Delft University of Technology

Mechanical Engineering Bachelor Final Project

Department of Cognitive Robotics

# Colored Noise in the Slip Patterns of a Jackal Robot

Authors:
Juriaan von Asmuth (1534084)
Freddy Bos (4457471)
Max Sibeijn (4447042)
Laurien Stubbé (4367049)

Supervisors:
Dr. Ir. M. Wisse
A. A. Meera

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BSc program Mechanical Engineering,
Faculty of Mechanical, Maritime and Materials Engineering
Delft University of Technology

**Abstract**

Active inference is a theory by neuroscientist Karl Friston, explaining how the human brain works by constantly making predictions about its environment to avoid surprises, therefore making it work more efficiently. The aim of this research is to see if a certain robot brain suffers from time dependent disturbances, or so called colored noise. If such a pattern were to be found, that would mean that there possibly is a way to make the robot deal with these disturbances more efficiently by implementing an active inference algorithm that can predict these disturbances.
The noise measured in this research is the noise in the slip of a Jackal robot, made by Clearpath Robotics. The robot is given commands to drive in circles while its movements are being recorded by an OptiTrack system, consisting of multiple cameras tracking the reflective markers placed on the robot.
This research reflects that the Jackal indeed suffers from some form of colored noise. This is concluded from the fact that the magnitude of the noise is position dependent and the fact that there is some autocorrelation in the velocity and angular velocity measurements.

# Contents

# Chapter 1: Introduction

A recent theory by prominent neuroscientist Karl Friston, referred to as "active inference"[1], states that the human brain constantly makes predictions about its environment in order to avoid surprises. According to Friston, this principle could also be implemented in a robot, which would make for an efficient robot brain. A robot brain, a processor executing a control algorithm, suffers from disturbances, also called noise. An active inference algorithm should be more efficient in dealing with noise than conventional control systems, because it can make predictions about this noise. However, for the active inference algorithm to outperform traditional algorithms, which consider all noise to be white noise, it has to be proven that this noise is in fact colored noise and thus contains some sort of structure. Therefore the aim of this research is to find structure in the noise experienced by a moving robot. This would be the first step in proving that active inference can be a superior algorithm for robot state prediction and control, compared to existing algorithms.
The noise studied in this research is the noise due to the slip of a Jackal robot. The Jackal is a small four-wheeled ground vehicle robot, made by Clearpath Robotics[2]. The main research question is: Does the Jackal robot suffer from colored noise? In order to find an answer to this question, three sub questions are formulated. Does the measurement system suffer from colored noise? Is the noise position dependent? What is the autocorrelation in the noise? The main hypothesis is formulated as follows: the Jackal robot suffers from colored noise.
In this research the noise in the Jackal's movements will be examined by looking at the robot's velocity. In order to determine its velocity, movements and orientation, the Jackal robot will be tracked using an OptiTrack motion capture system. This consists of multiple cameras that register reflective markers placed on the Jackal, which enables it to follow the displacement of the robot. When comparing this data with a reference, the noise caused by slip patterns can be isolated. Hereafter, this noise is analyzed to see whether or not a predictable pattern can be found.
After this introduction, the theory is discussed in which the background information behind this study is further explained. Following this, in chapter three the experimental method will be explained, describing the systems used and the experiments conducted. The results of the experiments will be given in chapters four to six. In these chapters the three research questions will be discussed as well. In the seventh chapter a conclusion is drawn from these results and recommendations are made for future research.
This research has been conducted as part of the Bachelor Final Project for mechanical engineering students at the TU Delft in the third year of the bachelor.

# Chapter 2: Theory

In order to understand the relevance of the stated research questions and the conclusions drawn in this research, some knowledge about the theoretical background is required. This background is further explained in the following chapter.

## 2.1 Active inference

Active Inference is a theory by neuroscientist Karl Friston. The theory describes how the human brain is constantly making predictions and thereby minimizes the amount of entropy the brain faces[1]. This approach is relatively new and rather complicated. A simplified version to describe this concept, is that the human brain is trying to avoid surprises. This is done by constantly modeling the environment by making predictions. These predictions can be made because a model of the environment, built from experience, is stored in the brain. An example illustrating this would be, that if it rained last night, the brain will predict that the grass is wet, even though it has not seen the grass yet. This prediction can be made with a very high probability, because of the model of the environment that the brain has made. This model is based on earlier experiences of the grass being wet when it had been raining. According to Friston, active inference can be applied to a controller in a robot[3]. This controller would measure past noise, and use active inference to anticipate upcoming noise and compensate for it in advance. In order to make predictions about the noise, this noise has to contain some form of structure. Friston's theories go into more depth to explain how the human brain functions according to this principle[4], however for this research project it is sufficient to know the basics.

## 2.2 Colored noise

If a signal contains unwanted disturbances, this is called noise. Whenever there is a predictable pattern to be found in this noise, it can be considered "colored noise". For example, when measuring the speed of a plane, the wind can be considered noise, since random turbulent flows of air create disturbances in the flight trajectory. However, since the wind speed and orientation at one point is dependent on the speed and orientation at an earlier point, this can be considered colored noise. A robot brain also suffers from noise. Usually, this noise is considered to be white noise and filtered out, but if this noise is measured instead and some kind of pattern or structure that is dependent on time is found, it could be proven that there is colored noise affecting the movement of the robot. The noise being measured in this research, is the pattern of slip that the wheels of a Jackal robot make while executing turns. If this is proven to be colored noise that the robot suffers from, the noise could be predicted with an Active Inference algorithm, enabling the robot to anticipate future noise.

## 2.3 Autocorrelation

Autocorrelation is a property of a signal, which indicates the similarity of said signal with a delayed copy of itself. Plotting the autocorrelation function will present a graph showing the autocorrelation coefficient as a function of the lag. At zero lag, the signal is an exact copy of itself, and will have an autocorrelation coefficient of one. When a high autocorrelation is found at a certain point in a signal, this indicates that there is a repeating (predictable) pattern present in the noise. Since the aim of this research is to find a structure in a noisy signal, this is a useful property to analyze.

To understand what to expect from an autocorrelation plot, a random dataset was created in MATLAB with 1000 values. This dataset can be considered as white noise because there is no relation between any of the datapoints, they are all random. A resulting autocorrelation plot of this dataset is shown in figure 2.1. It looks like there is some correlation, but the blue lines that mark the 95%-confidence interval are never exceeded. This means the correlation can very likely be considered as coincidental and therefore negligible. In this case this is correct, because the data is completely random.
If the noise found in this research is indeed colored, the autocorrelation of the noise should display a more slowly decreasing autocorrelation coefficient compared to the white noise, which immediately decreases to almost zero.

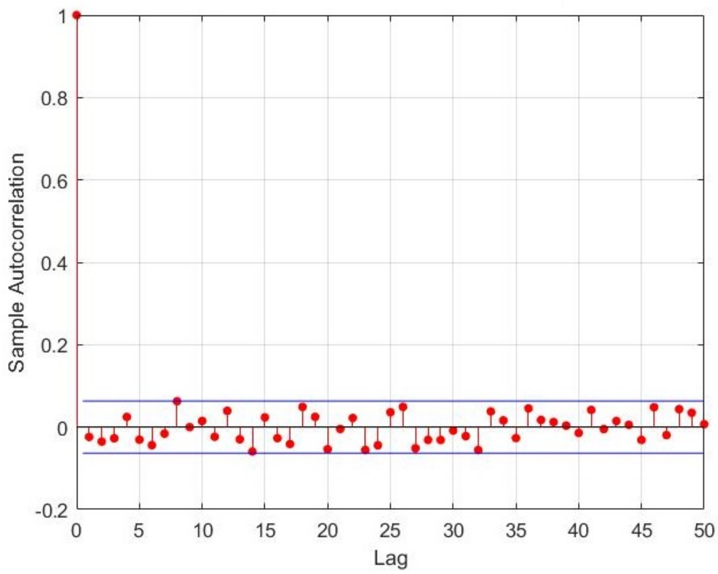


Figure 2.1: A typical sample autocorrelation function of white noise. Blue lines indicate 95%-confidence intervals.

# Chapter 3: Experimental Method

In order to test the noise characteristics in a mobile robot, an experimental method is selected. This includes a representative robot, a measurement system, and software for controlling the robot, acquiring data and analyzing data from the experiment. The hardware and software that will be used, along with their limitations, are described in this chapter.

## 3.1 ROS

The system used for controlling the Jackal robot is called ROS[5], which stands for Robot Operating System. This is an open-source system designed for robot software development. ROS contains nodes that each have their own function which, for example, control the motors driving the wheels of the robot. These nodes can communicate by using so called topics to send messages to other nodes. This way, a network is created that can control the robot by giving it commands. Various topics contain various types of information that control the robot or contain measurement data from the robot. ROS will also be used to gather data, both from the Jackal robot and from the OptiTrack motion capture system. Data is gathered by subscribing to various topics in the ROS network during the experiment, and saving the messages published to these topics in a file using the rosbag format. Relevant data can then be extracted from the rosbag file using MATLAB.

## 3.2 OptiTrack system

To measure the robot's movements and orientation from outside the Jackal robot, an OptiTrack system will be used. This is a motion capture system which can follow objects through the use of multiple cameras, directed towards the ground where the robot will be driving around, see figure 3.1. By placing reflective markers on the robot in different places, it is possible to follow the multiple points on a computer and thus determine the position and orientation of the robot. In this test, five markers are placed on the robot, one directly above every wheel and one above the center of rotation of the Jackal. In the Jackal simulation software, it can be seen that Clearpath Robotics determined the center of rotation to be exactly in the middle. Following this assumption, the fifth marker is placed in the geometric center of the top plane of the Jackal, see figure 3.2. This center was measured with a precision of $\pm 1$ millimeter. This way there are enough points to form a rigid body in the OptiTrack system. This body can then be tracked to determine the position and orientation.

Figure 3.1: Picture of the setting of the experiment, showing the Jackal and the cameras tracking it.

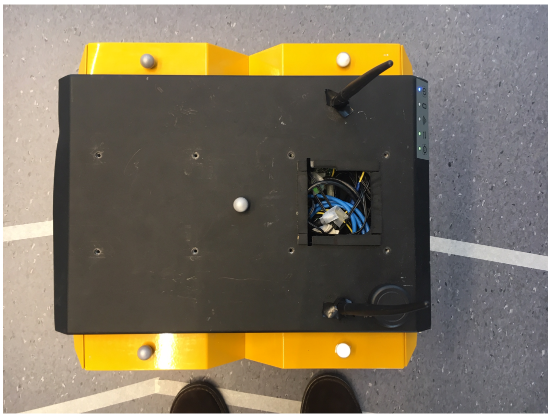

Figure 3.2: Position of the reflective markers placed on the Jackal robot during the measurements.

## 3.3 Experimental set-up

The noise that will be measured is the noise in the slip the Jackal robot makes while turning. This is measured by calculating the difference between the velocity commands, sent to the robot through a python script, and the derivative of the position data measured by the OptiTrack system, converted from the world fixed frame of reference to body fixed frame of reference belonging to the Jackal robot.
To start, two baseline tests will be done with the robot standing still, to gather information about measurement noise in the OptiTrack system.
The test path that the Jackal will be driving consists of a circular motion with a constant velocity and angular velocity. For the first ten tests, the velocity commands that will be sent to the robot are a linear velocity of 0.3 meter per second and an angular velocity of 22.5 degrees per second for 48 seconds. This is approximately three circles. After this, five more tests will be conducted where the robot will drive the same path, at a slightly higher speed. The velocity commands that will be given are a linear velocity of 0.4 meter per second and an angular velocity of 30 degrees per second for 36 seconds.
During these tests, data from various ROS topics will be stored in a rosbag file for analysis:

- **/cmd_vel**: This topic in the Jackal's ROS network receives velocity commands, which will then be passed on to the motor drivers. The python script driving the Jackal broadcasts to this topic.
- **/imu/data_raw**: This topic receives data from the Jackal's inertial measurement unit (IMU). This includes the measured angular velocity around the robot's z-axis, and the linear acceleration along the robot's x-, y- and z-axes.
- **/feedback**: This topic contains various types of diagnostic information about the Jackal system, including the measured angular velocity of the Jackal's wheels.
- **/tf**: This topic is part of a separate ROS network running on a laptop, which receives position data from the OptiTrack system. This data is stored as the relation between two coordinate frames, one fixed to the world and the other fixed to the tracked object, in this case the Jackal robot.

Data from the OptiTrack system is first sent to a desktop PC running OptiTrack Motive software through a LAN network. From here, the position data is broadcast over the network and received by the laptop running ROS.

## 3.4 Sampling frequency

The OptiTrack system can measure at different frequencies. Therefore, before starting the tests, the optimal sampling frequency should be determined. To determine the position of a moving object accurately, a high sampling frequency is desirable. However, when using the data for calculations, it is also desirable to have minimal deviations in the time interval between measurements. The maximum sampling frequency that can be obtained using the OptiTrack system is 360 Hertz. In order to find the optimal frequency, a stationary object with markers placed on top is measured with the OptiTrack system at different frequencies, starting from 30 Hertz up to 360 Hertz in steps of 30 Hertz. By taking the mean squared error of the time interval and the difference in x-position and plotting them against these frequencies, the graph from figure 3.3 is obtained. Here it is seen that the mean squared error of the difference in x-position only varies very minimally from 150 Hertz on. However, it is also clearly visible that the mean squared error of the time interval length approximately stays the same until 240 Hertz, after which it shoots up a noticeable amount. At frequencies above 240 Hertz, the OptiTrack Motive software also started giving warnings about dropped frames. Therefore, the optimal sampling frequency using the OptiTrack system is determined to be 240 Hertz. This means that for all other experiments a sampling frequency of 240 Hertz was used.

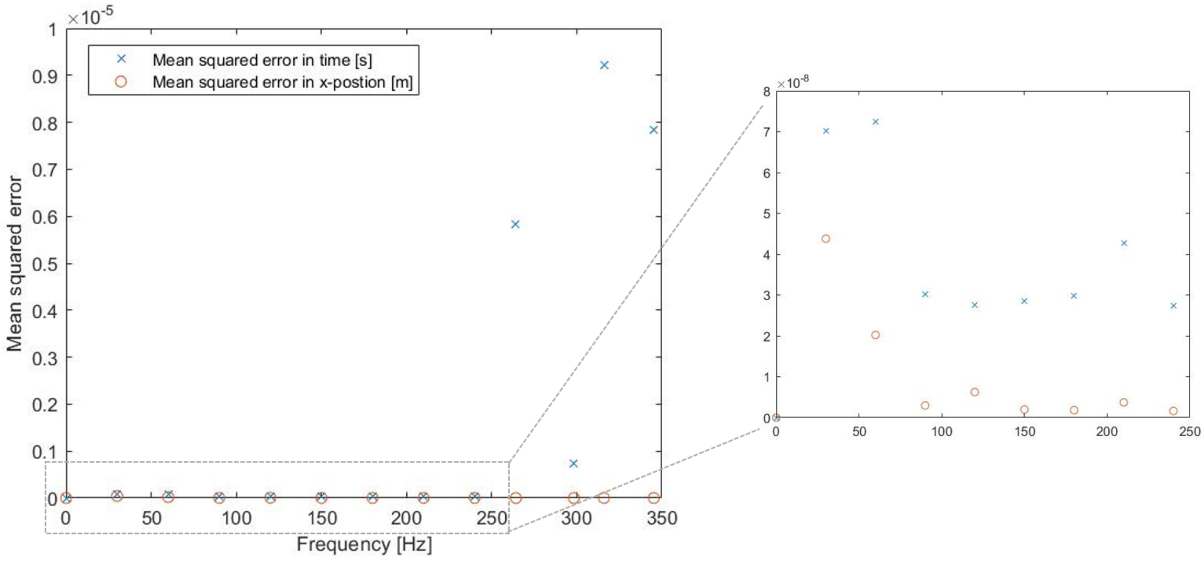


Figure 3.3: Graph of the mean squared error of the time interval and the difference in x-position plotted against the sampling frequency. This figure shows that the measurement sample time becomes unsteady at sample frequencies higher than 240 Hertz.

## 3.5 Time delay

Another important factor to take into account is the time delay in the measurement setup. Data is gathered by subscribing to various ROS topics on a laptop. When messages on these topics are received by the laptop, they are given a timestamp and saved to a rosbag file. In order to determine the time delay between different topics, an experiment was conducted where the robot was made to quickly accelerate and then make a full stop several times. Data was gathered, and the velocity commands received by the robot (topic /cmd_vel) were used as a reference. Delays were determined by comparing the moments in time when the different topics recorded movement of the robot. An overview of the measurement setup, different ROS topics that were recorded and the measured time delays can be seen in figure 3.4.

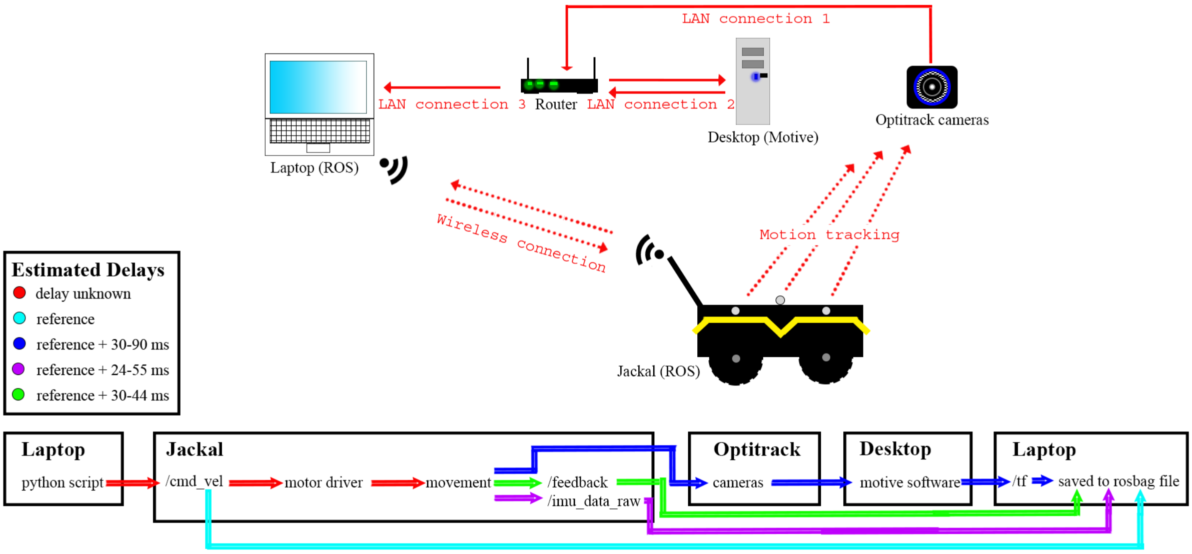


Figure 3.4: Overview of the measurement setup that was used, along with estimated time delays in the setup. These delays will need to be taken into account when making comparisons between data from different ROS topics. However, such direct comparisons are not made during the rest of this research, so synchronizing the different topics is not required.

The time delays shown in the figure are a rough estimate based on a limited number of recorded movements. The measured delay is different for each measured point, likely because not all ROS topics receive messages at the same frequency. Additionally, due to noise in the OptiTrack measurements, it was difficult to determine the exact moment that movement was recorded with a high degree of accuracy, and the delay is still unknown for several steps within the process. Additional measurements are not required to draw conclusions within this research, since no direct comparisons between data from different ROS topics are used that would require synchronization. However, anyone wishing to use this experimental setup in the future to compare different topics will need to take these delays into account. In this case, if precise delays are required to synchronize data, further research into these delays is encouraged.
For an illustration showing how these delays were determined, please refer to the appendix, figure A.1.

# Chapter 4: Noise in OptiTrack System

In order to analyze the noise in the measurements, the noise of the system itself needs to be identified. This means the first sub question, whether the OptiTrack system suffers from colored noise, has to be answered. In this chapter the results from the robot standing still will be displayed and explained.

## 4.1 Measurement noise

First, the noise in the position measurements of the system was determined. When looking at the x-coordinate position data it seems the noise is somewhat discretely distributed. This becomes more obvious when looking at a histogram of the noise.

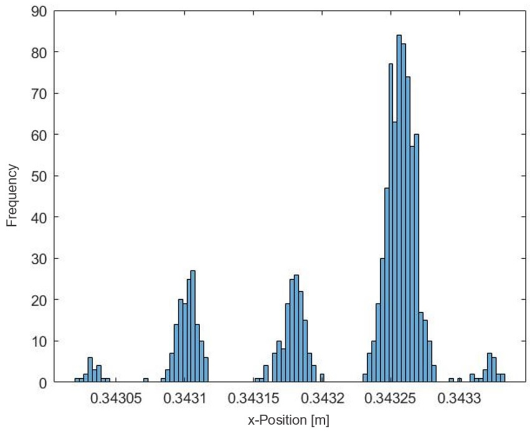


Figure 4.1: Histogram of x-position from OptiTrack data for robot standing still.

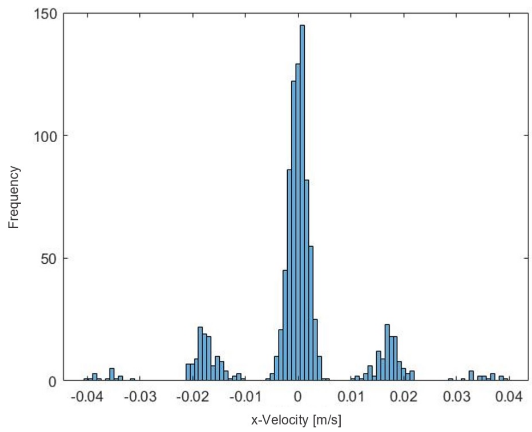


Figure 4.2: Histogram of x-velocity differentiated from the x-position data from OptiTrack for robot standing still.

The histograms above show that there is not simply a Gaussian distribution for the noise in the OptiTrack system. The histogram for the x-position of the robot is divided into five discrete parts that all seem to be normally distributed, seen in figure 4.1. The distribution for the x-velocity, in figure 4.2, is more symmetrical than that of the x-position, with a large peak in the origin. It remains very difficult to say exactly why this is happening and what conclusions can be drawn from these results. However, since the other peaks are much smaller in the velocity measurements, for the rest of the research the measurement noise will be regarded as Gaussian white noise. This way it is still possible to draw some conclusions from the other measurements.

## 4.2 Magnitude of the measured noise

When looking at the total noise in the velocity for the rest of the experiments, a distinction can be made between four different types of noise. The first is the noise when the robot is standing still. When calculating the velocity, this is the standard noise originating from the OptiTrack system. The second is the noise when a disturbance is introduced, for example when someone is walking past the test area. This increases the noise in the measurements of the x-position. However, the noise in the x-velocity does not increase with more than ten percent, and sometimes this noise even decreases. Because of this, this change in noise was ignored, and the magnitude was considered constant. The third is the steady state driving noise. This is the noise when the robot is driving and is not experiencing any irregular noise. The fourth is the increased driving noise. This is when the robot is driving and experiences increased noise. For these types of noise, a certain interval of the x-velocity was selected. For each interval the standard deviation was calculated. This was done for multiple tests and the averages of these standard deviations were calculated. These standard deviations are given in 4.3. In this figure the x-velocity measurement of one experiment is also given as a visualization of the intervals that were selected.

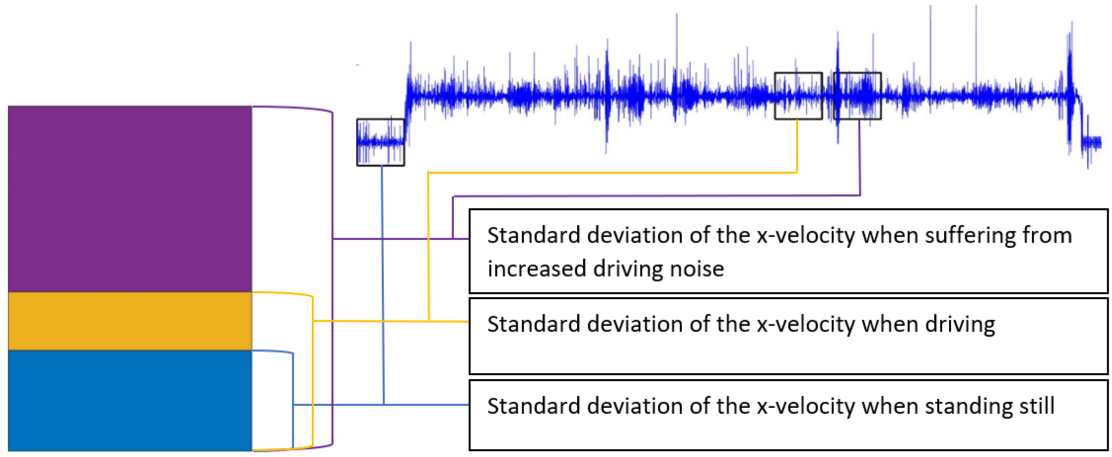


Figure 4.3: The standard deviation in the robot's x-velocity in meters per second where blue is the deviation when standing still, yellow the standard deviation when the robot is driving and purple the standard deviation when the robot suffers from increased driving noise. The complete measurement of one test is also given in order to visualize which intervals were chosen.

As can be seen from 4.3 the biggest noise increase is from the increased driving noise. In order to find an explanation for this increase in noise, this will be studied further in chapters five and six.

# Chapter 5: Position Dependency of the Noise

The second sub question for this research states: is the noise position dependent? If the answer is yes, this means that the intensity of the noise experienced by the robot can be reliably predicted based on it's position in space, and it can therefore not be considered white noise. In this chapter, this sub question will be answered based on the data gathered during the performed experiments.

## 5.1 Measured velocities

The results of experiments 2 to 10 will be examined to see if a position dependent structure is present in the measured noise. The first test is disregarded, since it started from a different position than the remaining tests. As mentioned before, the noise measured is the noise in the velocity of the robot's body frame. In this chapter only the noise in the x-velocity will be discussed, the y-velocity and angular velocity behave in the similar way and the plots can be found in the appendix, figures A.2 and A.3. In figure 5.1 the x-velocities of tests 2 to 10 have been plotted against the time. From each consecutive test a certain value of 0.7 meter per second has been subtracted in order to make the plot more comprehensible.

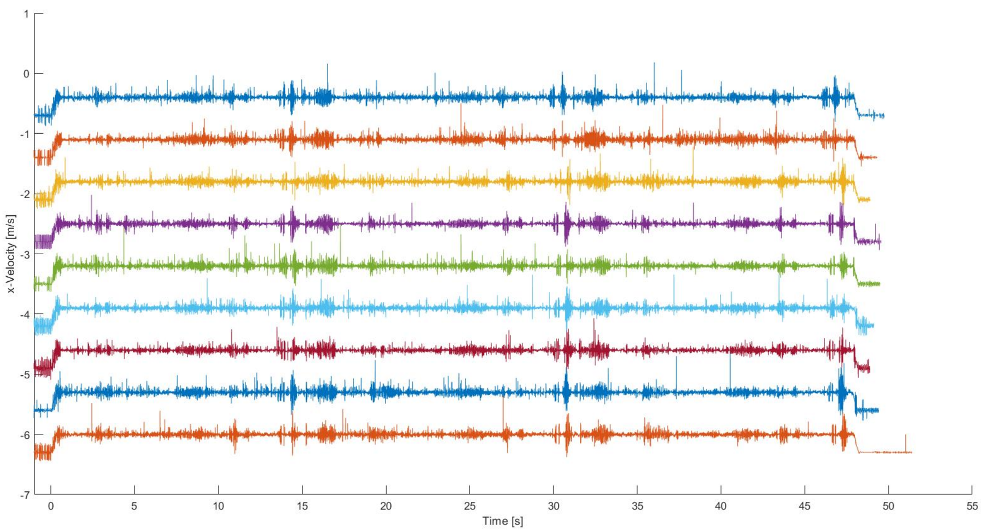


Figure 5.1: Velocity [m/s] in the x-direction in the robot frame plotted against the time [s] for experiments 2 to 10. A value of 0.7 meter per second has been subtracted from every next plot to make the plot more comprehensible.

## 5.2 Noise in the measured velocity

In figure 5.1 it can be seen that on certain time points an increase in noise is measured for all experiments. In order to determine whether this indicates a position dependency, this data was first compared with the next five tests, which were conducted with a higher velocity. Here, a very similar pattern was found. Next, the deviations in the robot's path are plotted along the theoretical path in circle form. Along the circle a range of positions was chosen and for each position the standard deviation of the x-velocity was calculated. This was done to find a magnitude that quantifies the noise at each of the positions. In order to visualize the position dependency of the noise figure 5.2 was constructed. In this figure the the middle circle is the theoretical path of the robot. The inner and outer lines are the visualizations of the standard deviation in the x-velocity. The outer path is the robot path plus the standard deviation and the inner path is the robots path minus the standard deviation.

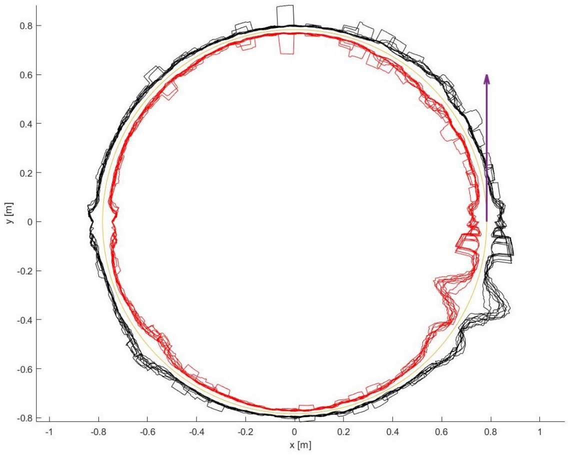


Figure 5.2: The robot's theoretical path as the center line with the theoretical path plus and minus the standard deviation in the x-velocity as the outer(black) and inner(red) paths respectively.

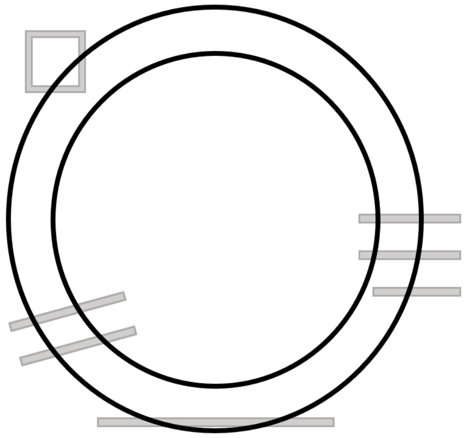

Figure 5.3: A schematic overview of the most important pieces of tape present along the path of the robot.

As can be seen in figure 5.2 the nine experiments behave rather similar at a given position along the path. In order to find an explanation for this the path on the floor of the lab was examined. The most important features that were present on the floor were the pieces of tape used in other experiments. In order to find a relation between the increased noise and the tape on the floor a schematic drawing of the most important pieces of tape was made. This drawing is given in figure 5.3. As can be seen from a comparison of both figures there seems to be a relation between the tape on the floor and the magnitude of the noise for the x-velocity.

# Chapter 6: Autocorrelation in the Noise

This chapter discusses the final sub question: what is the autocorrelation in the noise? Experiments 1 to 10 have been analyzed, and they all showed similar behaviour regarding their autocorrelation functions. To compute the autocorrelation of the test data, the 'autocorr' command in MATLAB is used. This command computes the sample autocorrelation function of a given time series.

## 6.1 IMU data

The analysis of the IMU data was done by taking a steady-state section of the original angular velocity signal from experiment 8 and substracting the mean angular velocity. This results in a noisy signal that is seen in figure 6.1 in black. The autocorrelation command is applied to this section of the signal to obtain figure 6.2. The autocorrelation coefficient in this figure is above the confidence bound from 0 lag until a lag of 23. As explained in chapter 2.3, this indicates that there is correlation, and therefore, provides some evidence that the noise could be colored. However, the discovered autocorrelation could be due to a filtering effect of the robot dynamics. Besides this, two maxima can be seen. The first is located at a lag of 103. The second peak is located at a lag of 207. These points translate into a time lag of 1.39 and 2.96 seconds respectively.

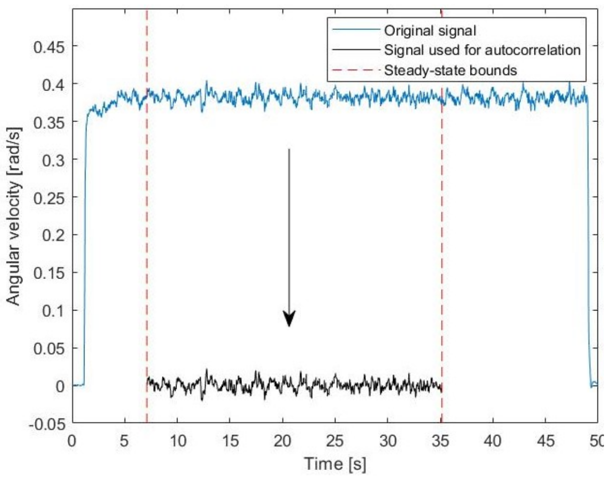


Figure 6.1: Angular velocity as a function of time, from raw IMU data. The blue signal is the raw data from experiment 8 measured at 72 Hertz. The black signal is obtained by taking steady-state data and substracting the mean angular velocity.

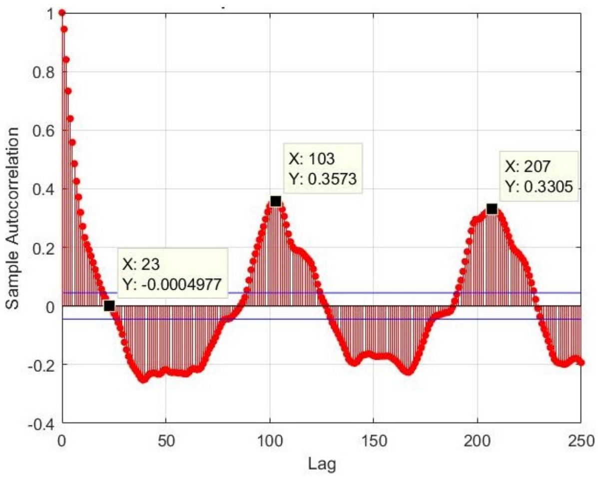


Figure 6.2: Sample autocorrelation of the black signal in figure 6.1 plotted for 250 lags. Blue lines indicate 95%-confidence interval.

## 6.2 OptiTrack data

The results from the IMU data can be compared to the data obtained from the OptiTrack system. The angular velocity measurements are too noisy to find any pattern, however, the autocorrelation plot of the body frame y-velocity in figure 6.3 shows some very similar behaviour to the plot in figure 6.2.

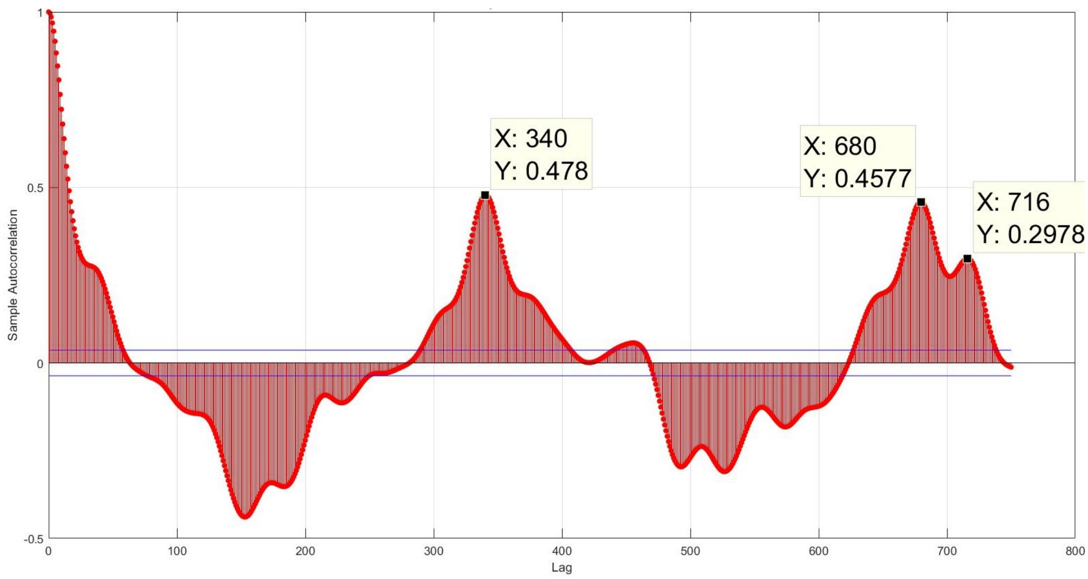


Figure 6.3: Sample autocorrelation of the Body Frame y-velocity, plotted against the lag, using (lowpass) filtered OptiTrack data from experiment 8.

Figure 6.3 displays three interesting peaks in the autocorrelation plot from y-velocity data. The two main peaks are at exactly the same distance apart. The period of this suspected oscillation is 1.41 seconds, and closely matches with the earlier found peak in figure 6.2, at 1.39 seconds. There is, however, also a third smaller peak. This peak is located at a lag of 716. When converted to time lag, this peak is at 2.98 seconds and corresponds to the second peak found in 6.2, which was at 2.96 seconds.

To find an explanation for these similarities, the data from the feedback topic was analyzed. For the first set of experiments, the average period of rotation of the wheels on the right was 1.43 seconds and 2.99 seconds for the wheels on the left. This too, seems to correspond to the earlier found peaks in the autocorrelation plots.

To provide some more evidence, all of the previous results were also analyzed for the second set of experiments, with higher velocity and higher angular velocity. The same relation was found, with higher frequencies. See figure A.4 and A.5 in appendix.

It would appear that the frequency of the wheels is related to the autocorrelation function. In this case, the frequency of the outer wheels has a bigger impact on the y-velocity than the frequency of the inner wheels, while the inner wheel frequency has larger impact on the noise in the angular velocity.

# Chapter 7: Conclusion and Recommendations

In this chapter, a conclusion will be drawn, based on the findings discussed in previous chapters. The main research question will be answered, and some recommendations will be made for further research.

## 7.1 Conclusion

The main question of this research is: Does the Jackal robot suffer from colored noise? The hypothesis is that this noise is indeed colored. To confirm the hypothesis three sub questions have been examined. First, does the measurement system suffer from colored noise? Second, is the noise position dependent? Third, what is the autocorrelation in the noise?
In chapter four it is concluded that the measurement system does indeed suffer from some form of colored noise. However, when converting the position measurements to velocity and looking at the different factors that impact the noise, the biggest portion of the noise is not caused by the OptiTrack system. Instead the biggest increase in noise can be found at certain intervals when the robot is driving. This means the OptiTrack noise in this research was considered Gaussian and further conclusions could be drawn from the driving noise.
In chapter five this increased noise from chapter four is examined and it can be seen that the noise is indeed position dependent. This noise can to some extent be linked to the tape on the lab floor.
In chapter six, autocorrelation has been found in both the robot's own IMU angular velocity data and the filtered velocity measurements of the OptiTrack system. The clear correlation found in the first part of the graphs provides some evidence that the noise could be colored. Also, the peaks in the autocorrelation function have been linked to the rotation of the robot's wheels.
As a main conclusion of this research, the hypothesis has been confirmed. The position dependency of the noise increase and the autocorrelation in the robot's movements do confirm there is some form of colored noise. This means that an active inference algorithm could theoretically be implemented in the Jackal robot to improve performance. However, there are still a lot of unknowns regarding the OptiTrack system and the exact nature of the noise. These will be discussed in the recommendations section.

## 7.2 Recommendations

In order to build further on the findings of this research, a few recommendations for future work are made. It is recommended to dive deeper into the time delay in the measurement set-up. By further researching what components influence the time delay and how big these influences are, a better understanding is created of how these factors impact the measurements. It is also recommended to look into the discrete distribution of the measurement noise. With better understanding of both the time delay and the discrete measurement distribution, the noise in the OptiTrack system can be quantified and possibly filtered out. Furthermore, it is encouraged to carry out more experiments on different surfaces to learn more about the position dependency of the noise. Finally, more research into the autocorrelation of the gyroscopic velocity is required to further confirm structure in the noise.

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# Appendices

# Appendix A: Additional Figures

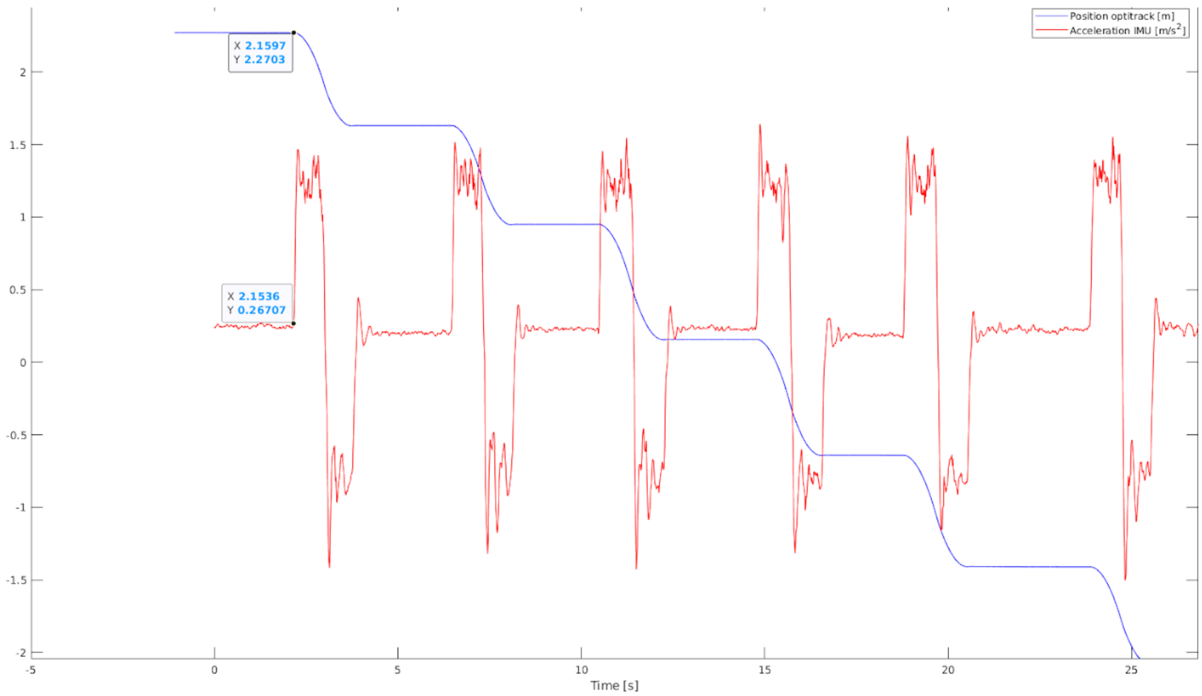


Figure A.1: Measurements by the OptiTrack system and the Jackal robot's inertial measurement unit during the time delay experiment plotted against time. The delay between the OptiTrack /tf topic and the Jackal's /imu_data_raw topic was estimated from this graph.

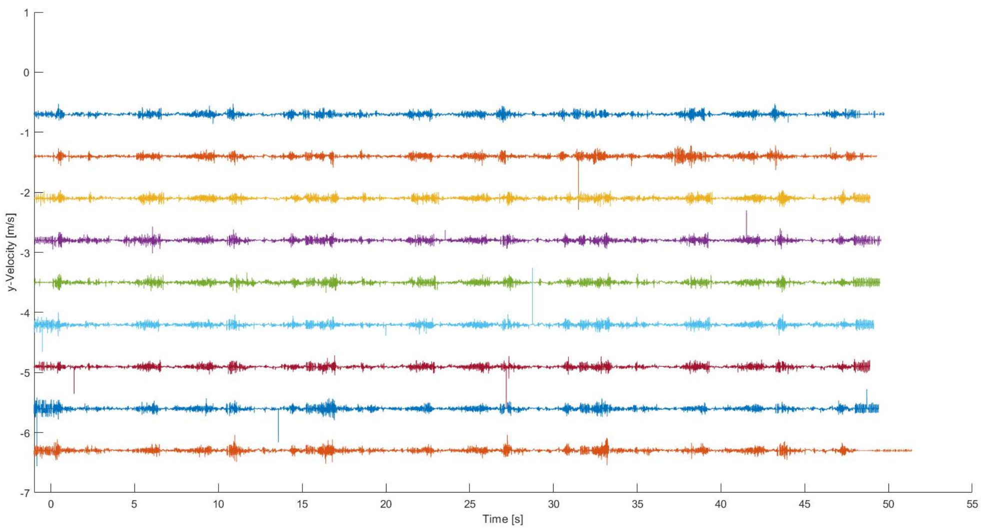


Figure A.2: Velocity [m/s] in the y-direction in the robot frame plotted against the time [s] for experiments 2 to 10. A value of 0.7 meter per second has been subtracted from every next plot to make the plot more comprehensible.

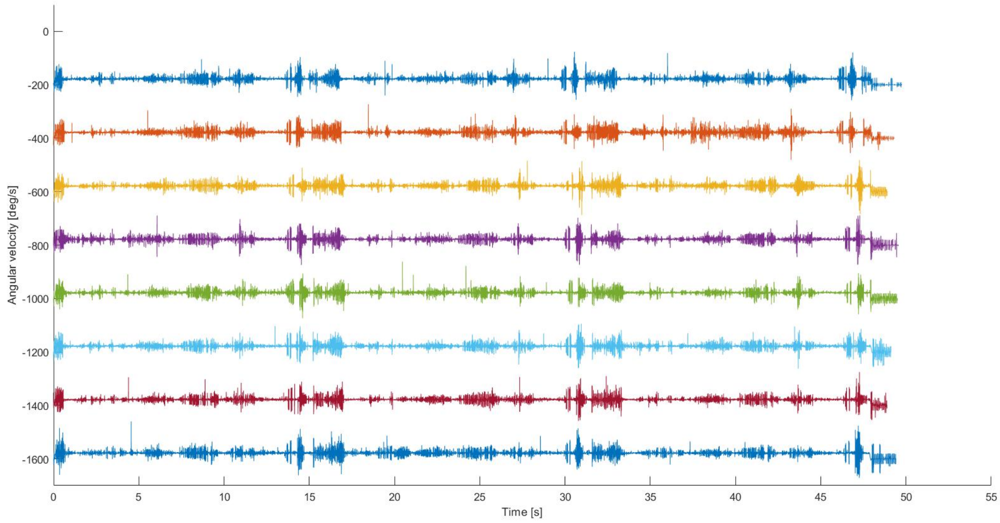


Figure A.3: Angular velocity [deg/s] in the robot frame plotted against the time [s] for experiments 2 to 10. A value of 200 degrees per second has been subtracted from every next plot to make the plot more comprehensible.

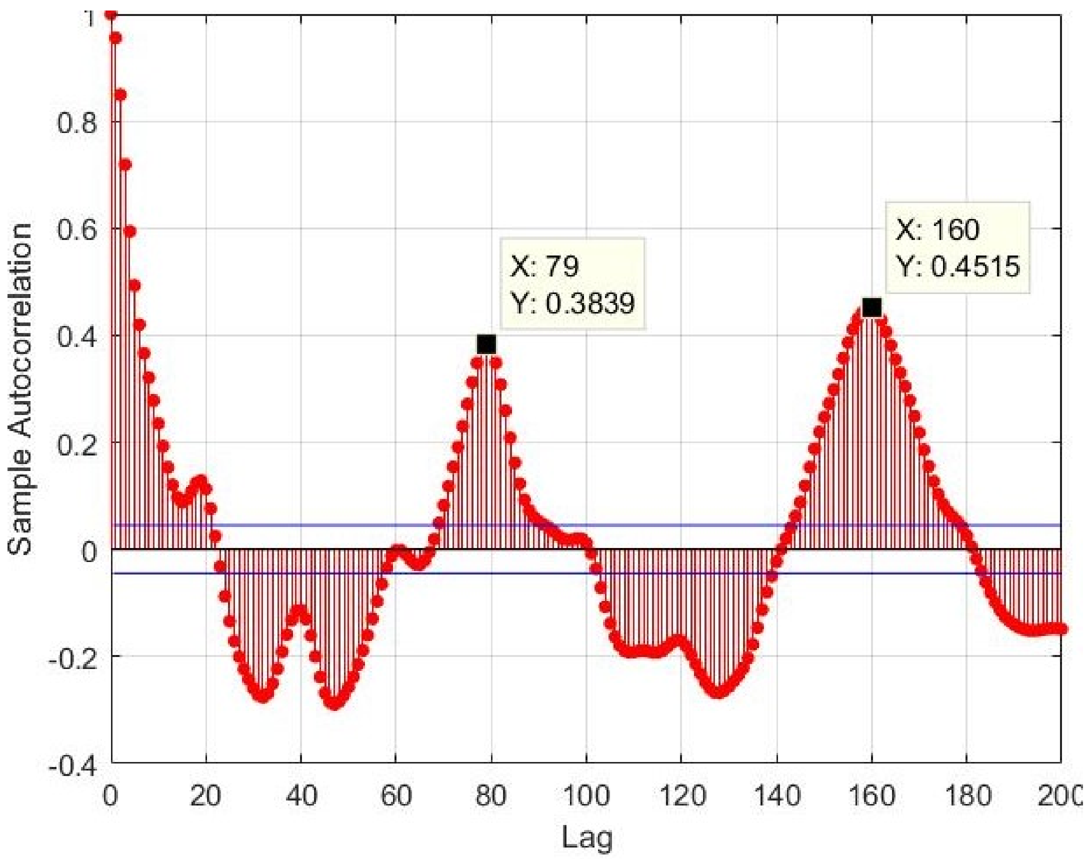


Figure A.4: Sample autocorrelation of angular velocity as a function of the lag. Steady-state raw IMU data from the Jackal robot is used from experiment 1 out of the second set of experiments. t(79) = 1.05 seconds, t(160) = 2.12 seconds.

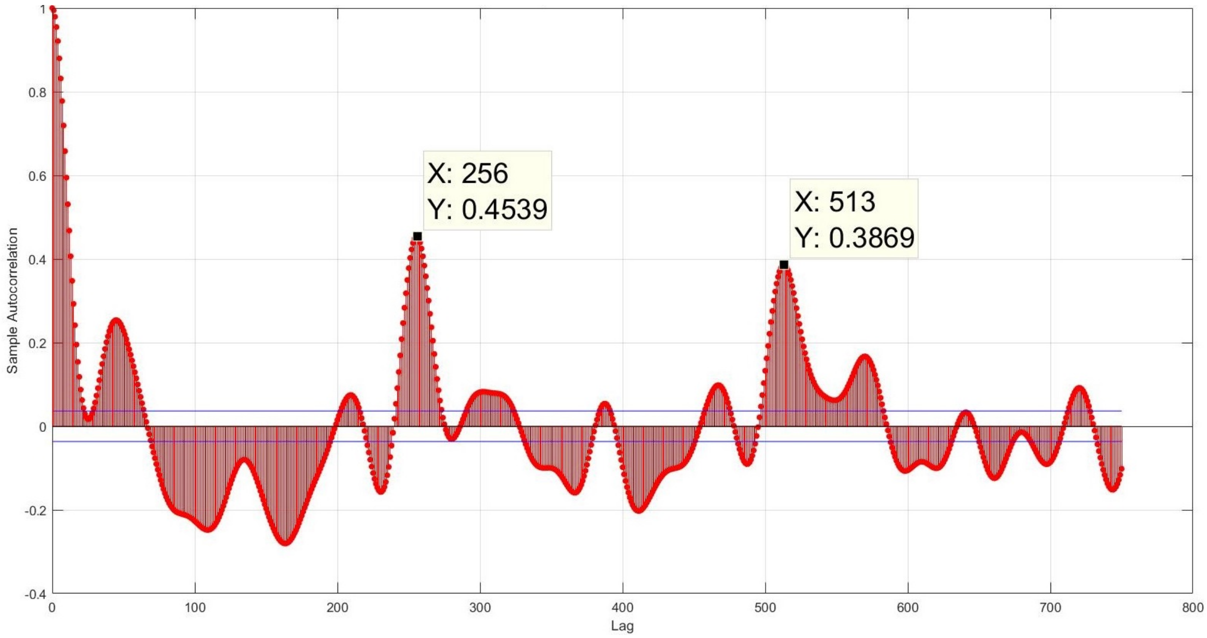


Figure A.5: Sample autocorrelation of the Body Frame y-velocity, plotted as a function of the lag, using (lowpass) filtered OptiTrack data from experiment 1 out of the second set of experiments. t(256) = 1.06 seconds, t(513) = 2.13 seconds.