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Institute of Computer Science
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Roman Matvejev

Air-flow sensing for applications in autonomous driving

Bachelor's Thesis (9ECTS)

Supervisor(s): Naveed Muhammad
Yar Muhammad

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Abstract:

Sensing fluid flow has gotten increased attention of underwater robotics community in the last decade. The field of fluid flow has also been of interest in aerial robotics. It has however not been investigated much in the field of autonomous ground robotics to that extent. The goal of this research is to investigate potential uses of air-flow sensing in autonomous driving and validate potential applications of air-flow sensing in autonomous driving using computational-fluid-dynamics (CFD) simulations. The aim of this work is to investigate whether it is possible to estimate the truck length in front of the autonomous vehicle using data from the air-flow sensors.

Keywords:

Perception, flow sensing, autonomous robotics, computational fluid dynamics

CERCS:

P170

Võimalikud rakendusi õhuvoolu mõõtjale autonoomse autode jaoks

Lühikokkuvõte:

Viimasel aastal vedeliku voolu tajumine saanud suuremat tähelepanu veealuse robootika kogukonnas. Väljavedeliku vool saanud tähelepanu ka õhurobootikas. Autonoomse maarobootika valdkonnas pole seda siiski palju uuritud. Selle uurimistöö eesmärk on uurida õhuvooluanduri potentsiaalset kasutamist autonoomses juhtimises ja kinnitada õhuvooluanduri potentsiaalseid rakendusi autonoomses juhtimises, kasutades arvutusliku vedeliku dünaamika (CFD) simulatsioone.

Võtmesõnad:

Tajumine, õhuvoolu tajumine, autonoomne robootika, arvutusliku vedeliku dünaamika

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1 Introduction

In recent years autonomous robotics has gotten increased attention from researchers all around the world. The uses of autonomous machines vary from autonomous cars to military drones. One of the examples of autonomous cars is the autonomous buses[1] invented by students and researchers from TalTech which are currently being tested in Tallinn as well as in some other countries. Big tech companies are also interested in autonomous robotics. For example, Amazon is using autonomous robots[2] in its warehouses to assist workers to sort parcels more accurately and does require fewer resources to increase the capacity of the storages without the need for recruiting more personnel.

With the decreasing cost of the flow sensors and sizes of computers, remarkable results have been achieved in the field of autonomous aerial and underwater robotics as well. Despite the fact that the biggest part of aerial robots relies on IMUs and GPS to predict their location, some kind of air-flow sensor is also in use to estimate the speed of the wind [7,8,9]. In the case of the underwater environment, it was discovered that underwater localization is achievable by using flow-sensing technologies [3,6].

Autonomous driving is still the biggest part of autonomous robotics. Some BigTech companies, such as Google [1] or Tesla [2], are working on autonomous driving applications. There are a lot of possible applications of self-driving cars in our everyday life, for example safer, more efficient and convenient transportation [4]. A wide variety of car manufactures are now focused on applications to assist drivers with everyday tasks such as parking or the prevention of life-threatening situations. One example of application of this technology is Tesla autopilot, which allows customers to use Auto park, Auto lane change and many more driver assistance features [2]. Despite the fact that self-driving cars are inevitable in future, as for now, they are still far away from being perfect, and there is plenty of space for improvement.

However, the combination of autonomous ground robotics and flow sensing technologies has not been researched well yet. Though it could help to achieve results that are impossible to achieve by using data from the image processing techniques which are now mainly in use in ground robotics. One of these tasks is predicting the length of the vehicle in front of the

[1] https://news.err.ee/974526/gallery-first-passengers-ride-driverless-bus-in-tallinn
[2] https://www.nytimes.com/2019/07/03/business/economy/amazon-warehouse-labor-robots.html

self-driving car. This task is very important as it allows autonomous vehicles to behave more safely and efficiently on the highways as it allows the car to overtake trucks, buses, and other low-speed long vehicles.

The goal of this thesis was to investigate and validate the potential uses of air-flow sensing in autonomous driving. The main task of this thesis was to find a way to predict the size of a truck in front of a car using CFD simulations. This could be achieved by combining the existing autonomous driving and flow sensing technologies. In this work, literature on aerial as well as underwater flow sensing latest achievements were researched. The noise created by the crosswind is also investigated in this work.

The remainder of this manuscript is structured as follows: The second chapter gives an overview of the current state of flow-sensing technology and its uses in autonomous robotics. It also describes flow-sensors currently available on the market and the latest research on air-flow sensors and their advantages.

The third chapter focuses on CFD simulation technologies used in this work, and the process of creating the experimentation scene for this work.

The fourth chapter describes CFD simulation results and proposes the model for estimating the length of the vehicle in front of the autonomous car.

The fifth chapter summarizes the results and suggests future works on air-flow sensing for autonomous driving.

2 Related works on flow sensing for robotics

The following subsections give an overview of the research done on flow-sensing technology for autonomous robotics. Unfortunately, to the best of the author's knowledge, there is no research yet on application of flow sensors in autonomous driving. Nevertheless, below we describe the relevant literature from flow sensing in the fields of aerial and underwater robotics, which form the basis for our work.

2.1 Applications of flow sensors in underwater robotics

In recent years, flow sensing has received increased attention from the wide research community. In this section related works on underwater localization are described as well as their importance to this work.

Some studies on map-based underwater localization show that it is possible to perform localization using only structural maps and CFD simulation techniques [3,5,6]. The underwater sensing result is important for this work as they give an overview of which tasks are possible to achieve using flow-sensing technology.

Underwater localization method could give us an overview on how the flow changes in different environments and which features are better to use. However, the difference between water and air environment in density means that results may not be as clear as it was in a water environment.

In [3], small-scale real-world experiments were done for the application of robot localization. For the experiment, a rainbow trout shaped robot equipped with 15 pressure sensors was used. The data from these sensors was used to estimate depth and flow-speed. Flow-speed was measured by looking at the differences in pressure in each of the sensors. Simulated flow-speed maps were obtained using the OpenFOAM CFD tool.

In [5], a rainbow trout shaped robot equipped with 16 piezo-resistive sensors was used. However, only data from the nose sensor was used. The experiment was conducted in two phases, stationary and while moving. The map-based localization technique used in this work is the same as in previous work.

Both works showed promising results, concluding that it is possible to use flow-sensing technology for localization in underwater environments. There are currently two approaches to the result analysis, first is Particle-filtering and the second is Loop-closure. For Particle-filtering, each particle has a weight factor. At the initial state, particles are distributed randomly. Then after each motion particle set is recursively updated. In case of Loop-closure, a loop-closure occurs when the robot visits the already visited location. The current feature is compared with previous features "and if the histogram distance falls within the threshold distance, the current feature is considered as a candidate for loop-closure detection" [5].

However, as for the real-world application of this model, there is still a lot of research that needs to be done. The current model is based on a generated flow map, meaning that for everyday use we need to generate a map for the whole environment. Also, the underwater vehicle itself as well as underwater animals such as whales could create noise, which could cause errors in measurements.

The above mentioned, and related, research shows that there is a potential for flow sensing to complement the existing underwater localization methods such as sonar and vision. In the unforeseen events, when other underwater localization methods stop working, flow-sensing technology could help prevent life threatening situations.

2.2 Applications of flow sensors in aerial robotics

The application of flow sensors in autonomous airships has gained increased interest in the robotics community.

The localization of aerial robots has also been investigated with the aid of flow sensing, in both online and offline modes [7].

For localization, similar algorithms similar to those mentioned earlier in the context of underwater localization have been used.

There is also research on improving existing particle-filter algorithms by decreasing calculation time, so in that case online localization will take much less time [7]. The method was tested in the complex indoor environment and showed improvements in terms of localization compared to the standard particle filter.

The problem of estimating wind velocity on a hexacopter using data from onboard sensors is also being researched [8]. For estimating the wind speed aerodynamics of the air vehicle also should be considered. The experiments done in [7], showed that it is possible to reconstruct the vertical velocity if the horizontal velocity is known. (This is very important for this work as well, as for autonomous vehicles we already know the horizontal velocity of the car.)

One of the reasons for using air-flow sensing for aircraft is a constant decrease in the price of sensors. Nowadays, simple and quite accurate sensors are easy to fabricate [9]. [9] presents an easy to fabricate flow sensing system and its capability.

The idea of this kind of sensor is that the thermal element relies on the direction of the heat, as the flow cools it. So, as the temperature of the element decreases, the resistance of the element changes, and it provides information about airflow. The result showed that even low-cost hot-film sensors are able to demonstrate an accurate measurement for real-scale aircraft [9]. However, the sensor unavoidably overheats which results in noise in data.

However, not every study in the literature relies on air-flow sensing for wind estimating [10]. In [10], the air velocity predicting method using only IMU and GPS-velocity for quadrotor is presented. The main reason for using IMU and GPS instead of air-flow sensors is that the quadrotor itself creates airflow by its rotors and it creates the noise in the measurements. The main idea is to look at the GPS data changes by using the tilt and power of the rotors. For example, in the case of the opposite wind, the quadrotor will fly the shorter vector than in non-windy weather. The results showed that it is possible to estimate the air velocity of the quadrotor in this manner. And the measurements are accurate, and the only problem was caused by the low-cost IMU sensors. In addition to air-flow sensors, sonars are also frequently used, as it helps to estimate quadrotor location more accurately [7,8,9].

2.3 Air-flow sensors

With the rapid growth of usage of the quadrotor applications, the needs for the new cheaper and more accurate sensing have increased. A variety of approaches have been taken to create an artificial air-flow sensor for the different environments. Micro-scale environment seems to be most attractive to the researchers as they are mainly used in the quadrotors.

In this section some of the currently used and recently discovered new interesting sensors are presented.

In [11], an easy fabricated flow sensing system inspired by animal hair cells is presented. The device [11] is inspired by the construction of a hair cell, which uses the calibration of hair to measure the flow direction and speed. The device is mainly used in underwater environments. However, it was also tested for air-flow measurement and showed a good flow detection at low flow velocities. The device is sensitive to temperature changes, so for the correct measurement constant temperature should be used. In conclusion, the device is very sensitive and could be used for micro scale environments.

In [9], the Hot-Film sensor is presented. The principle of this sensor is that a thermal element relies on the direction of the heat, as the flow cools it. So, as the temperature of the element decreases, resistance of the element changes, and it provides information about air flow. However, sensor unavoidably overheats which result in noise in data. In conclusion, it is possible to apply these sensors to real-scale aircrafts [10].

There is also work [12], which presents a new method for estimating the wind velocity using optical flow sensors. The experiments showed that this algorithm could estimate wind speed without any troubles. As well as estimate the wind direction with an average 0.6sec sample period [12].

In conclusion, there are plenty of sensors which could be used for the air-flow sensing for autonomous driving.

3 Simulation tools and methodology

The following subsections give an overview of the tools and methodology used for this work.

3.1 Computer Fluid Dynamics

Computational fluid dynamics, later CFD, is a technology that uses numerical analysis to analyse the fluid flows. Due to a lack of research on air-sensing technology for autonomous driving, it was decided to conduct the research using the simulations, which later could be applied for real-world applications.

The main advantage of the CFD technology over the real-world simulation is that it allows us to receive accurate results using only computer calculations, which could allow us to save a lot of time on preparing the experimentation environment and conduct simulations more easily.

There are many different toolboxes for CFD simulations. For this work, the OpenFOAM [13] toolbox will be used. Due to the lack of the author's previous knowledge in CFD simulation composition, application with the visual interface is preferred.

3.2 SimScale

SimScale is a cloud service which allows to conduct CFD, Finite Element Method (FEA), and thermal simulations in one online platform [14]. CFD simulations, which are used for this work, are done using OpenFOAM open-source toolbox.

The main reason for selecting SimScale for this work is its straightforward and accessible visual interface, allowing even not experienced users to easily create a simulation. In addition to that, there are a wide variety of tutorials available [15]. It is also important that SimScale is a cloud service, meaning all the calculations are done at SimScale servers, which allows even low-end machine users to conduct complicated simulations.

However, as SimScale is not an open-source but a commercial product, it has its own pricing [16]. Fortunately, SimScale has a Community license, which allows using only 3000 computation hours for one account, however, this is more than enough for this project.

3.3 Creating a scene

The scene, i.e. the simulation experimental setup for this thesis, is an environment with the two vehicles (a truck and a car) moving after each other, simulating the real-life situation of the cars moving on the highway. The main aim of that was to experiment with the different speeds, lengths of the truck, and distances to the car. To accomplish these goals, it was needed to answer four questions. What models to use, which lengths to use, which speeds to use, and which distances to use.

Due to the lack of the author's knowledge in 3D modeling, for the simulations the free models from the GrabCAD website[17] were used. Unfortunately, SimScale has a high requirement for the models, meaning that only a small part of the free models will work with that. The most common error was with the intersecting surfaces.

For the experiment with the different lengths, it was decided to use a single truck model, changing the size of the trailer. The main reason behind using the single truck model is that the aerodynamics of the cabins are different for each truck and may cause noise in the results. For the model of the car, BMW model E36 was selected, which is very popular in Estonia among the youngsters.

Before starting working on the project test simulations were done to estimate the computational time for the simulations in the way that the SimScale community plan will satisfy our needs.

It was also considered to use a simplified model of the cars with a low number of polygons to speed up the simulations. However, after the testing simulation turned out that 3000 hours is more than enough for the project as one simulation at average took 100 computational hours to complete. Based on this information it was decided to select only two speed levels and two truck sizes to experiment with.

For the scene, two different sizes of the truck were selected, 10m which is common for cargo trucks, and 18.75m, as the maximum length of the truck in Europe [18]. Speed levels for the cars are also selected based on the Estonian Traffic Act [18]. The most common speed on the single line highways are 90km/h for outside built-up areas and 50km/h for built-up areas.

Distances between cars were calculated based on the Estonian Traffic Act. It is stated that the time to cover the distance between cars should be two seconds in the built-up area and three seconds outside the built-up area. Therefore, 90km/h outside built-up areas (50m distance), 50km/h in built-up areas (27.7m distance) [18].

Creating the scene was done using 3D editor Blender [19]. The main reason for using Blender for this work is that Blender allows us to convert files into STL file format, which SimScale allows to use for simulations. Unfortunately, not all models are done in STL, meaning that they cannot be used in SimScale without conversion.

Blender also has an option for measuring the size of objects in metrics. This option is later used for creating an accurate scene.

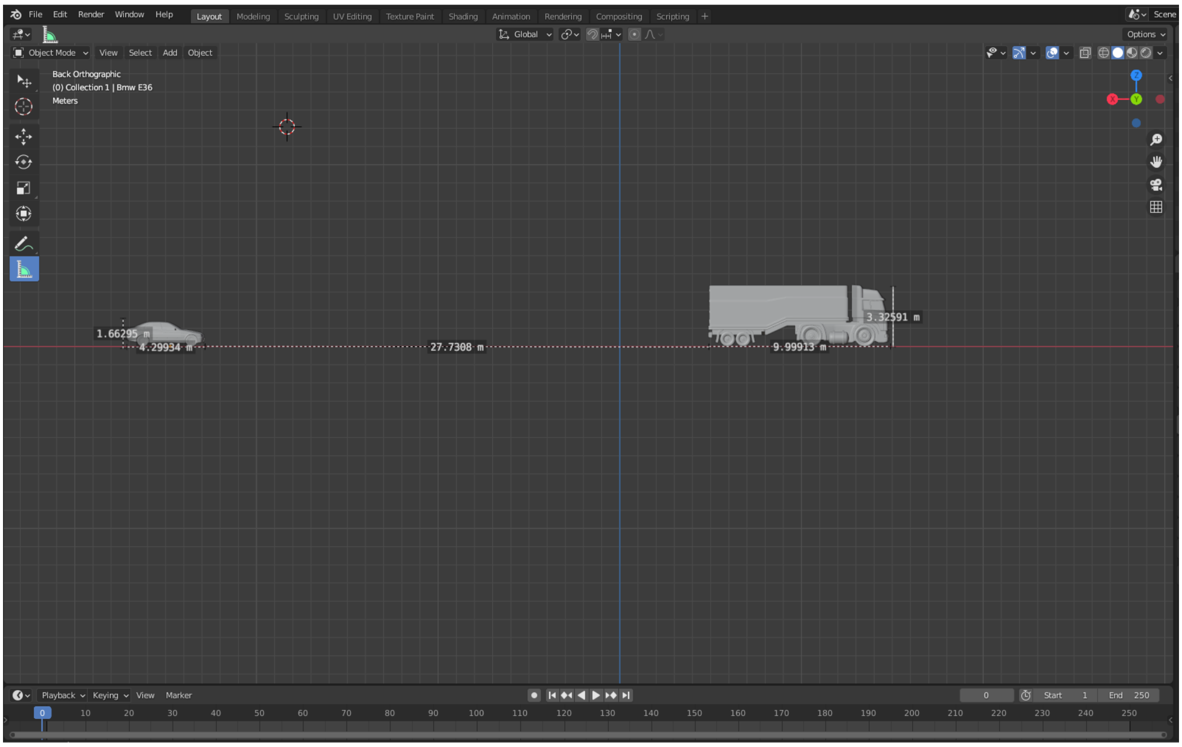

Figure 1. Example of the scene created in Blender.

There are 2 different approaches to the CFD simulations. The first is when the car itself is moving, the second one is the wind tunnel, when the car stands still as a static object and only air inside the scene is moving. The second approach is easier to simulate therefore it will be used for this work.

The main problem with this approach is that it requires time for air inside a chamber to settle down and start giving correct results. For this work, test simulation was conducted to decide how much time does it take for the air to settle down. The reason for that is that we want to start reading a result from the point when the data is already accurate and there is no more noise.

For the validation, a simulation for 2000s was conducted, with a saving interval of 100s with calculations done for every second. Unfortunately, SimScale does not allow to get data from the single points on the model, therefore the result should have been manually downloaded and used in another program. For analyzing the results ParaView [20] was selected, which is mainly used for analyzing the CFD data.

As SimScale uses OpenFOAM toolbox, almost every data generated is saved and is available for analysis. For the analysis was selected to use k-omega value[3], which shows us the turbulence in the chamber [21]. For the analysis it was decided to select 5 points on the surface of the car in the longest scene and look at how it changes over time. The reason for using the longest scene is that it has the most amount of air and it will take more time to settle down. From the results shown in figure 2, it is clear that after the 1000s there are no spikes in data, meaning that 1000s is enough for the airflow to settle down. Therefore, a simulation cycle for 1000s was selected to be used for this work.

[3] K-omega – common two-equation turbulence model, used to predict the turbulence in a specific point in space.

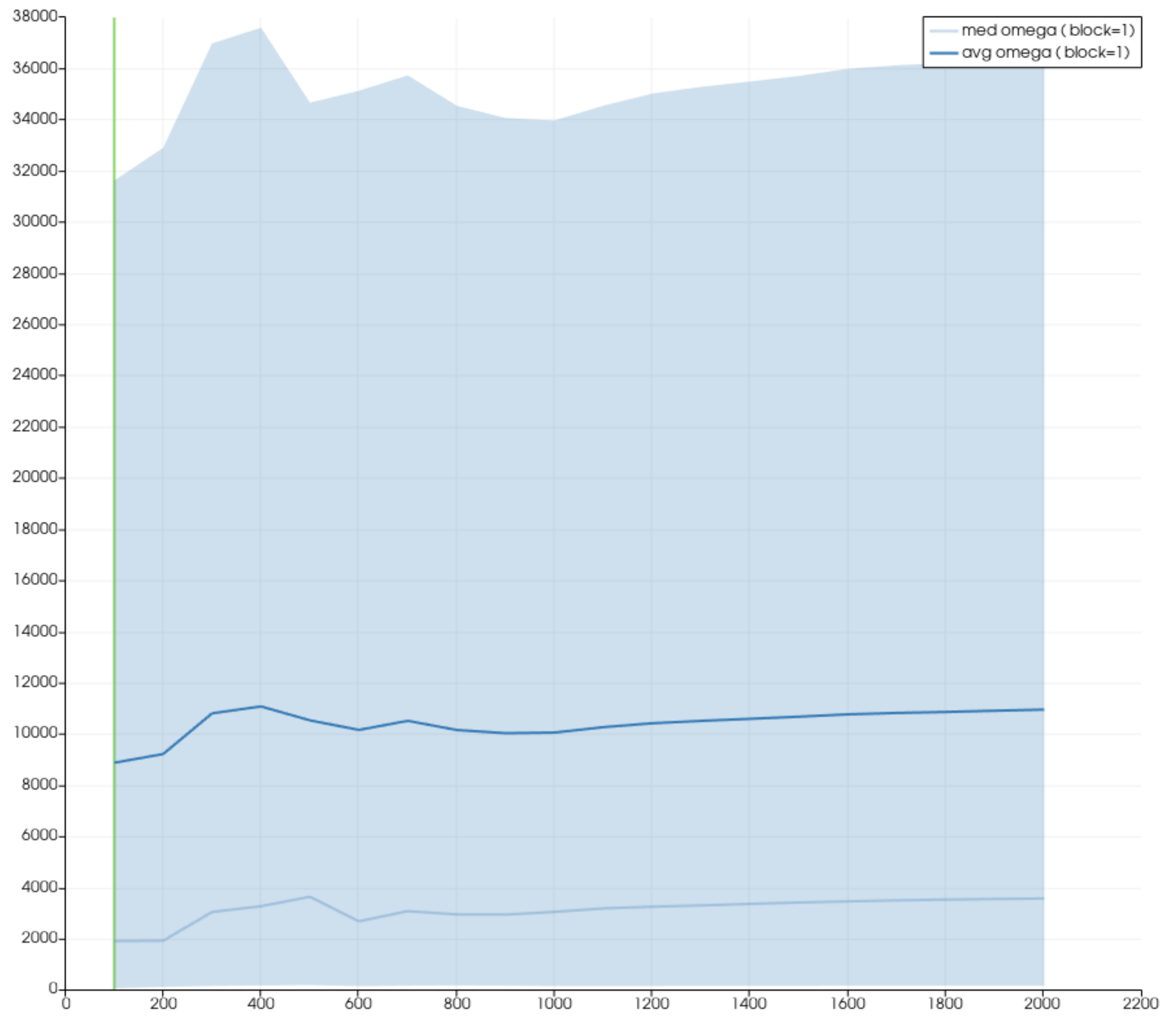

Figure 2. Omega SST data from the car surface over the simulation.

The second problem is to decide which testing result to use for validation. SimScale allows us to save data for each second of the simulation. For the validation it was selected to conduct a test simulation for 5 seconds and look at the result to see how they change over time. As we can see from the result shown on Figure 3, p-value[4] data does indeed change over time. However, the changes in data are insignificant compared to the data itself. In a pressure range of 2-90 units, we have only 0.3 unit change over the 5 seconds. Based on these results it was decided to work with the single data from 1000s, as it saves disk space and computation time, allowing us to conduct more simulations more effectively.

[4] P-value – pressure value in specific point on car surface

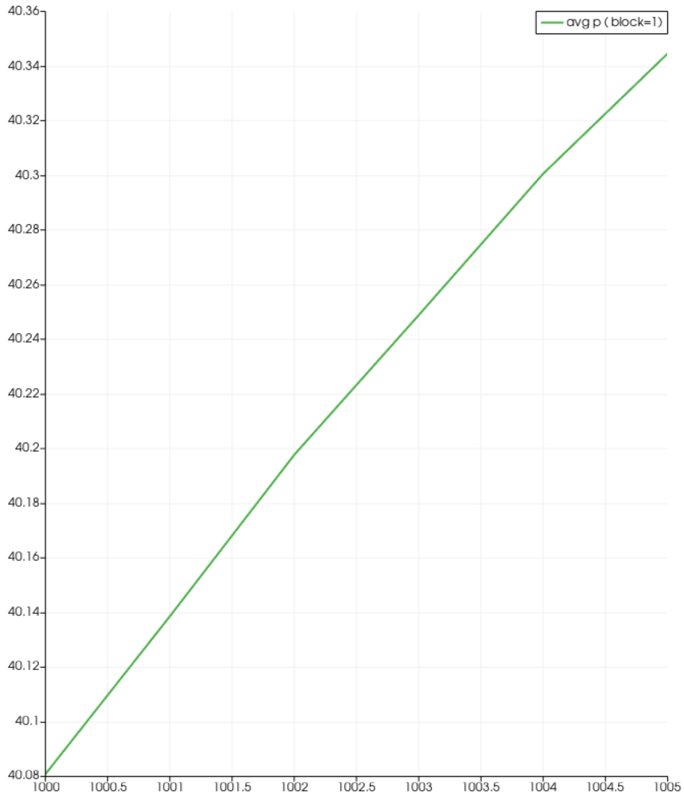

Figure 3. p-value data from the car surface over the simulation.

The next question is data from which part of the car should be used. It was decided to select 5 points on the car surface, where the pressure data changes the most for the different simulations. These points were selected based on comparison pressure maps from simulation for 60km/h for two different truck lengths. The pressure maps are shown at figure 4. The possible sensor locations are shown at figure 5.

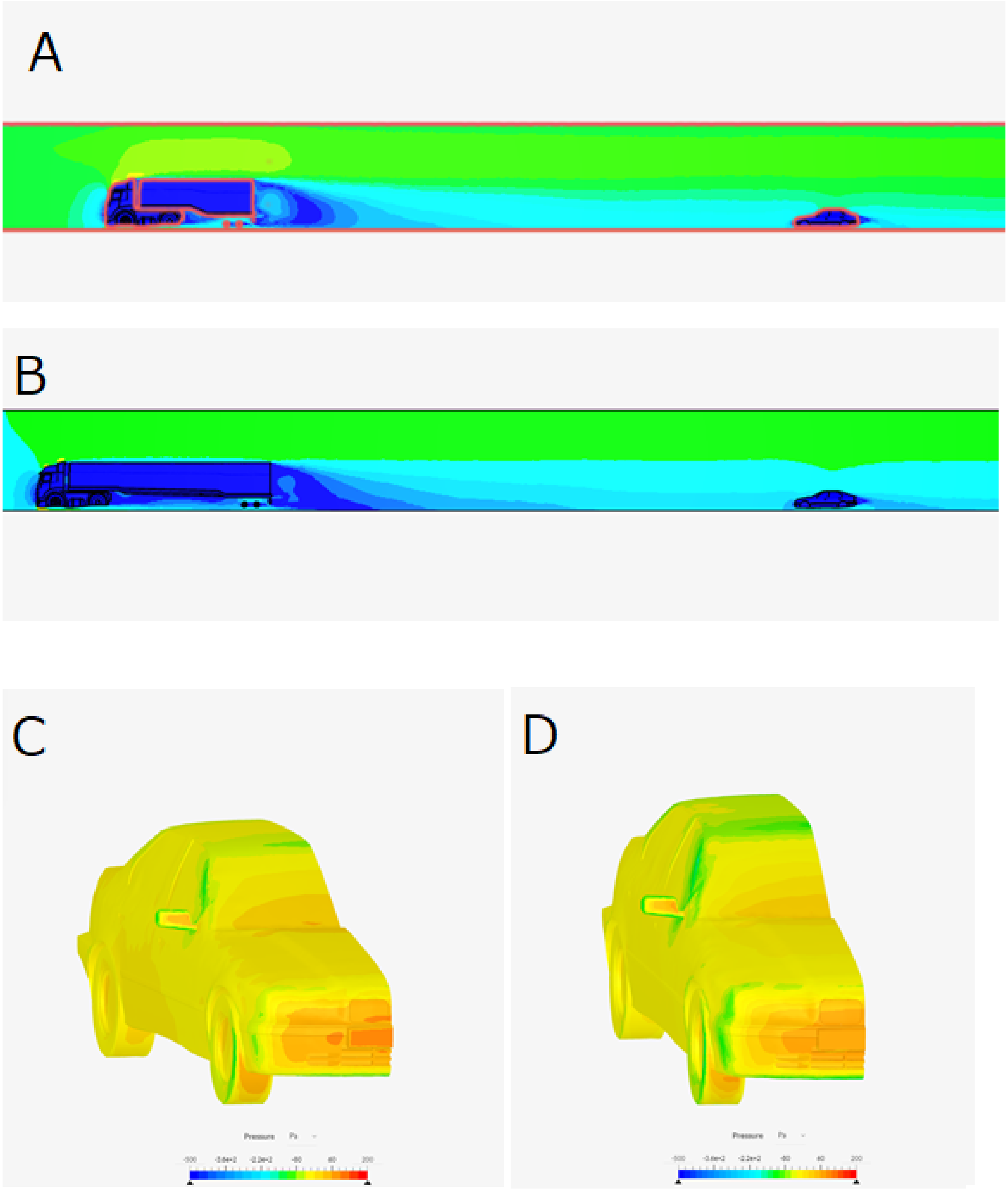

Figure 4. Comparing the pressure maps of the car behind 17m(A,C) and 10m(B,D) length trucks.

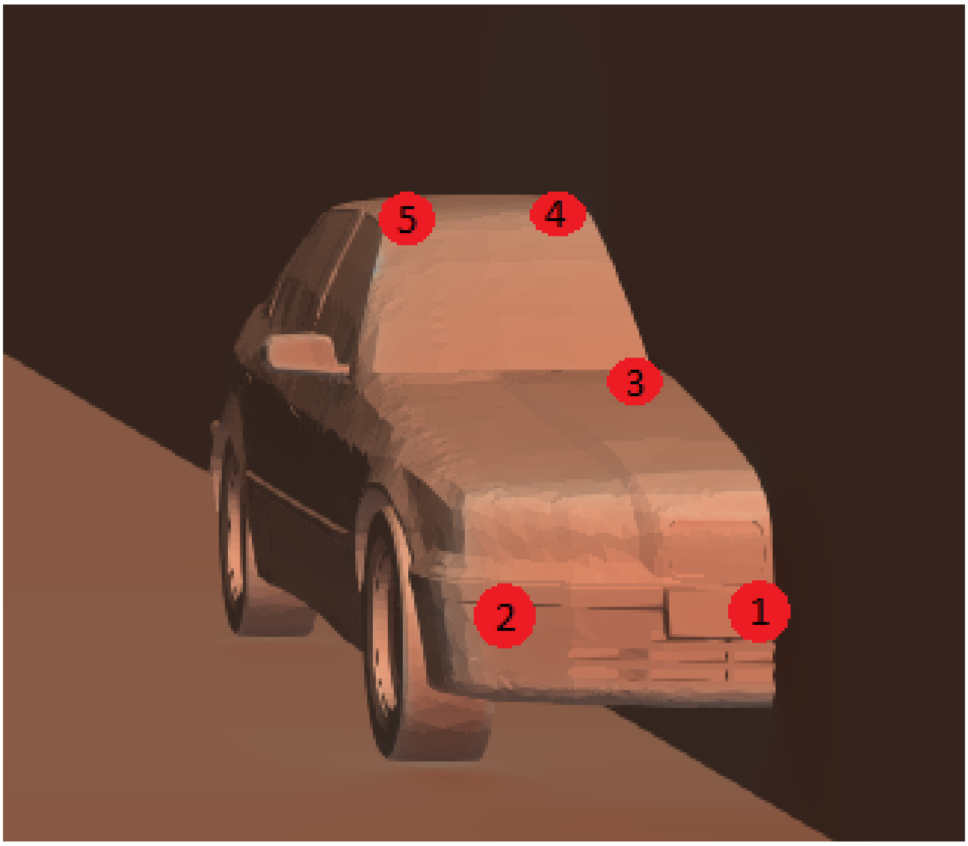

Figure 5. Proposed locations for air-flow sensors.

4 Simulation results

The following subsections show the results achieved by the simulation experiments.

4.1 Results

In this section simulations results are described. In total, were conducted 10 simulations, testing two speed levels and two sizes of trucks. For the saving interval, 1000s were selected. For the analysis data from 5 points on the car is used (as described earlier in section 3.3 and shown in figure 5).

For each simulation, data from each point was collected using the ParaView probe tool and to be analyzed later on. Data from each point showed distinguishable results, meaning that it is possible for each of the proposed points to be used for the project.

Results of the simulations are presented in tables 6,7,8. From the results it is clear that data from all sensors differs based on size and distance between vehicles.

The data from the pressure sensors is done in incompressible flow simulation meaning that the values are relative. The reason for selecting the relative data over absolute values, is that we are working with the pressure differences, which are more visible and understandable in lower values, compared to the absolute values.

Environments	1) Car number plate	2) Right side of the front	3) Hood, close to window	4) Roof centre	5) Roof right
60km/h 10m truck	99,83	62,93	19,59	-59,42	-49,13
60km/h 17m truck	88,68	45,69	4,82	-96,12	-77,14
90km/h 10m truck	221,4	121,83	12,98	-176,09	-145,29
90km/h 17m truck	272,86	145,58	20,72	-196,1	-157,58

Table 1. Simulation results for safe distances (Pa)

Environments	1) Car number plate	2) Right side of the front	3) Hood, close to window	4) Roof centre	5) Roof right
60km/h 10m truck (2x safe distance)	85,46	46,92	-0,8	-78,4	-66,04
60km/h 17m truck (2x safe distance)	114,69	59,62	10,27	-90,7	-72,32
90km/h 10m truck (1/2 safe distance)	206,86	135,31	44,43	-123,71	-99,86
90km/h 17m truck (1/2 safe distance)	95,15	63,61	-9,09	-57,31	-57,41

Table 2. Simulation results of different distances between truck and vehicle (Pa)

In addition to the initial simulation, two additional simulations were also conducted. First is for a 14m truck to compare the results with the initial simulation to find the relationship between data and the correlation in the results. Second is for the windy environment with 5m/s wind coming from the side.

Environments	1) Car number plate	2) Right side of the front	3) Hood, close to window	4) Roof centre	5) Roof right
60km/h 10m truck	99,83	62,93	19,59	-59,42	-49,13
60km/h 14m truck	127,4	63,67	11,86	-72,58	-69,71
60km/h 10m truck wind 5m/s	147,84	108,41	29,77	-73,32	-51,8

Table 3. Additional simulation results (Pa)

In addition to the pressure data from the possible sensor locations, air velocity maps are also shown in figures 6, 7. The data from the velocity maps shows the airspeed applied to the car and how it changes for the longest distances between car and truck.

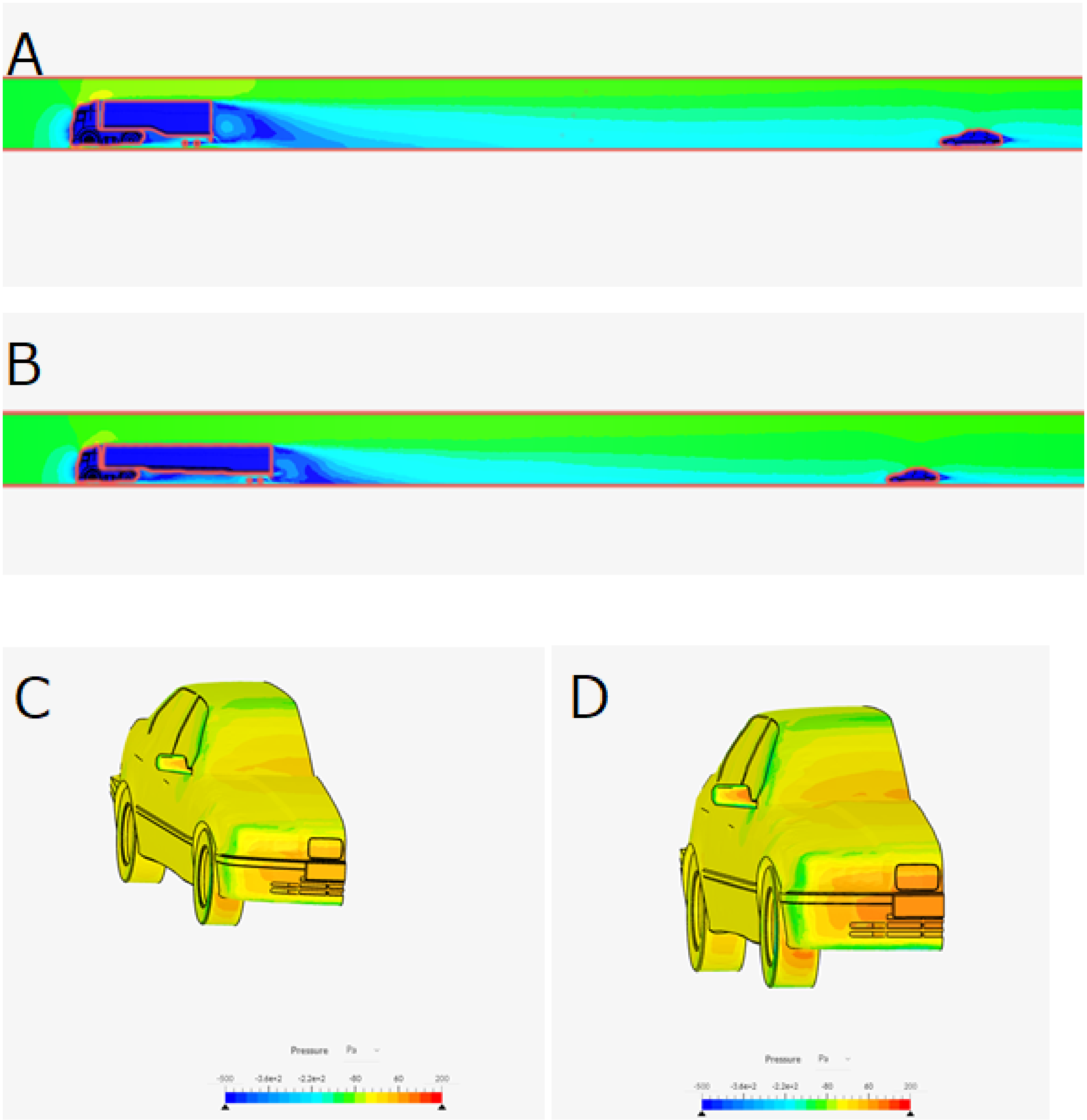

Figure 6. Air velocity map from 60km/h 2x safe distance simulation (10m (A, C), 17m (B, D))

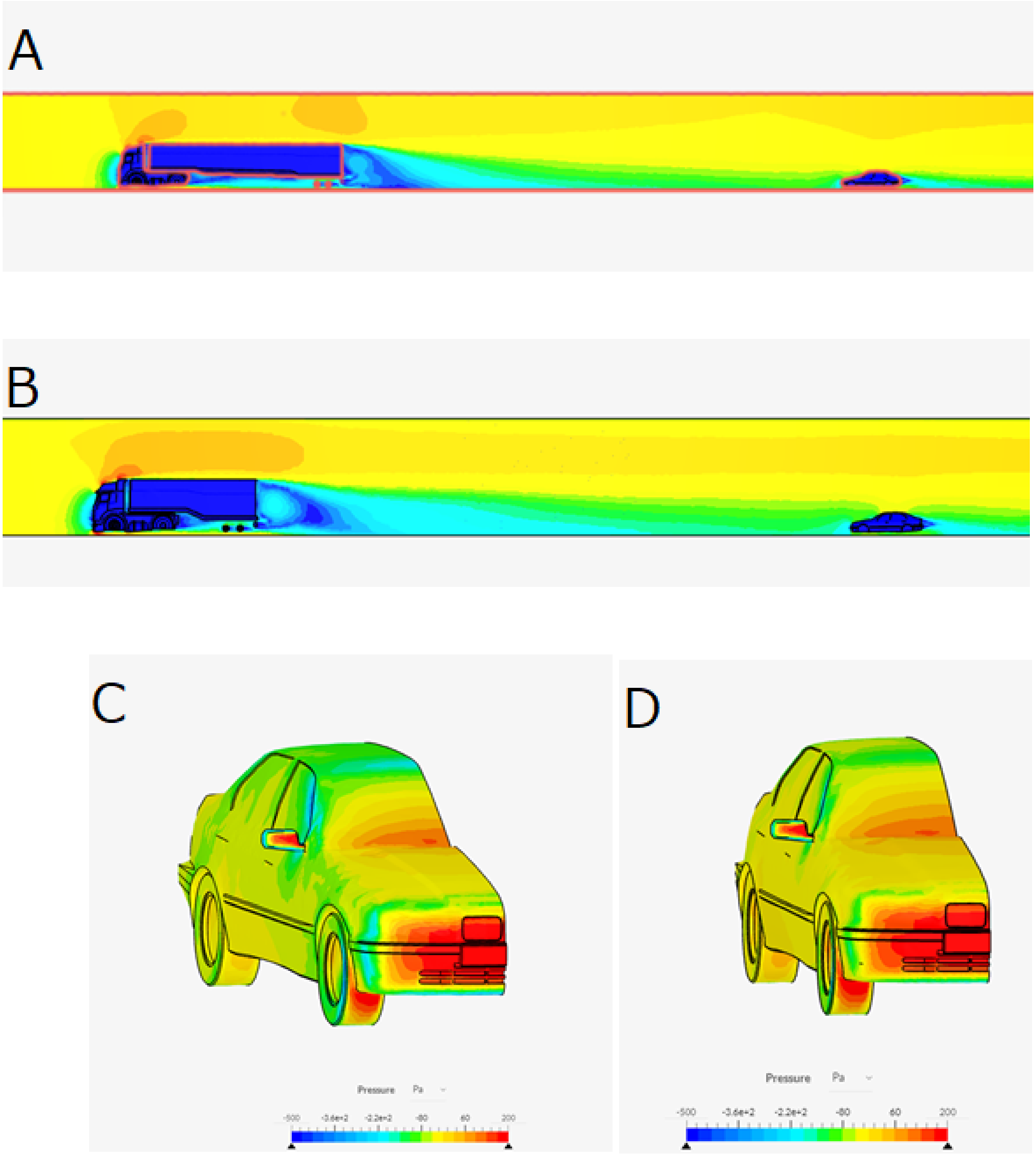

Figure 7. Air velocity map from 90km/h ½ safe distance simulation. (10m (A, C) and 17m (B, D))

4.2 Analyzing the results

It is clear that data from the same environments and different truck lengths do differ in the same direction as the length of the truck changes. However, the Pressure value for 60km/h does decrease with the length of the truck and is increased, while 90km/h does otherwise.

This may be caused by the differences in safe distances, which will be discussed later in this section.

Based on these results, unfortunately, it is not possible to accurately predict the length of the truck due to insufficient data amount. However, the data may be used for creating the lookup table. The lookup table may be used for estimating the length of the truck with the given data from the sensors. For example, we may expect the 9m long truck to give us data, which is slightly lower or higher than the data from the simulation experiments for a 9m long truck.

However, the next question is whether it is possible to predict the size of the truck in front of the vehicle. For answer to that question, it was decided to conduct an additional simulation with the new size of the truck and look at how the data change.

It was decided to create a new model of truck with a length of 14 meters. The hypothesis is that it is possible to find a relationship between length and pressure data.

The additional simulation did find the correlation with a proposed hypothesis, meaning that truck length changes are in some relation. The results shown at table 3, showed correlation in data at sensor locations 1,2,4,5.

However, the real-world experiments could possibly show different results. The reason for that is the simulations conducted for this project used the model, where wind is coming only from the front side. Meaning that wind flows only from the front, creating turbulence in the scene while not accounting for the wind coming from the sides, as it is for real-world applications.

The changes in the distances with the distance between trucks showed very promising results. First, we may see that with the changes in the distances we have opposite relationships between truck lengths.

Second, as we get closer to the vehicle in the front, we get the different pressure values on some of the sensors. For example, data from table 1 for 90km/h 10m length simulation 3rd -5th sensors, we could see the increase, while on others sensors decrease in pressure. Knowing that we could possibly distinguish truck sizes more accurately.

It is also seen that for the 2x safe distance, the 60km/h model showed us almost the same results as for the 17m long truck in the initial simulation. This could mean that there could possibly be a relationship between the length of the truck and air-flow data. Unfortunately, due to lack of data, this relationship was not discovered in this work but may be further researched for the real-world environment.

5 Conclusion

5.1 Conclusions

In conclusion, the research showed some promising results. Most of the proposed locations of the sensors showed the distinguishable results. The relationship between the length of truck and air-flow data, unfortunately has not been found, however the results show that it might be possible to create a look-up table. Look-up table could be used for estimating the truck length.

Conducting the additional simulation, with a 14m long truck, showed the correlation between the simulation data and look-up table. The changes in the truck lengths showed promising results, correlating with the data from 3 out of 5 sensors. Meaning that data from the look-up table may be used for estimating the truck length.

Unfortunately, as the distances between vehicles changes so does the pressure data from the sensors. Therefore, the look-up table does not apply to the distances other than safe distances stated by the traffic act. However, the relationship between distances between vehicles could be researched in future works.

Overall, the number of computational hours provided by SimScale were enough for most of the simulations.

5.2 Future directions

In conclusion, the research showed some promising results, meaning that this topic could be possibly researched in the future. Most of the proposed locations of the sensors showed the distinguishable results, meaning that these locations may be used for further research.

For the future research, there are some problems which could be further researched, which are outlined as follows.

First, the wind effect on the results. The simulation conducted in this work did not find any promising results, what may be caused by the incorrect simulation method, compared to the real-world environment. The effect of side winds needs to be further investigated.

Second, the distances between vehicles other than safe distances could be further researched as well. In practice, such scenarios do occur in real-life traffic.

Overall, due to limitations in simulation applications, the real-world model is advised to continue research on this topic. It may also be beneficial to apply a machine learning algorithm for feature extraction on flow data, for estimation of vehicle length, insteading of using a look-up table.

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