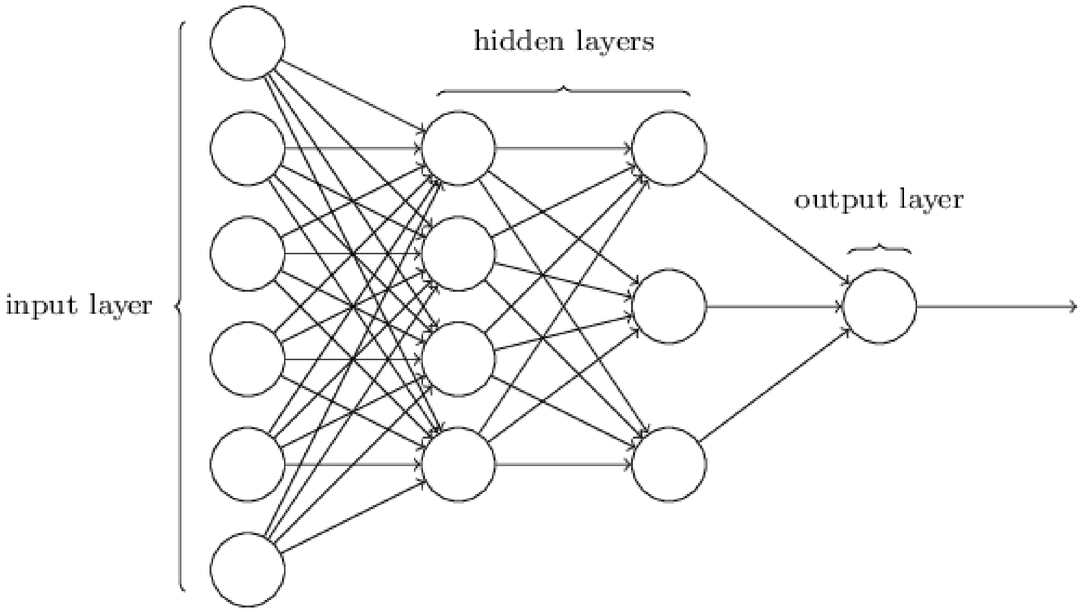

Figure 1. Representation of a neural network [12]

An MLP network is fully connected, which means that each neuron in one layer is connected to all neurons in the next layer and each connection has an assigned weight (*w*) value to itself which the signal (*x*) is multiplied with. These weights can be adjusted in the training process. A bias (*b*) is added to make sure the output will always be more than zero (0). The calculation is passed through an activation function (*f*) as explained in section 2.1.2. The new output of the neuron (*y*) is shown in the equation below:

$$y = f\left(b + \sum_{n=1}^{N} x_j w_j\right)$$

2.1.2 Activation function

The activation function is the last calculation in a neuron before becoming an output. There are many activation functions existing and which one you choose can depend on the objective, but traditionally the logistic sigmoid function (figure 2.) was the default function in neural networks. The logistic sigmoid function converts the input to a value between 0 and 1. In the late 1990's the shifted and scaled sigmoid function, hyperbolic tangent (TanH) which range between -1 and 1 (figure 3.), proved to have better predictive performance than the logistic sigmoid and became the preferred activation function [13].

In [13], Goodfellow explains the problems faced with the sigmoid functions and how the rectified linear unit (ReLU) function (figure 4.), because of its mathematical simplicity and fast computation, is becoming the new default activation function in modern neural networks.

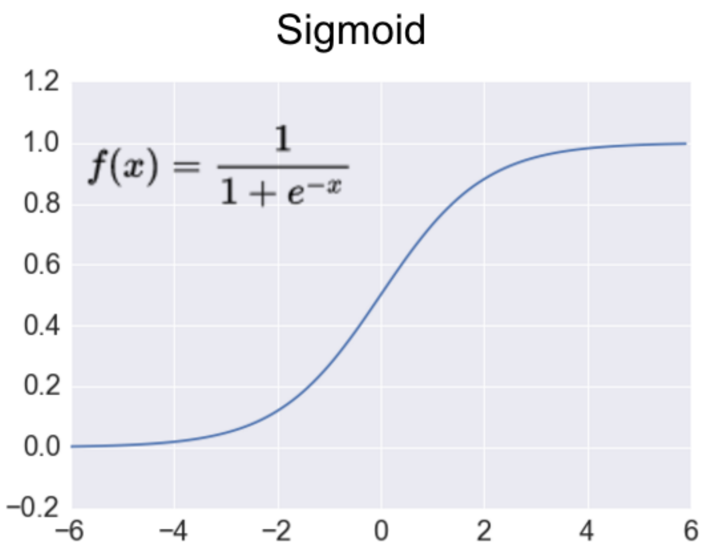

Figure 2. Graph of a logistic sigmoid function
Source: Adapted from [14]

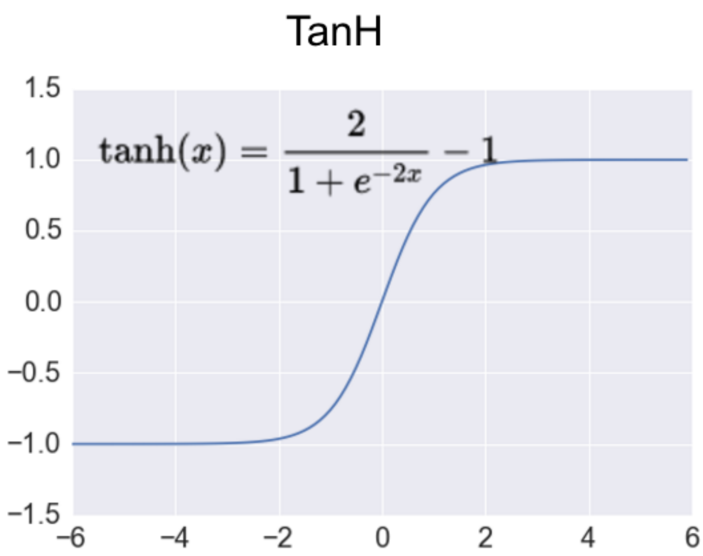

Figure 3. Graph of a hyperbolic tangent function
Source: Adapted from [14]

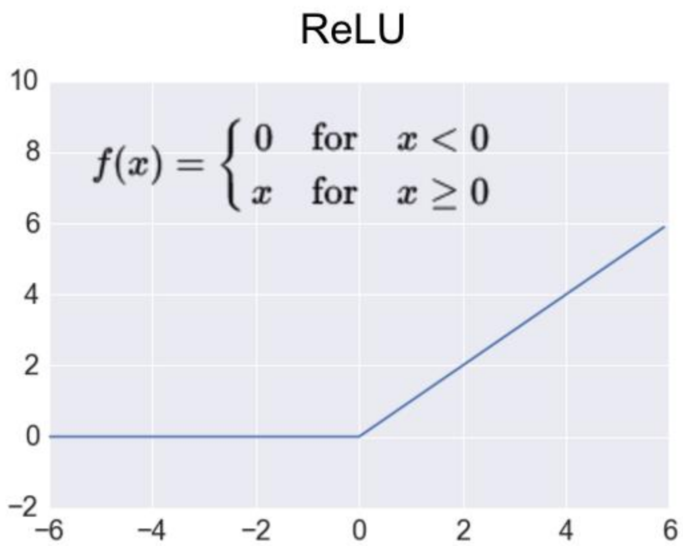

Figure 4. Graph of ReLU function
Source: Adapted from [14]

2.1.3 Learning

Like a human brain, the ANN needs to learn what is right and wrong. This is done by providing training data to the network. This study conducts supervised learning, which means that the ANN is provided the correct answer to each training data. Like a human brain, practice makes perfect. Each time the network is exposed to a training data the neurons in the network adjusts the weights and bias to achieve a more accurate prediction. Higher amount of training examples gives better performance and predictions. The network is then exposed to a set of test data. The test data is separate from the training data and is used to confirm the accuracy of the network.

2.2 Related works

A master thesis written by Norin [15] discusses the purpose of analyzing alternative methods of detecting external forces on an automatic lawn mower using different methods of control engineering. Norin [15] uses motor currents and IMU sensor data in his calculations. Bertilsson [16] made a similar bachelor thesis focusing on collision detection using machine learning methods MLP and KNN (K-nearest neighbor) with a Globe Group automatic lawn mower. [16] investigates if wheel motor currents and machine learning can be used as an alternative method to detect collisions and findings show 100% accuracy. On the basis of [15] and [16] this study will explore if MLP is also suitable for skidding detection and additionally analyzing if IMU data will improve detection.

3 Method and implementation

This section describes the methodology and experiment design of the thesis.

3.1 Design Science Research

This thesis will adopt the process of Design Science Research (DSR) method proposed by Vaishnavi et. al. in their article *Design Science Research in Information Systems* [17]. Figure 5 illustrates a typical DSR cycle process:

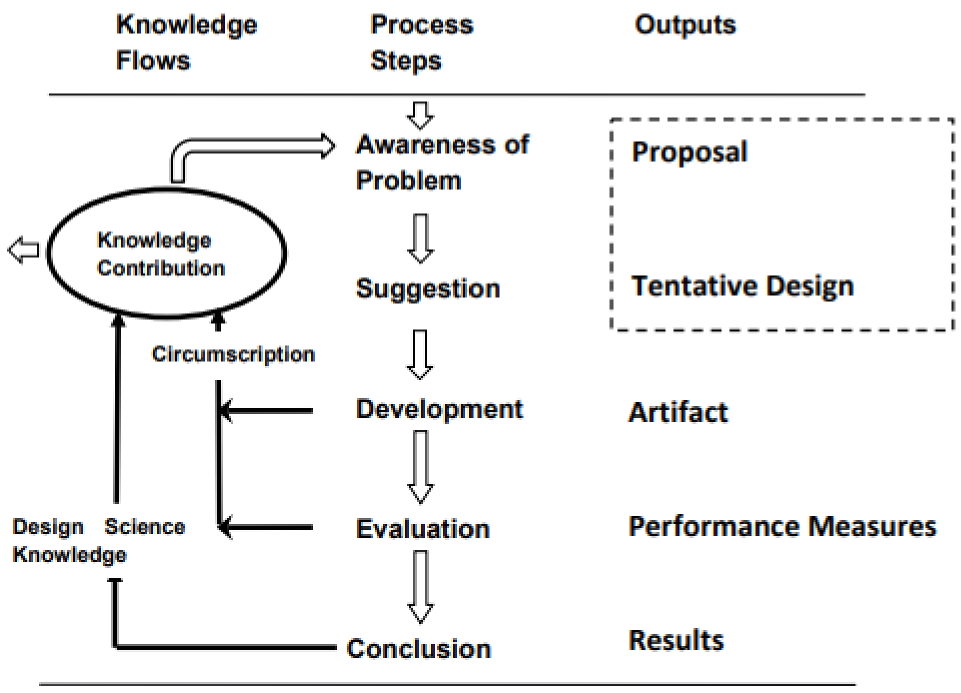

Figure 5. Design Science Research Process Model (DSR Cycle) [17]

Awareness of problem:

This phase identifies a problem and enlightens the issue that is needed of evaluation. The output is a Proposal for a new research. In this thesis, a study of related works were taken as basis into forming the new proposal.

Suggestion:

After identifying a problem and developing a proposal the process to create a solution starts. In the suggestion phase the goal is to theorize a Tentative Design which together with the Proposal will decide if the research is possible.

Development:

Implementation and development of the Tentative Design. An Artifact is created. The artifacts in this thesis are the machine learning MLP models created for evaluation.

Evaluation:

This is an analytic phase where you evaluate the artifact created from development with reference to the criteria made in the Proposal. The artifacts in this study are evaluated by conducting experiments which are then analyzed in chapter 4.

Conclusion:

The conclusion sums up the results and clarifies the knowledge gained from the research.

In Design Science Research the research process is made in cycles. Which means that the knowledge made in previous researches are used to make new research efforts, restarting the Design Science Research as shown in figure 5, by the original researcher themselves or by any other researchers.

3.2 Experiment design

An experiment is set up to generate data when the autonomous lawn mower is in conditions of skidding and non-skidding. The data collected from the mower is provided as shown in section 3.2.3.

To answer the first research question, the MLP model is developed in the programming language Python using the open source library Keras [18]. As referenced in section 2.1.3, the MLP network is provided with training data of motor currents collected from the experiment and then validated with the test data. In chapter 4 the findings are presented and analyzed.

The second research question is answered by training a new MLP network with the same training data with addition to IMU data and then compared and analyzed with first questions' result.

3.2.1 Equipment

An autonomous lawn mower provided by Globe Group was used to gather data. The mower was reprogrammed to output its motor current and IMU readings with a frequency of 20 Hz. An Arduino unit was used to read the output and save it to a memory SD-card.

An IMU (Inertial Measurement Unit) is a device combining sensors of accelerometer, gyroscope and magnetometer.

3.2.2 Software

TensorFlow

TensorFlow is an open-source library for machine learning developed by Google [19].

Keras

Keras is an open-source neural network library written in Python and used as a high-level interface to make it easy developing deep learning models. Keras is usable with several frameworks including TensorFlow [18].

3.2.3 Data

Table 1. Signals outputted from the automatic lawn mower

Signal	*Description*
Motor currents	*Measured motor currents from the two rear left and right wheels.*
Vertical G-force	*The vertical acceleration in g.*
Roll	*Measured in degrees from x-axis.*
Pitch	*Measured in degrees from y-axis.*
Angular velocities	*Angular velocities of x, y and z measured in rad/sec.*

The signals from table 1 are outputted simultaneously with a frequency of 20 Hz. Each output is accompanied by a Boolean flag indicating if the condition is a skid or non-skid. The gathered data is filtered from noise and divided into two thirds of training data and one third of test data. Test data is used to validate and evaluate the network's performance after the training session.

4 Findings and analysis

4.1 Experiment 1 – Motor currents

The graph below (figure 6.) shows the collected data from the experiment of 3045 data points where a third is divided into test data, resulting in 2218 training data points and 827 test data points. The orange represents non-skidding data points and blue represents skidding data points.

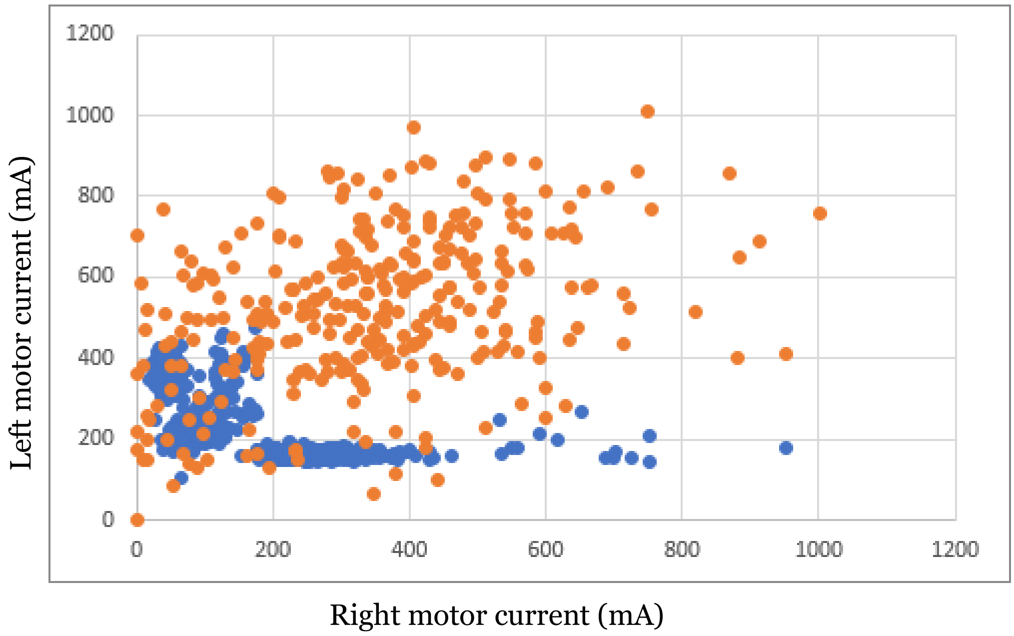

Figure 6. Graph representing collected data of motor currents. Orange represents non-skidding and blue represents skidding.

After optimizing the model an average was taken out of 10 training and testing sessions. The tables below show the accuracy of the model, amount of correct predictions and amount of incorrect predictions. The two last columns show the amount of false detections (predicted 1 when true is 0) and missed detections (predicted 0 when true is 1) from the incorrect predictions. The averaged results of using only motor currents is shown in table 2. The averaged results of using motor current and IMU is shown in table 3.

Table 2. Averaged results with motor only

Data type	Accuracy	Correct	Incorrect	False	Missed
Training	94.4%	2094	124	103	21
Test	92.86%	768	59	59	0

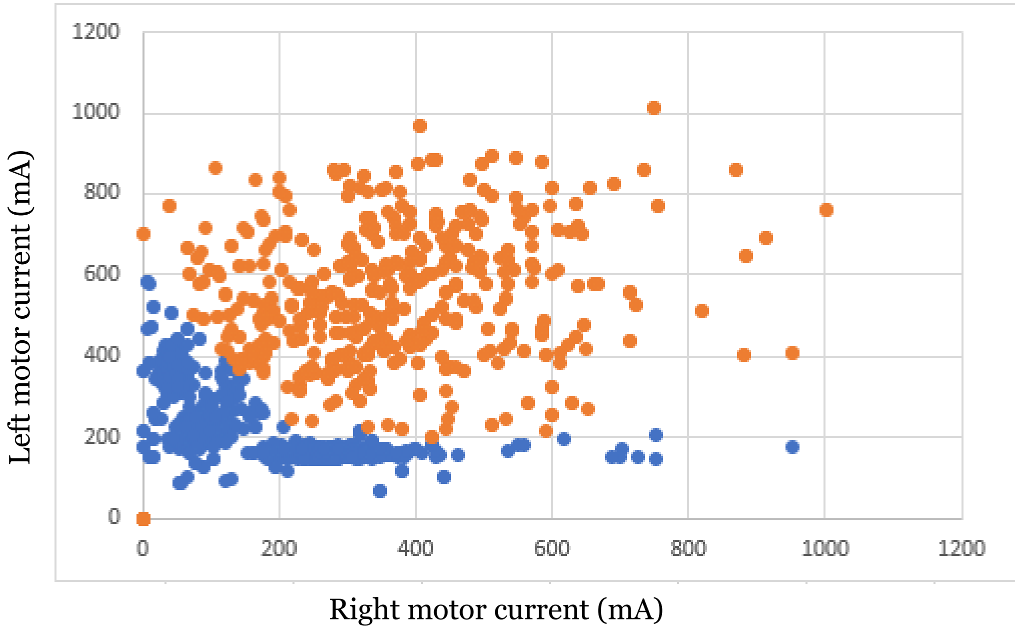

Figure 7. Graph showing the predictions on motor currents only after training session.

The decision-making shown in figure 7 tells that using only motor currents as input, the model was not able to separate the overlapping scenarios seen in figure 6. The orange dots inside the blue area in figure 6 are of greater minority to the blue and thus mistaken as blue after training. Figure 8 shows a clearer view of where the faulty predictions have been made.

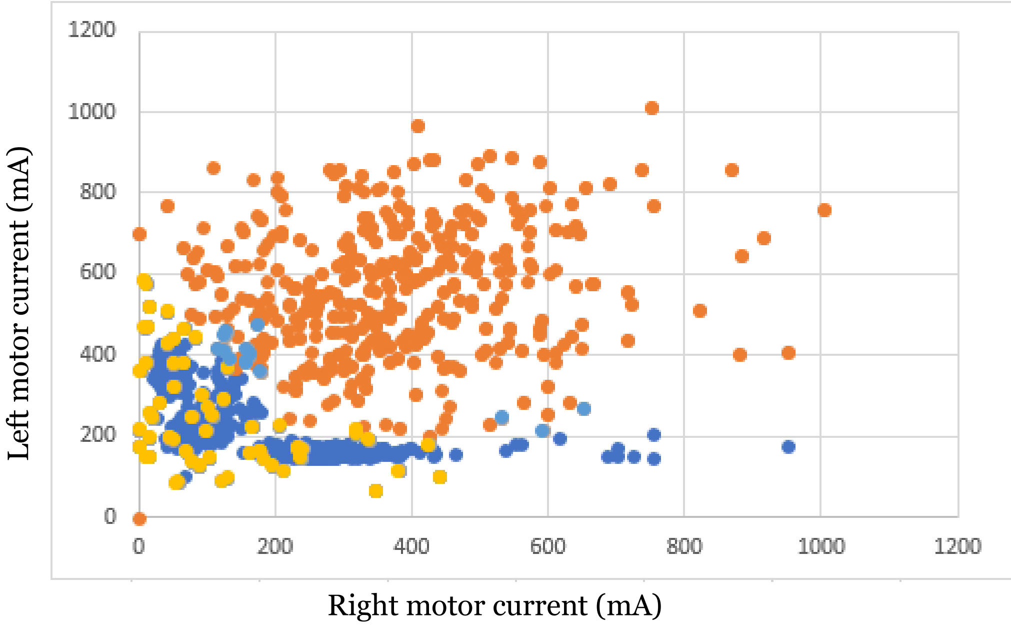

Figure 8. Graph showing the incorrect predictions after training session due to overlapping scenarios. Yellow dots mark false detections and light blue dots marks missed detections.

4.2 Experiment 2 - Motor currents and IMU

Table 3. Averaged results with motor and IMU

Data type	Accuracy	Correct	Incorrect	False	Missed
Training	98.5%	2185	33	25	8
Test	97.7%	808	19	19	0

After training a new model adding IMU as input signals, the accuracy is improved by 4-5 percent. As seen in figure 10, the errors are seen as thin ripples in the grey area. This would ultimately not affect the bigger decision in a skid detection.

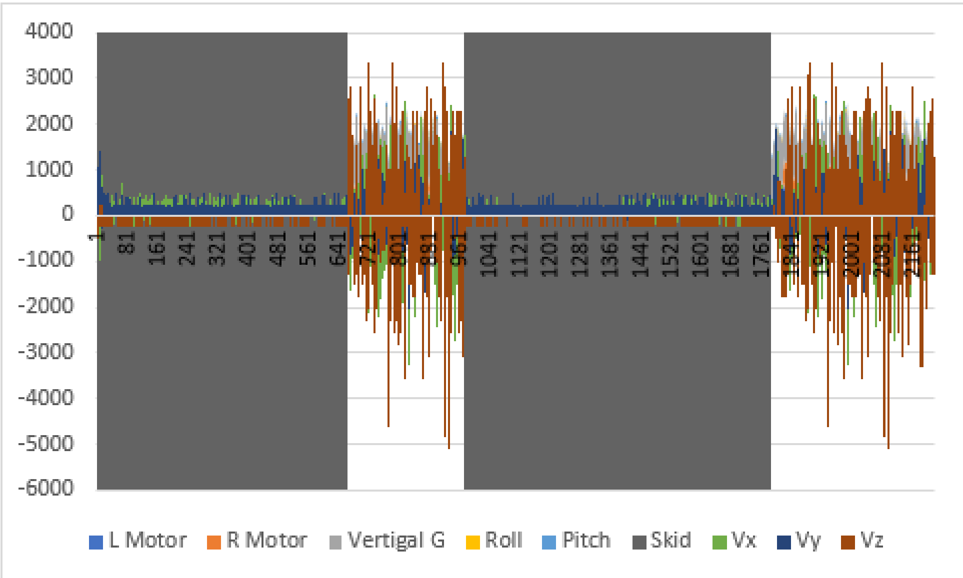

Figure 9. Graph showing training data with motor currents and IMU signals. Grey background marks skidding.

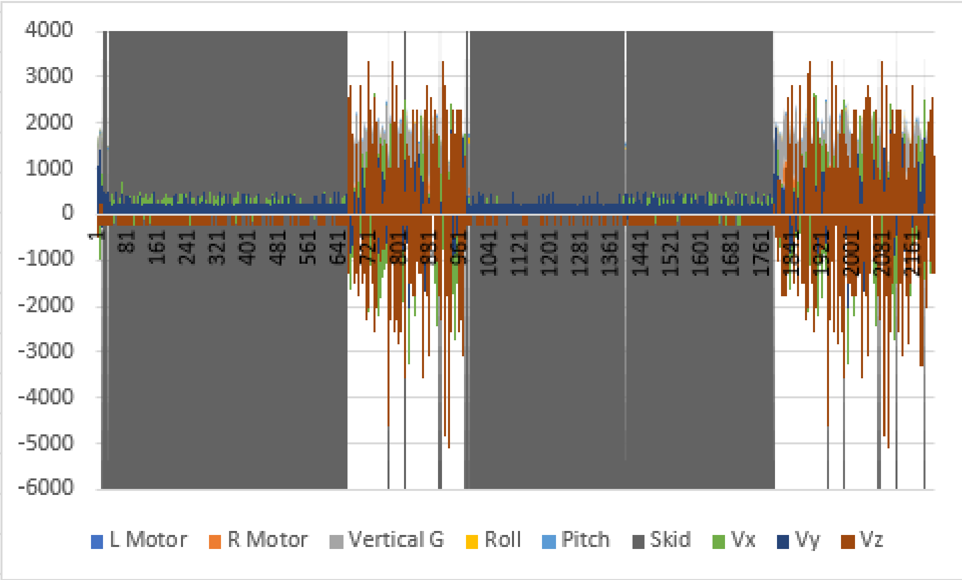

Figure 10. Graph showing prediction of skidding using motor currents and IMU signals after training session. Grey marks prediction of skidding and clear marks non-skidding.

Figure 11 is made as a comparison with figure 8. Both shows where the errors are made and where the first model could not separate the overlapping scenarios, this is succeeded when adding the IMU sensor.

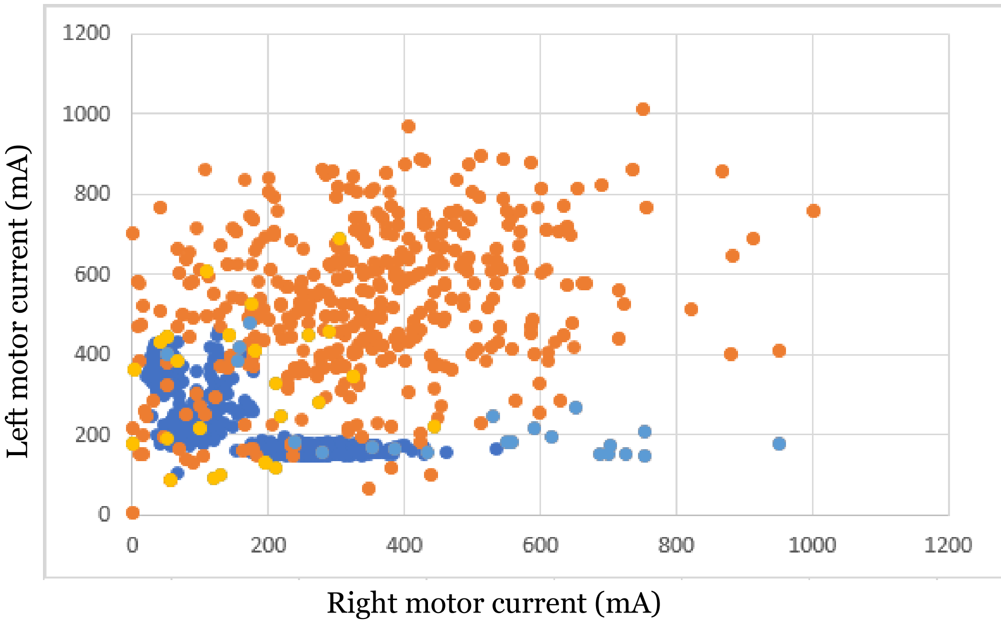

Figure 11. Graph of motor currents representing the predictions with IMU for comparison. Yellow dots mark false detections and light blue dots marks missed detections.

5 Discussion and conclusions

5.1 Discussion of method

The experiment has a strength of validity in the choice of real terrain which gives real data. On the other hand, the same fact can be seen as a weakness of reliability whereas the real terrain has too many variables for such a limited research and would require more data [20]. The source of the data is as well very valid as it is recorded directly from the mainboard of an autonomous lawn mower of Globe Group and how this study is limited to Globe Group mowers.

For this bachelor thesis the validity and reliability based on the chosen method in chapter 3 and findings in chapter 4 is satisfactory to achieve the objective in regard to the purpose and research questions in chapter 1.

5.2 Discussion of findings

The purpose of the study was to explore two techniques of how to detect skidding in autonomous lawn mowers. Using the motor currents and IMU from the mower, a neural network is applied to predict if there was a skidding or not. Below are the answers to the research questions.

5.2.1 What accuracy in prediction can be achieved when using MLP with motor currents to detect skidding in autonomous lawn mowers?

Accuracy on testing data showed around 93%. The results in table 2 shows that out of the incorrect predictions near zero are false negatives, which is preferred as a false negative is seen as more major compared to false positive in defined application. The accuracy found is limited to rough outdoor grass lawn in this experiment. As seen on the graph (figure 6.), the mower shows some irregularities in the motors where the left motor subsequently drew more current. The question is answered but could use further work for broader appliance.

5.2.2 How much is the detection of skidding affected in percentage when adding IMU readings?

The findings show that the accuracy was improved by 4-5 % when adding IMU readings. The accuracy went up to around 98% on the testing data. As in the first techniques results, the amount of missed detections is near 0. The found accuracy is limited to the experiment in this study but the relation with first question shows a great improvement and compensates for the motor current overlaps seen in figure 6 and 8. This could give the conclusion that using only motor currents to detect skidding is not enough in real life application.

5.3 Conclusions

The findings showed high accuracies in both techniques where adding an IMU sensor in addition to motor currents showed higher accuracy then only using motor currents. Both techniques showed low false detections and near zero missed detections which is a preferred feature, the behavior of the autonomous lawn mower benefits more from a false detection then not detecting a skid at all and get stuck.

Based on the accuracy of using only motor currents the author's conclusion is that the technique used in this experiment is not enough in real life application. The graph (figure 6.) shows too many overlapping scenarios due to the rough terrain. In a real-life scenario, the amount of overlapping scenarios would be greatly increased from events not here accounted for, such as turns, collisions, slopes, etc. In this experiment, the overlaps could be greatly reduced with IMU signals. Using another approach, perhaps the overlaps could be separated using different methods of machine learning e.g. Long short-term memory (LSTM) [21] or adding time series [22].

Even though the accuracy is not 100 %, the software of the mower would need an algorithm to handle the output of the model to respond accordingly in which the difference in found accuracy would be tolerable.

5.4 Future work

The experiment in this study only took use of one terrain, giving limited data to what an autonomous lawn mower could actually encounter. As seen in figure 6 the data points are scattered already, implementing more terrains will give more scattering and overlapping scenarios, thus adding the need to separate these scenarios. Suggested methods of achieving this is to use LSTM or adding time series to the MLP to be able to detect the skidding more as an event than a singular data point. This will give a better comprehensive view closer to the actual environments an autonomous lawn mower may encounter.

Another suggestion is to do the experiment on several autonomous lawn mowers, decreasing the error given by uneven motors.

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