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Swarm Behaviour for Path Planning

(Schwarmverhalten bei der Fahrplanung)

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Vor- und Zuname:	Simon Sebastian Rotter
Matrikelnummer:	4639055
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Erstprüfer:	Prof. Dr. Raúl Rojas
Betreuer:	Fritz Ulbrich

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Abstract

Swarms are a known and studied phenomenon in biology. In different scientific fields transferring of the swarm ideas is done to solve specific problems. In computer science swarm approaches are applied from computer graphics till mobile robotics. The main contribution of this master thesis is to transfer swarm behaviour to the autonomous car context of the AutoNOMOS Project of the Freie Universität Berlin - *A Swarm Behaviour for Path Planning*. Therefore a processing pipeline is developed, which generates a driving plan for the autonomous car from swarm based data. A detailed description of the different processing steps is given. The steps include the topics: 1) Swarm member selection, 2) velocity matching, 3) swarm member trajectory based path planning, 4) abstracting data from swarm member trajectories to generate clustered data, 5) cluster based path planning, and 6) plan smoothing with linear regression. Furthermore the developed approach is evaluated and experimental results in simulation and live tests on the autonomous car *MadeInGermany* are provided.

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1 Introduction

1.1 Motivation

1.1.1 Limitations of Map Based Path Planning

In general, a driving car is connected with the task to know where the car can drive and how fast it can drive. Consequently one of the main problems in autonomous driving is how to find a driving plan, on which the car is able to go. A driving plan (short called plan) in this context is a planned intended future trajectory (driving path) for the car. It consists of way points in the environment and a speed which is given to the car controller. The car controller is responsible for reaching this way points with an appropriate speed. This speed must be smaller than or equal to the allowed speed. Further this speed must be below or equal the maximum speed the car hardware can cope with. Especially in unfamiliar, dynamic and unpredictable situations this is challenging. Different problems occur in this context:

- Is a street available where the car can drive?
- Where is this street?
- In which direction can the car go? In scenarios with different lanes, there are existing situations with different directions at different times during a day.
- What is the current state of the traffic?
- How fast is the car able to drive?
- Are there lanes which are more preferable than others? This has to be considered from certain point of views: e.g. how likely is it to stay on a lane or alternatively, are often lane changes probable? Which is the fastest lane? Which is the safest lane?
- and so on.

Current solutions are based on given maps, which are predefined. Information is pre known about the environment (traffic lights, number of lanes on the street, speed limits ...) and stored in these maps. The autonomous car is using this information to calculate an intended own trajectory at the middle of a lane. See for a current state and implementations in the AutoNOMOS Project [Wan12].

A driving plan is generated, based on this predefined information from maps, by the software of the autonomous car. Therefore information from sensors like GPS (Global Positioning System), odometer or IMU (Inertial Measurement Unit) are taken into account. Thus the current position of the car is determined. Further the autonomous car refines points from the plan (e.g. GPS points) which it wants to reach. Velocities at this points are also given from the maps. A car controller controls the actuators of the car in a way, that the wanted aims are reached. Reactive interaction takes part during execution in the case of obstacles which may occur on the plan and in the case that collisions could happen. This is called reactive break. For further details about the controller architecture of the AutoNOMOS Project and the usage of a

controller in an autonomous car and further related ideas see [Göh12], [GWSG11] and [Wan12]. See further explanations around the autonomous car in the descriptions of Chapter 2.

With this current state situations can be handled which are very static. A lot of data has to be known exactly before execution. The GPS points of the streets are needed - a map. And data about the velocities at that points must be pre known - stored in that map. Reactively, obstacles are taken into account by the controller of the autonomous car. But what happens in the case of changes and highly reactive changes in which not enough pre known data is available about the infrastructure? Examples for such cases are:

- Roads are connected with changes, in general: So roads can be changed or can disappear over the time. This will lead to problems in the case of autonomous driving, if the "old" known map is not up to date. Or in other words - maps have to be hold in a very current state.
- Highly reactive changes can happen on the streets: Accidents, changing weather conditions and so on. This changes may happen so fast, that they cannot be inserted in a map: E.g. a new lane course after such a change: Accidents, dirty roads, snow covered roads, damage on the road surface, and so forth. In such a case the pre known lane data is suddenly outdated.
- No GPS data or other global propagated positioning data is available: For example in tunnels. And further no Car2X communication data is available - for example because of obsolete technology in other cars or different communication standards between the communicating units. Further no lane data is present for example because of a new unknown area or outdated maps.
- Traffic situations like in roundabout traffics, where cars are taking lanes which are different from the marked lanes. Or in general, if no lane markings are available. But cars with human drivers are orientating themselves on each other to pass through the traffic situations. This may happen in very chaotic traffic conditions. No pre known data about the "actual used" lanes is available in this situations.

In these cases a solution is preferable which copes with such situations or at least make improvements, if it is used in addition to the solutions of the current state. So if one of the above described conditions is present, such a solutions helps the autonomous car to continue autonomous driving. A way is findable to manage the current situation. This is object of this thesis. To find a solution for exactly this problem.

1.1.2 Swarm Based Improvements

Above described problem situations mostly involve other traffic. Other cars are on the streets. Other traffic participants are still driving and are able to perceive the current traffic environment (streets, lanes, ...) and the changes of the environment (construction works, snow covered lanes, ...). The single entities of the traffic take such information into account. This defines their own driving habit. Thus participating traffic is a valuable source for exactly the kind of information, which cannot be pre known for the autonomous car through maps. So through perceiving the habits of other traffic participants, help is given for the autonomous car to act in a way that the above described problems are solvable. For example a situation in which vehicles are driving through a roundabout. Following vehicles will orientate itself towards the leading vehicles. Thus driving lanes are defined by the traffic itself. This may be different from the lane markings. Even if no lane markings are available, "driving lanes" are defined by the traffic. If

the autonomous car follows that traffic members and takes their driving habit into account to define the own driving plan, no map data is needed to pass through the roundabout.

In this context, an important fact is, that at the moment most traffic participants are humans. These participants are able to react to changes in an intuitive way. Embedded into this environment it is perfect for an autonomous car to orient itself towards this traffic participants which are having more foresight. But this approach is not only restricted to the use case of human traffic participants. Even in an environment with only autonomous vehicles, all traffic participants in front of the autonomous car can perceive another part of the environment or have more vision. This is a positive effect if that information is used by the ego vehicle in an intelligent enough way. So even in the case of not human drivers an orientation towards other vehicles respectively an taking into account of the habits of the other traffic participants and a selection of them can lead to a gain.

So in that context cars in front of other cars give exactly three very essential information:

- Possible way points: If a car was driving through a certain point in the environment a few seconds before (and given that there where no abnormal happenings like accidents after it). Then at this point the own autonomous car can drive, too. Assumed it can reach it.
- Connection of possible way points: If a perceived car was reaching different way points over some time, then this is an indicator for a possible way between that way points.
- Speed: If a car is driving at a certain point with a certain speed, then it is highly probable, that the autonomous car can go through this point with the same velocity (or less if the hardware is not allowing it), because they are driving there with no problem.
- (Direction: included in above points because speed can be seen as a vector with direction and connections between points include that information)

In all points a temporal connection has to be given, which is small enough. Means that all situations underlie the time component. If too much time is elapsing between an observation, an usage is more likely to be impossible because the situation is changing over the time.

So an orientation of the autonomous car towards other traffic participants is usable to get information and later solutions for coping with the current traffic situation. That information combined and adjusted to the needs of the current situation of the autonomous car leads to an improvement of the current state. All of the descriptions in this subsection leads to the need for resorting to current knowledge in the swarm area.

As described before, situation specific information about the environment can be obtained from perceiving the surrounding of the agent. If the agent is orientating itself towards other agents, this can be compared with a swarm (see Figure 1.1). Swarms were described in biology and are used in different scientific fields. There have been made different approaches to describe or use the currently known insights into swarms. Facts about the current state of the swarm topic can be read in more detail in Chapter 3. If basic concepts are understood and transferred to the area of autonomous driving cars, there will be a strong and powerful tool to handle the described situations. An application of the swarm ideas is described in Section 4 and an evaluation is provided - Section 5.

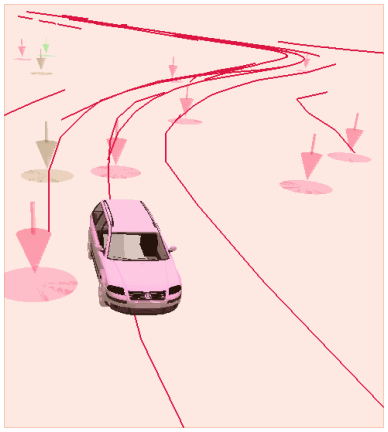


Figure 1.1: Ego car, and swarm members with their trajectories

1.2 Requirements

To reach this aim different requirements are defined. To transfer the swarm based idea into the autonomous car context of this project different points have to be reached. In Table 1.1 basic points are summarized. The AutoNOMOS Project of the Freie Univesität Berlin has an experimental vehicle which is able to drive autonomously (described in more detail in Chapter 2). Object of this work is it to contribute a component to the software which extends the current solution through swarm based approaches (**REQ01**). In this context it is important to transfer the ideas of swarms into the context of autonomous cars in (daily) traffic (**REQ02**). These ideas have to be implemented in software - so algorithms are needed to realize this (**REQ03**). Further appropriate data structures are required to get to that aim (**REQ04**). One important task is to embed this piece of software into the current software/hardware architecture. So interfaces are needed (**REQ05**). And further an appropriate way has to be found to integrate the currently available data which is already achievable through the current implementations (**REQ06**). In addition tests have to be made. On the one hand side simulations have to be done to test first implementations (**REQ07**). For the simulations, there will be need for a way to visualize the processing (**REQ08**). And on the other hand side real tests with the test carrier have to be done to validate if it is working under real conditions (**REQ09**).

1.3 Contribution

1.3.1 Application of Swarm Based Approaches in the AutoNOMOS Car

Main part of this thesis is to implement a module with algorithms and heuristics. This module is called "Swarm Behaviour Module" and applies swarming approaches. The output of the module is used to realize a swarm based path planning. Thus a swarm based behaviour is added to the project. There is currently existing a non swarm based behaviour. This behaviour works with pre given maps and reacts on dynamic obstacle changes. The "Swarm Behaviour" of the present work should be seen as a complement to that existing and established behaviour. It can be further seen as an extension for specialized circumstances as for the cases described above.

Further through the contribution of this work a "sub framework" emerged for the swarm behaviour. This can be used in the AutoNOMOS Project and it can be further developed and adopted to new requirements concerning swarm ideas. In general, the implemented ideas can be divided into two subcategories: Once a swarm member trajectory based path planning. And

REQ01	Swarm based extension of the current software solution for the autonomous test carrier
REQ02	Using swarm based ideas for the context of autonomous cars in traffic
REQ03	Implementation of algorithms to realize swarm based ideas for autonomous driving
REQ04	Implementation of data structures to realize swarm based ideas for autonomous driving
REQ05	Embed implemented software into the current AutoNOMOS Project architecture and define interfaces to existing modules
REQ06	Integrate data of current project modules
REQ07	Test implementations through simulation
REQ08	Visualize the swarm based data
REQ09	Real live tests with a test carrier of the AutoNOMOS Project

Table 1.1: Requirements

further a path planning based on abstracted trajectory data. In the last case, redundant data is used in a merging process to obtain more robust swarm based data.

While the swarm behaviour part is qualified for active interaction of the car, there is another gain for the project based on the swarm approach. Maps of current accessible traffic lanes on streets can be obtained. This is also usable for swarm based path planning. Further it is a possibility to gather information about the environment for further usage like exchange of current traffic data and build up of general driving maps in new locations. For this application a basic framework is provided, which can be used for applications in future work connected with swarm based path planning.

1.3.2 Testing Under Controlled Conditions

Further extensive testing is part of this work. As autonomous driving is connected with high safety risks for traffic participants if the software is not working properly. It it is important to test new software modules extensively. In that way not foreseen reactions of the software can be observed. So the software can be adapted and improved, based on that insights. Therefore a process with more steps during different phases was used to cover good testing:

Implementation

First the basic ideas were implemented. Swarm approaches were adopted to the autonomous car context and algorithms for heuristics derived. They were basically tested so that the software was running. Further data exchange of modules was tested. Important was to test the executability in connection with the existing modules of the project to exchange data.

Testing With Logged Data

Further logged data from past autonomous test drives were used. For that test drives a test carrier was used which is able to log different sensor and actuator data of the car. For further descriptions see Chapter 2. This was useful for the testing of the swarm behaviour implementations of this work. Specialized sensor data in special situations is used as input for the swarm behaviour implementation. So reactions of the swarm behaviour module in exactly that situations could be analysed. Special test situations in traffic could be classified into different use cases:

- Straight Stretches: One ore more lanes are going straight.
- Curves: Curved course of the roads.
- Roundabouts: Most demanding tests which includes above cases.

If considered roundabouts in combination with its entry and exit it contains the other cases. This case was consequently taken as a reference for most tests. The logged data of a real test carrier drive were used. The temporary reactions of the swarm behaviour module were analysed at certain points in the logged data. This allowed a fine tuning of the module.

Testing in a Simulator

As soon as the tests with the logged data caused a satisfying result tests with a simulator were performed. Here the habits of a "virtual" autonomous car can be executed and observed. The test is based on some logged data like in the phase before. In difference the simulator test allows to carry out longer and more complete tests. Further the logged data is used as input and is timely connected as in real life. Processing of the swarm data takes place. The output is given to the simulated hardware. A model car is carrying out the commands time related to the current logged situations. In that way a pre observation of the swarm behaviour module in real situations in connection with the autonomous car were checked.

Testing with an Autonomous Test Carrier

When the tests with the simulator were completed and reached a satisfying result, live tests with an autonomous test carrier (see Chapter 2) could be carried out. This is a similar interaction of the modules as in the test before but with a real car and real traffic environmental conditions. The car gets the control commands of the data processing modules and carries them out. A safety driver observes the habits of the car and intervenes if necessary. Therefore the special test area Tempelhofer Feld in Berlin was used. So that normal traffic and humans cannot be endangered.

2 AutoNOMOS Projekt

2.1 The AutoNOMOS Project

This work was developed under the AutoNOMOS Project of the Artificial Intelligence Group of the Freie Universität Berlin (see [Laba]). The project has its roots in 2006 and gained experience with different research topics around autonomous driving over the years till today. A more detailed description of the project and the test carrier follows.

2.1.1 History, Current State and Achievements

The project has different test carrier vehicles which are able to drive autonomously. First approaches were made with the car "Spirit of Berlin" in 2007 (see [Labc]). Later the car "MadeInGermany" were added (see [Labb]) and is applied nowadays together with an electric car called "iMiEV". These cars are used for testing new research topics and approaches like in this work. The experimental vehicle used for testing the implementation of the swarm approaches is "MadeInGermany" and is introduced below.

In 2007 the project was taking part in the DARPA Urban Challenge - where autonomous cars of different teams were participating [RRG+07, p. 2f.]. In that challenge real traffic scenarios had to be managed by the autonomous car. Further one of the main tasks was to develop the autonomous car so that it is able to coexist in the daily traffic of a crowded city. This was achieved in the city Berlin where "MadeInGermany" is able to drive (compare [Wan12, p. 49]). Over the years the basics of the project have been built out. New projects were evolving like the "Intelligent Wheelchair", "Pick me up!", "iDriver" or "BrainDriver" (see [Laba]). Current projects are focussing on new research topics and improvements of existing approaches.

Nowadays the AutoNOMOS Project provides a framework for new sub projects and ideas. With its test carriers a hardware architecture is available. Further there was evolved a software architecture with different working modules on different abstraction layers. So new ideas can be integrated and set up on the current foundation. Below a description follows, how the current hardware and software architecture is used to reach the aim of this work.

2.1.2 The AutoNOMOS Car

Different test carriers have existed in the AutoNOMOS Project. For the integration of the swarm behaviour approach into the project the autonomous car "MadeInGermany" has been used. A picture of the test carrier can be seen in Figure 2.1. It is based on the Volkswagen Passat Variant 3c which is used as the basic driving platform (see [Labb]). It has an automatic gearbox and is extended with further hardware. Via the CAN-Bus (Controller Area Network Bus used in vehicles to communicate data between sensors and actuators) data can be received from and given to the platform of the Passat. So an extension of the platform with further hardware is possible and a communication to the platform is achieved. For different built in sensors see Figure 2.2a from [Labb]. The sensors can be classified into groups. So a GPS (Global Positioning System) module, an IMU (Inertial Measurement Unit) module and an Odometer is used for the tasks connected with the localization of the car. Vision systems, Laser scanners and

Figure 2.1: Autonomous test carrier - MadeInGermany (MIG)

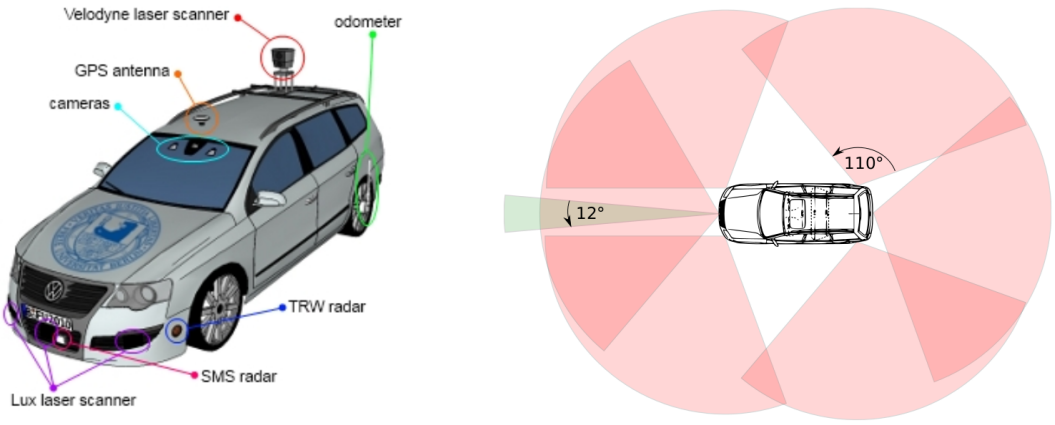
radar modules are used to perceive the environment of the car to enable further tasks connected with environmental observation. For a more detailed description of these hardware modules see below. For testing the swarming ideas at least one other car is needed in the test scenarios. For that reason the second test carrier iMiEV (see Figure 2.3) was applied.

Sensors for Self Navigation

Different sensors for self navigation are integrated. In the context of robots - especially autonomous cars - it is important to know the own position and further information like the own velocity. Such values of the own car are called "ego" data in the following. Ego data is needed for swarm based applications because the own data (especially position and speed) is needed. This data is further essential in relation to the data of swarm members. An **Odometer** is used to get data about the position and alignment of the car. Rotations of the wheels are counted. A covered distance can be calculated with that data. A **GPS (Global Positioning System)** antenna is integrated to additionally get position and alignment data of the car. Further the velocity of the car is obtainable. An **IMU (Inertial Measurement Unit)** is built inside the car. It is used to get more appropriate data about the position and speed of the car via measurement of inertia. This is required because in standard traffic contains areas where the GPS is not available e.g. in tunnels or if there is longer no GPS covering in some area.

Sensors for Environment Perception

If the own data about the car through the above described sensors is known, it is further important to percept the environment. In the swarm context it is necessary to get data about obstacles in the surroundings of the ego car. This information about obstacles is used to find moving objects which can be used as swarm members. The integrated **Velodyne Lidar** (light detection and sending) unit is of type "HDL-64E LiDAR". It sends out laser beams to measure the distance to objects in the environment. It is using a concept of a rotation of 64 laser beams to get a relatively detailed point cloud of the environment of the car. Through rotation a 360 degree view is possible. One **TRW radar** with a field of view of 12 degree and distance range of 200 meters - see [GWSG11] is further integrated. The radar is used to get object information. Further a **SMS radar** is used. Six ibeo **Lux laser scanners** are used for object information. They have a relatively wide field of view of 110 degree (horizontal) and a distance range of 200 meters - see [GWSG11]. Different types of cameras are used for **Vision**. They are applied for



(a) Autonomous car - Sensors of MadeInGermany (from [Labb])

(b) Autonomous car - Sensorrange of Lux Laser Scanner and TRW Radar (from [GWSG11])

Figure 2.2: Basic hardware and sensor ranges of the test carrier

different advanced projects. E.g. special Object detection like traffic lights.

Sensor Data Fusion

Different sensors are used to additionally get a (nearly) 360 degree sight around the car - see exemplary Figure 2.2b from [GWSG11]. This is important in the swarming context to percept the environment for possible objects usable as swarm members. For sensor data fusion used in the project see [GWSG11]. The basic idea is to take the advantages of the different sensors and combine them to overcome the special weaknesses of the single sensor types. Equally the cover range of a single sensor is fixed. So combining data of more single sensors of the same type in different direction leads to a wider view. In that way a 360 degree panorama view (at a certain distance to the car) can be reached. Further the distance range of sensors reaches up to 200 meters. So a relatively huge area around the car can be observed. For this purpose see Figure 2.2b were by way of example the combination of different Lux sensors together with the TRW radar is shown. A detailed description of the concept of the sensor fusion in the project can be found in [GWSG11]. Combining the data of the different sensor sources leads to the ability to detect obstacles and their characteristics. Examples are:

- size of obstacle
- speed
- direction

This data is fundamental for the swarm behaviour concepts. So the information gained by the sensor data fusion is basic for this work. The sensor based information is treated as abstracted from the sensors throughout the work.

Safety

A special safety concept is used in the project. In detail it is described in [GWSG11] and in [Wan12] (especially see Chapter 3.4 about the Software System Architecture and Chapter 7 about the low level controller). A generated plan with positions and velocities is handed over to a low level controller of the autonomous car. At that level safety checks are accomplished. Positions and velocities of obstacles are used to calculate a safe own velocity and distance. If distance and velocity to obstacles are not appropriate a break is performed.

Figure 2.3: Autonomous car - iMiEV

2.2 Framework

2.2.1 Software/System Architecture

The autonomous car can be seen as a robot agent. It has sensors to perceive the environment. Furthermore it has actuators to change the state of the environment - or better in this context to navigate through the environment. Between perception and actuation there is need of some processing. Therefore different modules are used which are responsible for solving different tasks. For this work a module for doing the processing for the swarm behaviour was created. It was integrated into the existing software architecture. Modules can be classified into different areas connected to localization, perception and computer vision, navigation and further modules which are managing the data flow to the hardware of the car. The general idea of the software architecture with data flows can be seen in Figure 2.4 from [Wan12, p. 64]. According to the work of Miao Wang [Wan12] the module categories have the following tasks:

- Vehicle Data and Localization Modules: responsible for providing data from the vehicle and data about the position - interface to the hardware of the car.
- CV (Computer Vision) Environmental Perception Modules: providing data about the environment based on cameras.
- 3D Environmental Perception Modules: providing data about the environment based on laser scanner, radar and ultrasonic hardware.
- CN (Cognitive Navigation) Modules: here the the logical modules are located which are connecting and processing the data of the different other modules described above.
- Control and Actuator Modules: are the interfaces between the logic and the vehicle. So that the vehicle can perform the orders of the logical processing.

The module for swarm behaviour of this work can be integrated into the CN Modules. It needs data from the vehicle and localization modules. Further it gets data about objects in the environment from the lateral modules. A communication with the hardware takes place via the "Control and Actuator Modules".

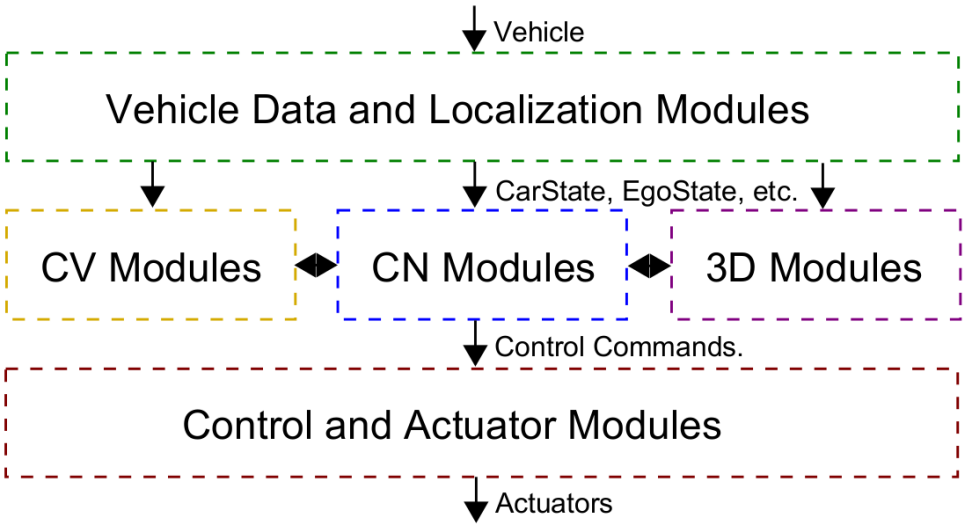


Figure 2.4: Overfiew of the general software architecture (taken from [Wan12, p. 64])

2.2.2 Orocos

As a basement for the project implementation the “Open Robot Control Software” (OROCOS) is used (see [ra13] and [ra08]). It provides the infrastructure for modules which are able to communicate with each other in form of C++ libraries. OROCOS is open source and used in numerous open source projects. To be flexible it has a modular structure, where the interfaces have to be described well (see [Bru01]).

So called OROCOS-Tasks (TaskContexts) are used to enable a distribution across different computers (compare [RRG+07, p. 6 f.]). These OROCOS-Tasks are code classes, which can process code. That tasks have different standard methods which are called at different lifetimes and which implement different functionalities. One of these methods is called, when the OROCOS-Task is started the first time. Here basic functionalities are implemented to organize and manage everything so that an OROCOS-Task is able to work in the following phases. Then there are methods which can be called periodically or event triggered. Here the general main functionality of a task is implemented. This is the code which mostly is running during the main runtime of the module. Algorithms for the later described "Swarm Behaviour Module" of this work are located here. Than there are further methods for functionalities like cleaning up at the end of a lifetime of a module.

An OROCOS-Task can have connections - so called ports. This ports are divided into input and output ports and are allowing to exchange data. So modular connections between different kinds of tasks can be established and data objects can be sent between different modules. Therefore functionalities can be distributed in a very modular way which is a big advantage for this project. For example the logic of the later described "Swarm Behaviour Module" and the visualisation of the result of the processing can be split. This is especially valuable for tests with the test carrier: visualisation of the current processes/ decisions while execution of the autonomous driving is possible. So interpretation and evaluation of the autonomous behaviour can take place and is accessible for the safety driver. In the OROCOS context combined with own implementations it is important to think about critical resources and possible deadlocks and use semaphores or mutual exclusions if needed.

2.2.3 Visualisation

For simulation, test and presentation reasons a kind of visualisation of the implemented ideas is needed. Therefore OpenSceneGraph is used which is "[..] an open source high performance 3D graphics toolkit, used by application developers in fields such as visual simulation, games, virtual reality, scientific visualisation and modelling" [Ope12]. It is based on C++ and OpenGL (see OpenGL web page: [Ope14]).

Scene graphs are modeled with the OpenSceneGraph toolkit. So a rendering of all relevant objects for the swarm behaviour and the car is possible (see simulation pictures throughout this work). Connections and data transfers between the logical algorithms of the swarm implementations and the visualisation with OpenSceneGraph is solved by OROCOS tasks and the port connections (as described above).

Additional visualisation is done directly with OpenGL ([Ope14]). Throughout the work, benefit from the existing project implementations and code examples was possible. In particular this was helpful in the context of OpenSceneGraph, OpenGL and OROCOS.

2.2.4 Environment and Further Tools

For integrating modules into the exiting software, XML-files are used. In these files configurations parameters are set. Further connections between ports of modules are set. As described above, an OROCOS-Task can have different ports. Between ports connections can be established. Exactly this set up is defined by the XML-files. A tool called "Remotecontrolcentre" is configured via this files, too. It is used as a Graphical User Interface (GUI) for simulations and starting different software modules.

Implementations of a road model are available from the existing project. This was very convenient for testing the swarm approaches of this work. Because data for a possible visualization of the "real" roads with its lanes could be used for comparison. Tracked and logged data is matched onto a map via GPS information for this purpose. With the data of the road model e.g. a comparison of swarm based paths to real world infrastructure can be tested and shown. The used technology for the road model was the Route Network Definition File (RNDF). For further information connected to that topic see [Cze14].

As programming language C++ with related libraries is used. To emphasise is the library "Eigen" - a powerful tool for linear algebra with matrices and vectors (see project page [Eig14]). Linux Ubuntu is the used operating system. Further different tools were used to accomplish the implementation and the project management. For version managing the tools Git (see [Git]) and Mercurial (see [Mer]) were used. Project tools for distributed compiling and simulating were applied.

3 Related Work

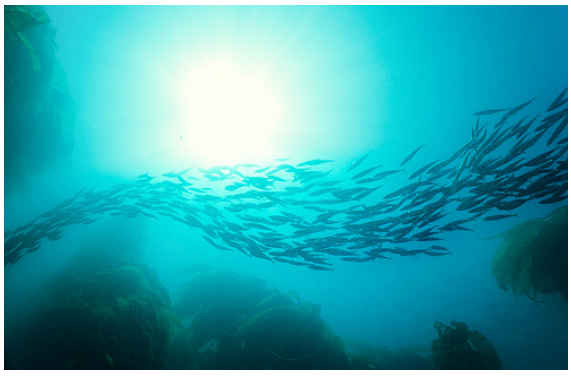
3.1 Swarm in Biology

Swarms occur in nature. Different kinds of animals are existing which are known to appear and act in swarms - see for example birds and fishes shown in Figure 3.1. Further examples from biology can be found like bacteria. Consequently swarms can be found in different living environments connected to the elements water, air and land. So nature "built up" the swarming concept to cope with different difficulties in these areas as following described. To mention just some examples (compare research work dealing with this swarms and related topics e.g. [CRB12], [Rey87], [GGT07], [HW90], [BDT99], [CDF+03], [TZ13]):

- Animals like sheep, cows or horses which are in herds
- Ants (e.g. managing their food provision or building constructions)
- Birds (e.g. flying in groups)
- Fishes (e.g. swimming in schools)
- Bacteria colonies
- Bees (e.g. finding nectar)

Even research around human crowds exists (e.g. see [Cou12] and [TZ13]). A lot of work has been done to try to analyse, to understand and to benefit from that part of the nature. In this context the term "swarm intelligence" is mentioned ([GGT07], [CRB12], [BDT99]). The basic idea is that many swarm members are acting in a relatively simple way, but the global behaviour of the swarm is relatively intelligent and brings gain to the swarm as a whole - see for example [GGT07] and [CRB12]. An interesting point which came out from the research about swarm intelligence is, that individual members of a swarm have only limited knowledge about the global situation (compare [GGT07, p. 5]). So the interaction in the swarm leads to a result

(a) Swarm of birds flying aligned in one direction - from [Tre09]



(b) Swarm of fishes (school) - a directed movement can be seen - from [Wan]

Figure 3.1: Different kinds of swarms in nature

which can be more than the abilities a single entity can provide. This is exactly what can be used in the autonomous car context - as described later.

Further in literature the word "Stigmergy" is used in the context of social behaviour between animals or agents. It is used to describe how agents are communicating and coordinating themselves through their actions and the resulting changes in the environment (see e.g. [GGT07, p. 5]). Corne et al. emphasize, that this kind of communication is indirect [CRB12, p. 3 ff.] and compare its fundamental "stigmergy structure" with a notepad which is used by the swarm members to leave cues.

Ants navigate with the help of pheromone deposition (which is a kind of stigmergy) to food sources (see e.g. [GGT07, p. 5] or [CRB12, p. 3]): Ants can set pheromones when a path should be marked. Other ants can follow that trails. In that way paths to food sources can be propagated and used amongst the ants. If we see the colony of ants as a swarm, that leads to advantage for the whole swarm. Food can be transported and consumed by the swarm by using the propagated information of single entities. So not all agents have to use their time with searching food. This is one further example, how the "intelligent" behaviour of a swarm can lead to an advantage.

Garnier et al. define four different organising functions between the task of social insects: "Coordination" ("[..] organization in space and time of the tasks required to solve a specific problem"), "Cooperation" ("[..] individuals achieve together a task that could not be done by a single one"), "Deliberation" ("[..] mechanisms that occur when a colony faces several opportunities") and "Collaboration" ("[..] different activities are performed simultaneously by groups of specialised individuals") [GGT07, p. 9 ff.]. Keeping that ideas in mind helps to find swarm solutions for the autonomous car project. Especially the functions "Coordination" and "Cooperation" were used as a inspiration for the work of this thesis.

As suggested by Garnier et al. knowledge about swarm intelligence can be used for control algorithms in artificial agents appearing in groups ("colonies"). So uncertain environments and changes can be handled (see [GGT07, p. 19]). Current research on understanding "collective dynamics" is done by P. Romanczuk. In [RSG12] a swarm formation and pattern formation with help of "selective attraction and repulsion" is analysed.

As we see there is existing a lot of knowledge from the biology. Research on understanding and transmitting the ideas is done. Compare in this context the descriptions and presentation of the current "research progress of swarm robotics" in [TZ13].

All of this knowledge can be used as an inspiration in the autonomous driving context:

- only locally perceptible environment for the autonomous car (surroundings of about 200 meters because of sensor range)
- intended globally good solution (e.g. drive through difficult traffic situations like roundabouts while considering static and dynamic conditions)
- use information perceptible from close by traffic (swarm members)
- no global aware access to the situation

3.2 Basic Swarm Approaches in Different Fields of Computer Science

Even in the area of computer science there has been made efforts to profit from the gain of swarms. The history of the development of this research area reaches from solving of optimization problems to simulations in computer graphics.

3.2.1 General Application of Swarm Based Ideas

Bonabeau et al. give in [BDT99] a good overview over different applications which have biological examples. Chapter two of [BDT99] gives explanations for "ant-based algorithms or ant colony optimization". These algorithms are used for solving optimization problems. Further algorithms for data analysis and graph partitioning are introduced by Bonabeau et al. Further examples can be found in [BDT99]. In this context "the most popular and successful algorithms that are associated with swarm intelligence" are described in [CRB12] with focus on natural inspiration: "ant colony optimization", "particle swarm optimization" and "foraging algorithms".

3.2.2 Application in Computer Graphics

One of the fundamental works for the scope of the present thesis is originated in the special field of computer graphics. Current works (e.g. [BLLG11]) connected with swarm ideas are using or discussing Craig W. Reynolds fundamental ideas to describe a swarm in their work. The so called Reynolds Rules - see [Rey87]. The basic idea was to animate different kinds of swarms like flocks, herds, schools of animals (in the following the different occurrences are subsumed under the word swarm) with computers. In his work Reynolds defined three rules which are basic for a swarm model (see [Rey87, p. 4]):

1. Collision Avoidance: avoid collisions with nearby flockmates
   short called **separation**
2. Velocity Matching: attempt to match velocity with nearby flockmates
   short called **alignment**
3. Flock Centering: attempt to stay close to nearby flockmates
   short called **cohesion**

When agents are interacting in a swarm it is important not to collide with other agents. Therefore rule 1 is in the model. Further a swarm has to be kept up. Rule 2 includes the demand to move and act in a way that the same direction is obtained. To add a rule which tries to center the swarm rule number 3 is inserted. In combination this rules allows to simulate a swarm and as already mentioned above are basic for current works which are engaged in the topic swarm and were published after the years of 1987 (see for example [OS06]).

3.3 Current Swarm Approaches in Mobile Robotics

In the field of mobile robots current approaches have been made to achieve a swarming behaviour of different robots. A. S. Barrera et. al are discussing an approach, based on a method called Particle Swarm Optimization (PSO), to get a model for swarm behaviour [BLLG11]. Important for that method is a given single target, which an agent wants to reach. In their future work they want to focus on a multi target approach. They see applications in multi-robot systems and unmanned aerial vehicles (UAV), see [BLLG11, p. 1]. Basics about Particle Swarm Optimization can be found in [KE95]. D. H. Kim shows an approach in [Kim10] to obtain a swarm behaviour in a group of mobile unicycle robots. In his work a modification of the Particle Swarm

Optimization technique is shown. He uses an approach were the robots want to reach a certain target. See also [KS06].

Existing projects with mobile flying robots show approaches of swarm ideas. In [NFJ+14] a project of the University of Glasgow with quadrotors in the micro unmanned aerial vehicle area is described. Simulations and ideas concerning swarm basics with multiple unmanned areal vehicles are shown. The work of Parunak et. al [PBO03] deals with solutions for advanced cooperation tasks by using a swarm of unmanned aerial vehicles. Formations and path planning are two of the discussed challenges. Further an inspiration from biology is described. Here an idea for coordinating of agents is used which is comparable to the pheromones used by "[..] colonies of social insects [..]" [PBO03, p. 8] like the pheromones of ants. The used idea is called a "Pheromone map". It is highlighted that the used method is well suitable for dynamic environments. Further ideas can additionally be read in [PPO02]. Where basics and thoughts to coordination of UAVs by pheromones are explained. A transfer of the biological pheromones to a digital model is described and advantages are given. Ideas can be used in the autonomous car context. The NASA Dryden Flight Research Center published in 2005 information about their experiments about two UAVs (unmanned aerial vehicles) in a swarm. In the experiments basic ideas from fish and bird motions were used to coordinate the UAVs "..for airborne monitoring and surveillance of natural disasters and for atmospheric sampling" [HD05].

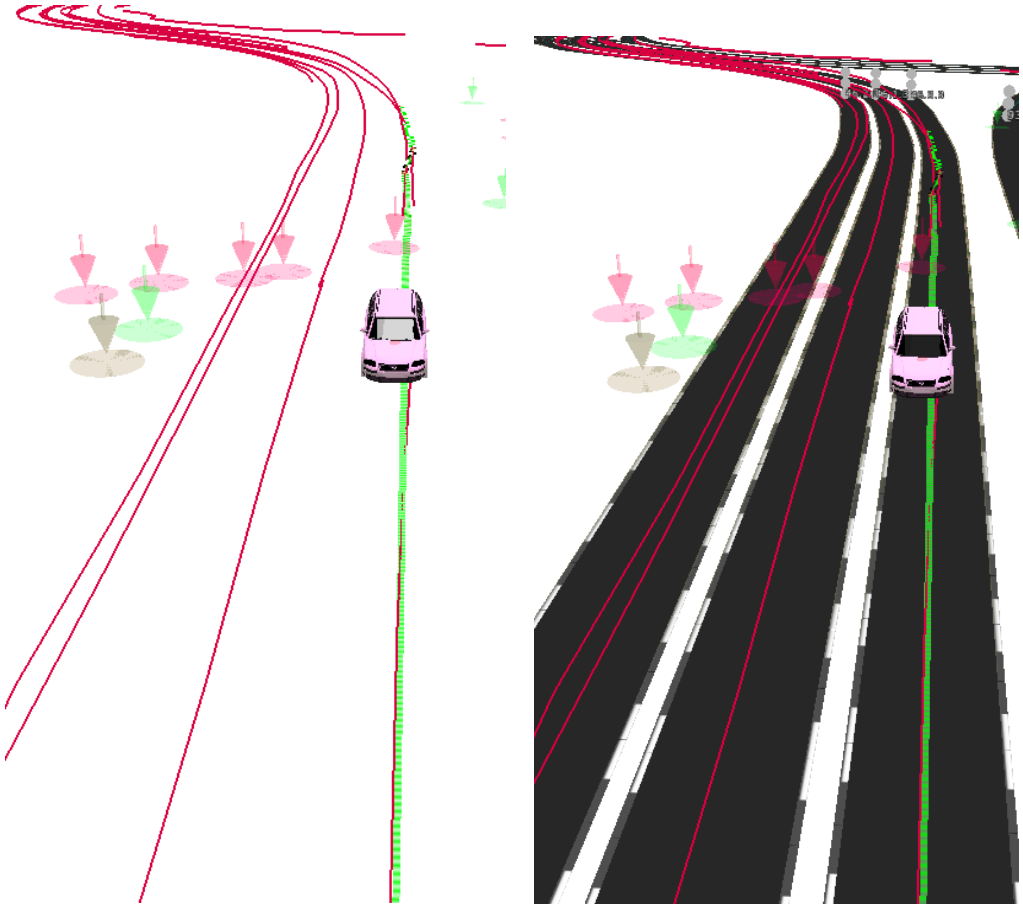
In this work will be introduced how the idea of swarms can be used for mobile robotics in a special field: Autonomous cars (especially connected with path planning). Here mobile robots are bounded to streets. On the streets there can be many cars which can act as swarm members. In this context, situations like many cars following a curve can be considered as an example. From all detectable cars these swarm members have to be selected and their data has to be evaluated. From this information valuable deductions can be made for the own decisions of the autonomous car - as it will be shown in this work. To reach this aim there was lot of inspiration from the very basics published by Craig W. Reynolds [Rey87]. However, approaches like the ideas around PSO, are having the limitation that they are requiring a target. This can be hindering in the autonomous car context as elaborated later. Still the work around PSO (e.g.[BLLG11] and [Kim10]) influenced the ideas of this work in sense of a starting point of thoughts how to transmit the biological idea of swarms into the field of robotics and further into the use case of the autonomous car of the Freie Universität Berlin.

4 Implementation of Swarm Based Approaches for Path Planning

4.1 Basic Idea of a Swarm Behaviour Module in the AutoNOMOS Project

A basic daily traffic scene is visualized in Figure 4.1a. The scene is based on real logged data from a traffic scenario in Berlin. It is visualized with help of the existing project implementations. The red lines are trajectories of dynamic obstacles. The arrows mark different kinds of obstacles in the environment of the car. The information about obstacles, trajectories and ego vehicle state were obtained from sensors of the test carrier and preprocessed. In the second Figure 4.1b for reason of comparison a road model is visualized. It is located with help of GPS data. The comparison shows: If the trajectories of other traffic participants are tracked and processed, data about possible driving possibilities (like lanes in this example) can be extracted - see one trajectory on both, the ego vehicle lane and the next lane right to the ego vehicle (in driving direction) and further two trajectories on the third lane. Other traffic participants are a valuable source of information about the infrastructure and the current situation. Bearing in mind the remarks about swarms in the introduction of this work, traffic participants can be considered as a swarm. The swarm can be used for planning of the ego vehicle's driving plan - see as an example the green line in Figure 4.1. Thus it is a valuable possibility to extend the current state of the autonomous driving implementations. Consequently if a tool in the autonomous car is available which processes the data of obstacles in the environment of the ego vehicle in a swarming context this lead to an improvement of the current state of autonomous driving. The word "lane" is used throughout the following chapters as a term to compare the swarm based "driving possibilities" with the real lanes of the traffic. "Lane" in the swarm context of this work does not mandatorily mean that a real marked lane is on the road. It can also mean that a lane is defined by the swarm. In this case the flow of traffic defines lanes.

To realize swarm behaviour for path planning such a framework is introduced in this work. The implementations are inserted into the AutoNOMOS Project via the "Swarm Behaviour Module". The schematic processing pipeline is visualised in Figure 4.2. Module names are used as in the project. The basic input comes from sensors and connected preprocessing. It is used to get current data about the ego vehicle - like the ego position, speed and direction of driving. That input comes from the project module "Ego State Snapshot Generator". Therefore GPS, IMU or odometer data is used. This part is abstracted from the architecture of this work. Further information about the environment is needed. Here obstacles are of interest. Data of different sensors is fused to get abstract information about obstacles. In the current project this is abstracted through the module "Obstacle Fusion". Obstacle information like position and velocity is important for swarming approaches. The general task of the "Swarm Behaviour Module" is to process that input data to get swarm related information about the environment. That information includes data about where to drive and what speeds are currently possible with respect to the current situation. Therewith a swarm based plan has to be generated which is given to the controller of the vehicle. So swarm behaviour for path planning is obtained. This plan gives the values of positions and corresponding velocities to the controller so that the hardware of the autonomous vehicle performs tasks to reach this values. The plan has to



(a) Trajectories of swarm members

(b) Trajectory data of swarm members in comparison to a road model

Figure 4.1: Trajectories of swarm members are usable to generate information about "lanes"

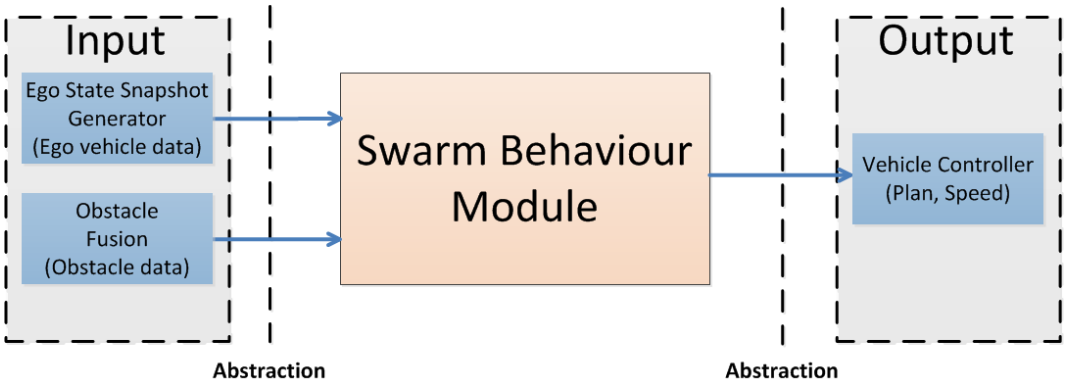


Figure 4.2: Schematic processing pipeline with abstraction layers and connections to project modules

be smooth enough to allow comfortable driving. So autonomous driving through swarm based data and processing is accomplished. Further visualization is implemented to test, evaluate and control the processes. Visualizations for obstacle data and generated swarm based plans are implemented.

4.2 General Processing Pipeline

The Swarm Behaviour Module is main object of this work. Its task is to apply swarm behaviour for path planning. One functionality is to generate a swarm based plan which is used by the controller of the vehicle to perform autonomous driving. Further, swarm based maps of the immediate environment are built to give drivable way options and velocities. A visualisation is needed to test and evaluate the algorithms.

An overview of all processing tasks can be seen in Figure 4.3. The input is on the left side, processing direction is from left to right and the output to the vehicle hardware is on the right side. The main input concerns basic "Ego Vehicle Data", data about objects in the environment ("Object Data") and "Trajectory Data" about moving objects. The "Ego Vehicle Data" is used from several modules on different places thus the input arrow in 4.3 is not connected to one certain module. It is used for getting a reference point in the environment. A visualization is realized in parallel to this processing. Therefore the modules in the "Display Swarm Behaviour Module" are used. Data from all processing steps from the above modules is used. The processing tasks can be categorized into 3 main tasks:

- Preprocessing: Input data is analysed, swarm relevant data is extracted and selections of certain data takes place. A clustering of trajectories of moving objects is done.
- Swarm Heuristics: Uses the data of the preprocessing step and applies heuristics to generate swarm based plans. Important values are positions in the environment and velocities at certain positions.
- Plan Processing: Generated swarm plans are post processed. Maintenance for plans and velocities takes place. Data formats have to be used thus communication to the car hardware is possible.

That general architecture is used to solve the tasks described in the following. In the "Obstacle Processing", object data is used. A classification takes place to distinguish between different kinds of objects in the environment. Swarm members are identified. The module "Trajectory

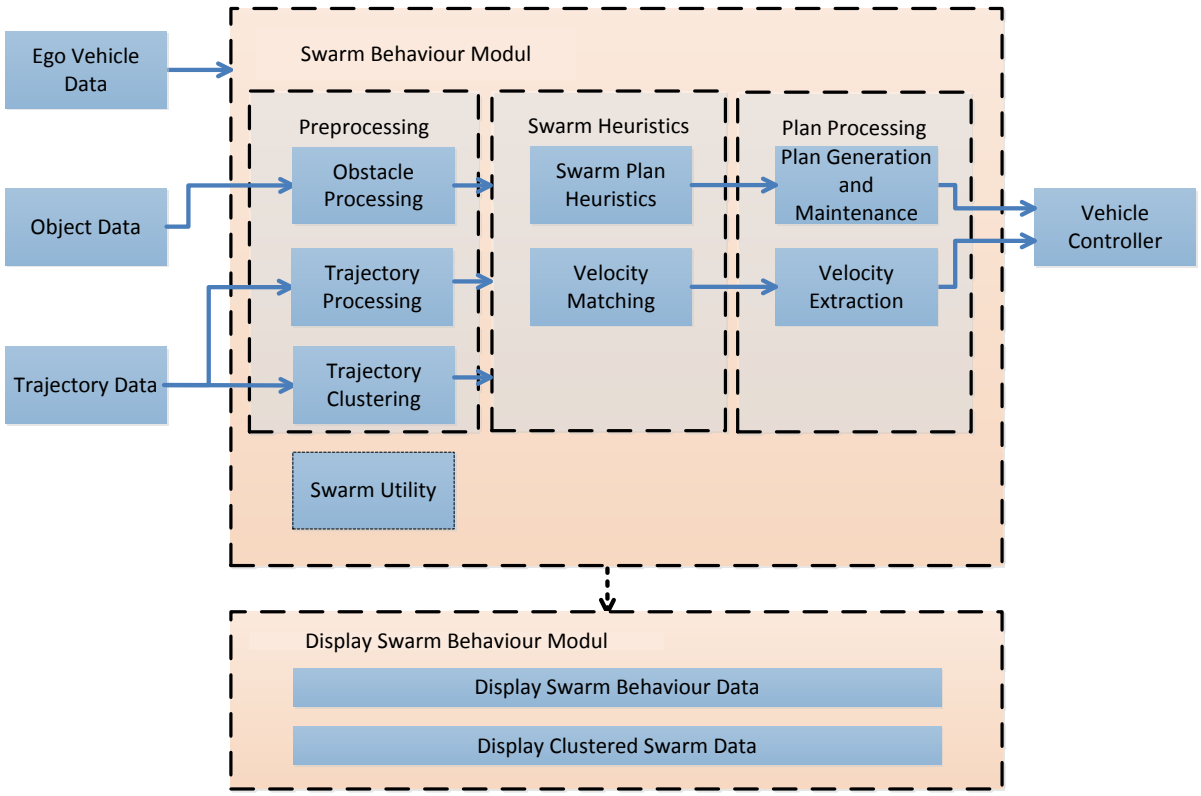


Figure 4.3: General architecture for swarm behaviour related tasks and interfaces

Processing" is needed to process and manage actual data about trajectories. Maintenance takes place for further usage of position data. In "Trajectory Clustering" relevant way points are extracted from trajectory data and merged after certain spatial criterions. A clustering process is applied to abstract the trajectory data. So "Clusters" are generated. They contain information about possible ways in the environment of the ego vehicle. The module "Swarm Utility" is used for general methods which implement general algorithms. That algorithms are used in different modules.

In the "Swarm Heuristics" category different heuristics are applied to generate driving plans based on swarming concepts. The presented heuristics reach from simple greedy ideas to more complex swarm member trajectory selection ideas and further to approaches working on the "Clusters" of the abstracted data. Further a "Velocity Matching" is performed, to get swarm related values for possible velocities in a certain area.

The output data is used as an input for the "Plan Processing". In the "Plan Generation and Maintenance" module the swarm based plan is used to generate and maintain a plan which can be forwarded to the controller of the hardware. It consists if position data and velocity data, which is ascertained in the "Velocity Extraction" module. Via the output data of the "Plan Processing", communication with the ego vehicle controller takes place. This already existing module converts that plan into control commands for the hardware. So autonomous driving based on swarm ideas is performed.

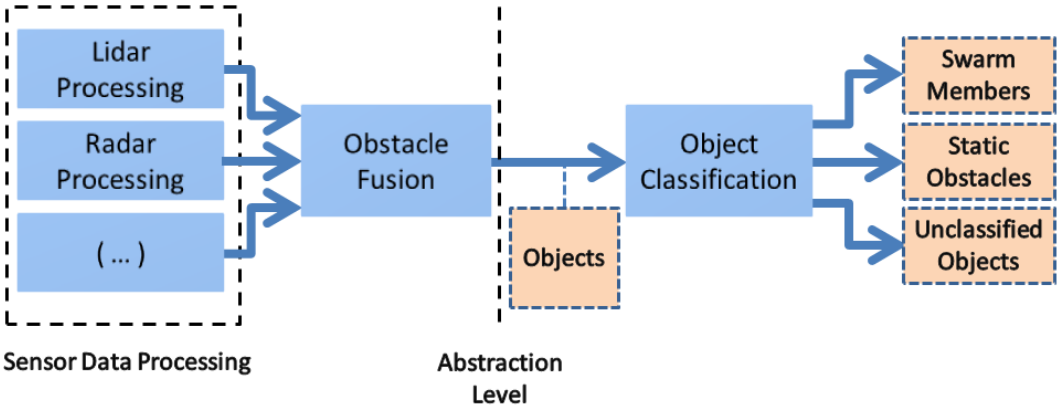


Figure 4.4: Processing pipeline of the swarm member classification process

4.3 Components of the Processing Pipeline

A detailed description of the tasks of the pipeline from Figure 4.3 follows. Specialised processing pipelines are provided. Thus a general idea is given of how the swarm based path planning is implemented in this thesis. So an understanding is given of how the swarm based driving of the autonomous car in this project is performed. Further how a map of drivable ways of the ego vehicle surrounding environment is created from swarm data, which is further usable for swarm based path planning.

4.3.1 Object Detection and Selection of Swarm Members

Swarm members have to be identified. In swarm related approaches it is important to detect objects in the surroundings of the ego vehicle. A selection has to be made: Relevant swarm members have to be identified and obstacles have to be considered.

From the previous existing project implementations, obstacle data can be used. In Figure 4.4 the processing pipeline for the object classification is shown. The interaction and data exchange of the old project modules with the new augmentations of this work can be seen. From the previous state of the project, a module called "Obstacle Fusion" was available. It provides data about obstacles. The data type is called "Base Obstacle" - summarized in Figure 4.4 with "Objects" in the lower bright red box. That data contains information about objects which are detected through the sensors. In the current state data from different modules are used as input for the "Obstacle Fusion". The sources are currently lidar and radar sensors. The obtained data is preprocessed through connected modules - the left dotted box with the sensor data processing modules in Figure 4.4. Here, an abstraction layer can be seen. In general different types of sensors helps to deduce information about objects in the surroundings of the car. Through combinations of different sensors as well as sensor data fusion, more accurate data can be produced. The modules of this work need information about objects, which are in the surroundings of the car. How this data is produced - via radar, ultra sonic, laser or other sensors and how it is fused - lies beyond the abstraction level. See in Figure 4.4 the dotted line for the abstraction level. The modules of this work are located on the right side of that line. The "Base Obstacles" (Objects) provide data like an id. So a tracking of obstacles is possible. This is very valuable in the swarming context because objects can be observed at different locations over the time and selections can be made. This is important for the later described path planning. Further information like the size of an object can be retrieved.

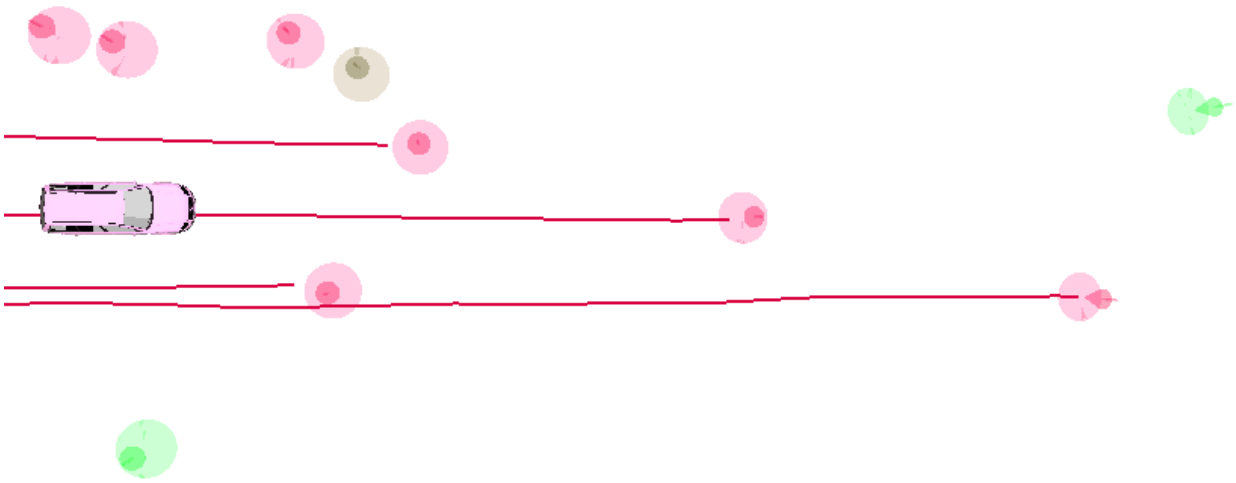


Figure 4.5: Swarm members with their trajectories (red), static obstacles (dark grey) and unclassified objects (green) and their trajectories

A classification process has to be applied to distinguish between different objects - see the "Object Classification" module in Figure 4.4. For ideas about different kinds of classified objects see also [Rey87]. In the current implementation a very simple method is used. This is currently enough, to identify relevant "Swarm Members" and other objects like "Static Obstacles" or currently "Unclassified Objects" - the output of the classification module in Figure 4.4. The "Base Obstacles" (Objects) from the "Obstacle Fusion" provide a "Movement State" of the object. Through the intern implementation of that module and tracking processes, it is possible to check, if an object was moving in a certain way in its past. So a statement about its state of movement is obtainable. A moving object is identified as a potential "Swarm Member" - see the red markers in Figure 4.5. An object which has not been significantly moving is a "Static Obstacle". See the dark grey marker in the Figure 4.5. And an object about which currently no statement can be made is called a "Unclassified Object" - see the green markers in Figure 4.5.

In general for the swarming approach in this work, the moving objects are of relevance. In Figure 4.5, a typical scene can be observed. The scene is based on real log data of the sensor data of an test drive with the test carrier through the traffic of Berlin. The general moving direction is from left to right. The Swarm Members provide data about their trajectories - the red lines, which are behind the red moving markers. These trajectories are used as described in the later sections of this work. A static obstacle can be seen in the top left third of the picture. It is important to consider these obstacles in the context of a swarming approach.

Further the swarm members and the unclassified objects can be obstacles, too and have to be considered in the sense of obstacles. Considering the ideas around Reynolds Rules (see Chapter 3) collisions have to be avoided. Here the previous implementation of the project gave a valuable basis. It has a controller which checks if obstacles (no matter if dynamic or static) are on the current planned way. If this is the case, it reduces the velocity, up to a stop. So collisions are avoided which is fundamental for the swarming approach. For the basic work of the controller in the project see the work of D. Göhring [Göh12] - especially ideas about static and dynamic obstacles and velocity calculations (pages 14-17).

With the object classification of this work an integration of detected objects in the surroundings of the autonomous car into further processing is possible. This was meant to be interesting for a first approach of the path planning using an aim (target). This approach was discarded - see following explanations: A spatial aim was set where the autonomous car should drive to. E.g. a point at a certain distance into the future of the current position following the current alignment of the car. This could be used to further make a selection of swarm members. Some literature connected to the ideas of Reynolds Rules, dealing with mobile robots used an approach with an aim (target) like [Kim10] and [KS06] and also [BLLG11]. It turned out that in the use case of the autonomous car, a fixed or dynamical self defined aim is hindering in some situations. Instead it is more preferable to follow any flow of vehicles in the surroundings. This flow implicitly gives the aim. Consequently a target has not to be defined by the autonomous car itself. Only the current surroundings of the autonomous car is observed and an aim is given by the dynamic of the swarm which is selected. In the scenario of traffic it is important to move. If no other information is given than the observed vehicles, then an orientation by those "swarm members" is happening. E.g. in a roundabout scenario. If a huge roundabout is given, where no further information is available. Concerning the current traffic situation, it may be impossible to define an aim. In case of no lane data it is hard to decide where to lay an aim into the environment: Should it be put a few meters into the driving direction, into the first exit of a roundabout, or behind the exit? This often depends on the traffic situation and the given infrastructure. In the approach of this work, the swarm has to be seen as a support to continue the autonomous drive. Even in a situation in which no aim is given, a continuation of driving should be reached. If no swarm members are detectable (no vehicles in the surroundings) it is better to slow down the car and break and wait until swarm members appear and an orientation is possible. In this use case this is considered to be the better action, instead of following a pre defined aim into an area where absolutely no information is given.

For that reason a more advanced classification of swarm members was not applied in the current work. The movement of objects is enough to define swarm members. With the current work, a pipeline exists, which allows other classification possibilities. This can be used for further work. E.g. for special situations and other swarm based approaches. This is left open for future work and may be connected with a specialized situation detection. In such a work swarm members can be selected based on special situations. Further the integration of swarm members into the implementation is intended for checking of the swarm approaches at visualisation level. This data structure and pipeline can be used for further work, too.

4.3.2 Velocity Matching

The velocity of the ego vehicle is essential to enable autonomous driving. Thus in this approach, the velocity has to be decided on basis of the swarm. The Reynolds Rules are described in Chapter 3. The second rule - alignment - is important for the autonomous driving in the swarm context. So it can be used as an example in the context of this work. It is not only important for the car to orientate itself by positions of the swarm members, it also has to be considered their velocities. In the context of driving in traffic, it is important to drive not too fast or too slow - according to the current traffic situation. Furthermore it is important to take heed of dangerous situations like narrow curves or construction works. At such positions the velocity has to be lower than in secure "standard situations" like straight lanes if the traffic state allows it. This information can be retrieved from the swarm members.

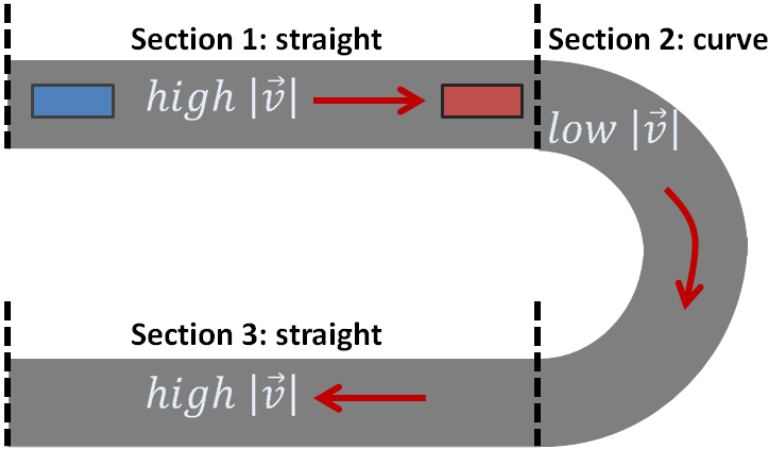


Figure 4.6: Scenario with velocity changes - autonomous car (blue) following a swarm member vehicle (red) in arrow direction

Current Speed of Swarm Members

In one approach the immediate surroundings of the ego car is observed. This approach is very similar to the Reynolds Rules idea. E.g. the mean of the surrounding swarm member velocities or the velocity of the closest swarm member can be used to define the own velocity. An advantage of that approach is, that an orientation of the ego velocity is happening very reactively to the current situation. If close by vehicles are slowing down, this can be an indicator for the ego vehicle that the current situation requires a lower velocity.

This approach was tested in a first live test with the test carrier and other vehicles as swarm members at the Tempelhofer Feld in Berlin. It was shown that major problems can occur in certain situations: If only certain swarm members are detectable, a velocity orienting problem evolves. So trajectories of vehicles at some distance in the front of the ego vehicle are available. This can be used in the swarming context to define the own way points for the planned ego trajectory (see explanations in later sections). But except the far distant swarm members, currently no swarm members in the immediate surroundings are observable. An orientation of the current ego car velocity by relatively far away swarm member velocities can lead to problems as in the following example described:

Example situations are as visualized in Figure 4.6. The blue box represents the autonomous car following one swarm member vehicle - the red box. A long straight lane (see "Section 1" in Figure 4.6) on which high velocities are possible with a narrow curve which requires low velocities (see "Section 2" in Figure 4.6). Followed by a long straight lane with possible high velocities ("Section 3" in Figure 4.6). If the described approach was used and the ego car followed the distant vehicle in the front with an velocity orientation of its current speed, the following situation occurred:

1. The leading vehicle was driving fast until the curve was close. At that point it was breaking to drive slow (transition from "Section 1" to "Section 2"). Consequently the ego car (still in "Section 1" and thus far away from the curve) was driving slow on a straight lane where much higher velocities were possible.

2. As soon as the leading vehicle was around the curve it accelerated to high velocities because of the reached straight part of the lane ("Section 3"). Hence the ego car (still located before

or in the curve) started to accelerate, too. Because it oriented itself on the only swarm member in the surrounding. Leading to the fact that the curve was passed through with a much too high velocity which was not appropriate for this situation.

The low level controller of the ego car admittedly was keeping the velocity to a safe number. Further situations with a higher degree of complexity, where such problems occur, are transferable e.g. a roundabout. According to the information, which can be derived from a swarm, this solution is not enough. The swarm gives more information, as shown in the next approach.

Way Point Related Velocities

Consequently another approach is applied to cope with that velocity problem. A location based velocity has to be used. For that idea the velocity and its direction of a swarm member at a certain point has to be stored. So this information is dependant from the location. Thus for each observed and used trajectory, position and information about the speed and the direction at that point is usable. The used speed for the ego vehicle in this case is the speed and direction, stored at the closest position to the ego vehicle. So a location based velocity is used.

Further Velocity Matching Ideas

A better solution may lay in a combination of both approaches to benefit from both advantages:

1. very reactive situation awareness, if enough close by swarm members are observable and
2. awareness of more static current lane restrictions through storing and merging velocities of leading swarm members.

A combination can be reached by application of a formula with different weighting terms. Such a solution was currently not tested and is left open for future work. Further situations have to be considered, which are not only solvable with the current swarming approach. E.g. situations with crossings combined with a traffic light. If the leading vehicle is halting but the traffic light switches to green at that time, the ego car is arriving. Then no slowing down of the ego car velocity is needed. A first approach can be the combination of the above described ideas.

Further Reynolds third rule gives basis for discussion in the velocity context. To maintain an existing swarm, the cohesion rule is very important. Considering the fact that the ego car can only follow vehicles, which are at some distance to the front of the ego car, it can be desirable to add some offset to the observed velocity of the relevant swarm members for calculating the own velocity. This would lead to a reduction of the distance between the ego car and leading swarm members on average over the time. Under consideration of a fixed swarm this would be of gain because it can happen, that the swarm members are reaching some distance (e.g. due to acceleration), which is out of the scope of the sensors of the ego car. Consequently a reduction of the distance over the time would be better than an enlargement and could be obtained by a small offset. Nevertheless in special situations a loss of the leading swarm members can happen. E.g. a long lane with slow velocity followed by a long lane with a much higher velocity. If leading swarm members are accelerating at the second part, the distance is enlarged because the ego vehicle still has to drive slow. A loss of sight can happen if the ego car is not catching up fast enough. In consideration of that still existing disadvantage and the fact that a higher velocity than the observed velocity can lead to safety problems, an adoption of the approach was rejected.

Further the swarm in the context of this work is seen as a dynamically changing configuration of vehicles (as the surrounding traffic). For the autonomous ego car, decisions are calculated on

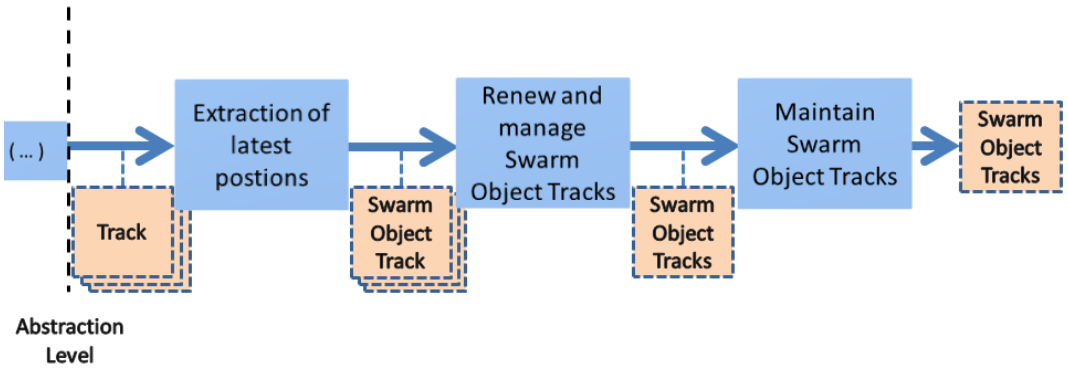


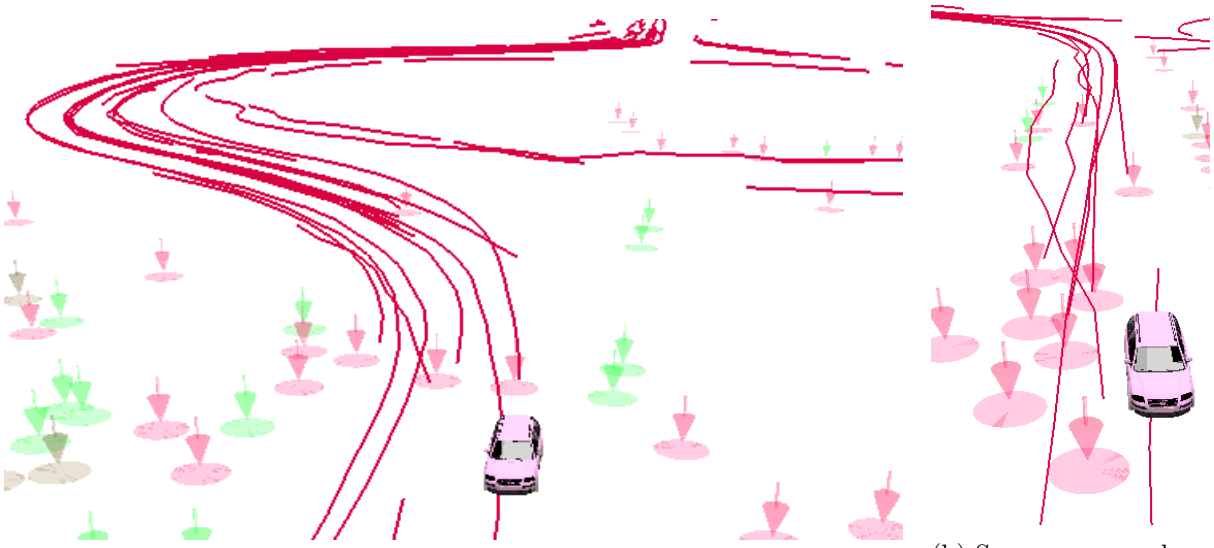
Figure 4.7: Pipeline for extracting, managing and refinement of trajectories of swarm members from "Track"s

basis of the current situation. So based on this situation, swarm members and relevant trajectories and velocities are selected. If old swarm members disappear then new swarm members have to be found. In the worst case - if no swarm member is detectable - the car is slowing down till it stops. As long as no new swarm members are detected, which lead to a new swarm based orientation. In future work appropriate behaviour has to be evaluated to integrate this habit into the traffic. An idea is to drive to the right of the street, as far as possible and stop, as soon as the swarm is lost and no orientation can be found.

4.3.3 Swarm Member Trajectory Processing

An essential task is finding positions for the autonomous car. These positions are basis for usage of driving plans. In the swarming context trajectories of swarm members can be used to get ideas where the autonomous car can drive. So it is important to get and process position data of objects. Thus position data is relevant in the context of the trajectories. In Figure 4.7, the relevant steps of processing of trajectories of swarm members are visualized. As described before an abstraction level can be seen on how the relevant data is preprocessed and from which sensor it comes from. On the left side in the figure, that is signalized through the dotted line and the dotted blue box which can be seen as a prototype of any sensor preprocessing. In the current implementation, again tracked object data, based on sensors like radar and lidar, are handed over to the modules of the trajectory processing. Different "Track"s are containing that data about objects over the time. The processing pipeline is tried to be applied with a relative high frequency of 10 Hz. In cases of more input, data processing takes longer. With that frequency good results in simulations and tests were reached.

In each call updated sensor data (if available) is processed. Assignment of data happens via ids of tracked objects. At first an extraction of the latest data takes place. Only the newest positions are of relevance. Because of the relative high frequency of updates, new data points are only dislocated of small distances to the last ones. That is still accurate. Enough data points over the time are stored to build trajectories with an accuracy, which is sufficient for the application in traffic. Here a new data type called "Swarm Object Track" is used to store the relevant data about different objects and their trajectories for the autonomous car context. Further a managing of that data is applied. Updates of old "Swarm Object Track"s are done and new ones are added. Irrelevant trajectories are managed. If a trajectory is too small to use it, it is still important. It is stored for the case, that it will become relevant after some time if the length has increased. Therefore the data structure of "Swarm Object Tracks" is used. A



(a) Swarm members and their trajectories in a roundabout (Berlin - Ernst-Reuter-Platz)

(b) Swarm members and their trajectories

Figure 4.8: Visualization of obstacles, swarm members and trajectories

further maintenance takes place to keep only relevant data stored for efficiency of later applied algorithms on the data points of the "Swarm Object Tracks"s:

1. Distance of trajectories: Traffic can change very dynamically. The distance between the trajectories and the current ego position of the car should be small. If the distance is too huge, the trajectory of the "Swarm Object Track" is not relevant for the near future and it is deleted. Here a heuristic is used: The euclidean distance is calculated between the ego position and the latest point of the trajectory. If the distance is beyond a certain threshold, the trajectory can be deleted. In a test this showed good habits and the calculation time for later algorithms is kept smaller because the size of stored data is reduced compared to keeping all far away trajectories. A good applied value is a threshold between the ego position and the latest trajectory position of 300 meters. So a bit more than the sensor range of the current modules.

2. Distance of old stored positions: Distance differences of all points of trajectories, which are more far than a certain distance from the ego position. Trajectories can be kept, but become recut. This is important for spatial long trajectories. After a principle of locality only the closest positions of that trajectory are relevant. Far away positions are deleted. This again reduces the size of stored data. Again a good value is a threshold of 300 meters.

3. Length of trajectories: Trajectories of small length have to be sorted out. They appear because of sensor errors or mismatches and sometimes because of occlusions. If the length of a trajectory is too small, it is be marked as irrelevant. So a threshold for the length is keeping trajectories for further processing at a certain length. Small trajectories will either stay irrelevant or their length will increase over the time and their status will be changed to relevant. That leads to improvements for later used approaches. Because small trajectories based on sensorial errors are sorted out. Further only trajectories of significant length are stored. Later usage of that reduced trajectory data in algorithms consequently leads to more stability. A good value is a threshold of 5 meters.

4. Distance between consecutive positions in trajectories: Too small distances between positions can lead to a lot of data points which lead to longer processing times for following

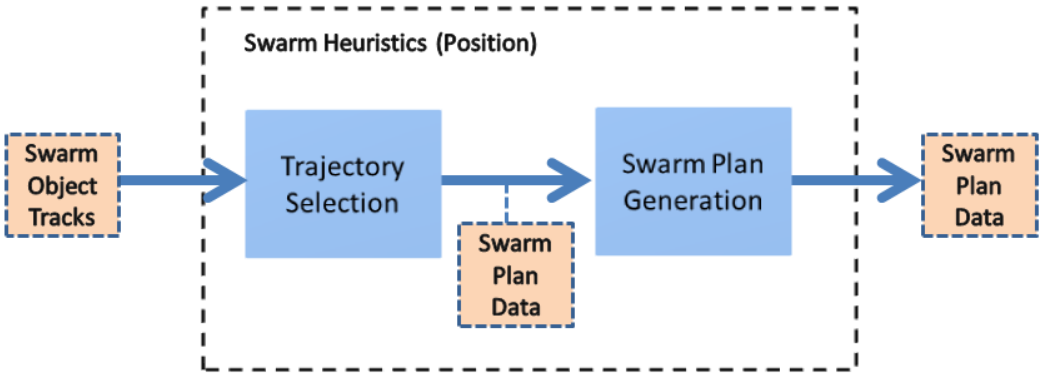


Figure 4.9: Pipeline for building a plan from trajectory data of swarm members

algorithms. So it is useful to pre filter the positions. The current approach is to define a minimum distance between the latest old position in the trajectory and a potential new position. Only if that distance exceeds a threshold, the new position is added. With that distance threshold, a balance between less data points, connected with higher performance rates of later algorithms and a redundancy, connected to a possibility of application of more accurate algorithms, have to be found. Here, a good value is to take a distance of less than 0.1 meters. So a good resolution for the traffic use case is reached. Data storage is reduced.

The trajectory processing was tested with logged data from test drives with the test carrier in Berlin. Results are visualized in Figure 4.8. Figure 4.8a visualizes the data of "Swarm Object Tracks" at the Ernst-Reuter-Platz, a roundabout with several lanes. The shape of the roundabout can be seen only through the trajectories. Further information like possible lanes, areas where lane changes happened, or driving options, are visible just with the information gathered from swarm members. In Figure 4.8b another scene can be seen. Logged data of a straight test drive after a curve is visualized. The ego vehicle is located next to a big group of swarm members, producing trajectories. Different information can be seen. Lane changes are happening. Further it is apparent, that on different lanes some kind of clustering of swarm members is happening. This can be used in later described approaches. In the figures a suppression of trajectories with small length took place.

4.3.4 Trajectory Based Path Planning

The basic task of this part of the work is to generate a plan (driving plan). A plan is used by the controller of the car. So autonomous driving is reached. This plan is based on swarming principles. In the process of generating a "Swarm Plan", at first trajectories have to be analysed. Second, relevant tracks have to be found. After application of heuristics the best fitting one has to be taken and a "Swarm Plan" has to be generated based on the previous "Swarm Plan" together with the new data. In Figure 4.9 the general pipeline idea is shown. The main tasks are:

1. Trajectory Selection: From a pool of given trajectories, special ones (see later descriptions) have to be selected. They should be suitable for the swarming concept.

2. Generating a Swarm Plan: Some methods have to be applied to these previously selected trajectories. The old Swarm Plan has to be renewed. So either old Swarm Plan data is combined with new data or old Swarm Plan data is replaced with new data.

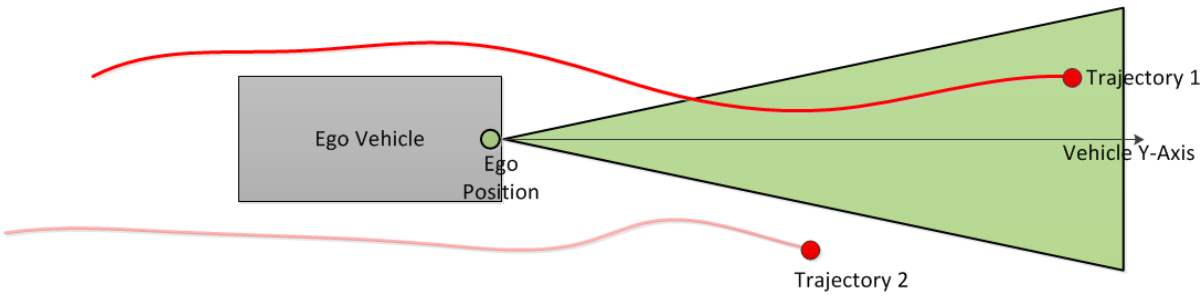


Figure 4.10: Selecting trajectories by defining a valid area (green) with an angle in front of the ego vehicle. Trajectory 1 is selected because the last point lies inside the valid area. So Trajectory 1 is reachable in terms of the heuristic.

The data about trajectories is given by the swarm member trajectory processing described before (see Section 4.3.3). It contains information about swarm member positions. All together, these are trajectories which indicate used ways in the environment of the ego vehicle. In the first task - "Trajectory Selection" - different ideas can be applied. A simple greedy idea is described and different complexer selection ideas are presented.

"Greedy" Selection of Trajectories

The simplest idea is to select the first trajectory which is found in the environment. With this "greedy" approach a swarm plan is generated as soon as a moving swarm member is detected. But this has some disadvantages. There are cases in which a "greedy" selected trajectory is short or far away from the ego position. This means inconveniences compared to longer or closer trajectories. So selection of shorter trajectories results in more often changes of trajectories. This leads in some situations to a chaotic behaviour because of often changes. Further this means more often uncertain movements through parts of the environment which have no trajectories. Because areas between trajectory changes are mostly uncovered of swarm trajectories. These gaps without information from swarm members have to be bridged by the autonomous car itself. That gaps occur in the cases of a longer trajectory selection not so often. More distant successive trajectories implicate the same problem with gaps. So farther and consequently more dangerous position changes of the autonomous car are likely with the "greedy" approach. But these disadvantages can be solved better if more "intelligence" is put into the selection process.

The application of the greedy approaches is not adequate for real traffic situations. Consequently following a trajectory, which is very close to the ego position, is the basic idea for advanced heuristics. Here different selection ideas are implemented. Different ideas have been applied and tested as shown in the following parts. Disadvantages and advantages of different methods are explained and a final solution for path planning based on a swarm member trajectory selection is given.

Selection of Trajectories by Concerning Reachability

This approach has the property to be more oriented towards a more applicable solution. Comparing the reachability of trajectories, gives a criterion for a good trajectory in terms of using it as a basis for a swarm plan. If the trajectory is reachable from the current ego position of the car, the ego car is able to drive onto this trajectory and use it from this position on as its own plan. To reach this aim a heuristic is used which compares just the last position of the trajec-

tories of swarm members. If that point is reachable, then the trajectory is reachable (at least the last point of it). Through movement of the swarm member, additional positions will follow in the future, which are reachable from the current last point, since the last point is currently the latest position of the trajectory generating swarm member. So a selected trajectory in that way gives a good heuristic for finding followable trajectories. To implement these heuristics two main questions concerning selection have to be answered positive:

1. Lies the last position of the swarm trajectory in a plain in front of the ego car and not in the back?

2. Lies the last position of the swarm trajectory in a certain area in front of the car. This certain area should be reachable through steering options.

Both question can be solved by applying a simple heuristical idea using angular mathematics: A certain angle is defined. The origin of the angle is located at the current ego position. From this point the angle between two vectors is measured: the vehicle y-axis (corresponds to the forward direction of the ego vehicle) and the vector from the ego position to the last trajectory position. Compare the visualisation in Figure 4.10. The swarm trajectory position is reachable if this angle is a very acute angle. Compare the green area in Figure 4.10.

The selection process is now accomplished by iterating over all trajectories and checking if it is reachable. If the old selected trajectory is still in the pool of reachable trajectories, it is prioritized and it is further used. Else new trajectories are selected by the process. To solve this task a helper method was defined in Swarm Utilities to reuse that kind of processing.

This is a relative fast method because the last position of a trajectory is quickly retrievable. For each trajectory calculations for one point has to be made. Experiments showed good results with acute angles of four degrees. Two degrees to each side of the y-axis. The very acute angle helps to avoid strong steering. This approach is very inflexible. The very small area is a disadvantage which can be solved in a better way as described below.

Once having such a toolkit for selecting trajectories it can be further used. If one selected swarm trajectory is ending, a following trajectory is searched to get a longer plan. For that task exactly the same method can be applied. Always the last point of the plan is the new reference point for evaluating following trajectories. In that case for the calculation process, the ego position is exchanged with the last position of the last used old swarm trajectory. The vector in that case is defined by the last point of that trajectory to the last point on the new trajectory. For the direction not the ego y-axis is used. Instead the alignment of the last part of the old trajectory is applied. That is calculable through computing the vector between the last two positions stored in the old selected trajectory. In tests angles of 40 degrees were applied to both sides to get good results. Successively swarm member trajectories are selected in this way, which are connectible.

Selection of Trajectories by Different "Safety Zones"

Selecting a swarm member trajectory based on the idea above, makes a prioritisation of different trajectories difficult because distant endpoints are treated equally. This problem is tackled with the help of "Safety Zones". A "Safety Zone" is a predefined area in the environment of the car. Trajectories are searched in this area. The usage of these "Safety Zones" leads to a more complex but more precise selection of trajectories. Reference point of such a zone, is the ego position of the car (in the front part of the vehicle). The ego vehicle front direction is the reference direction.

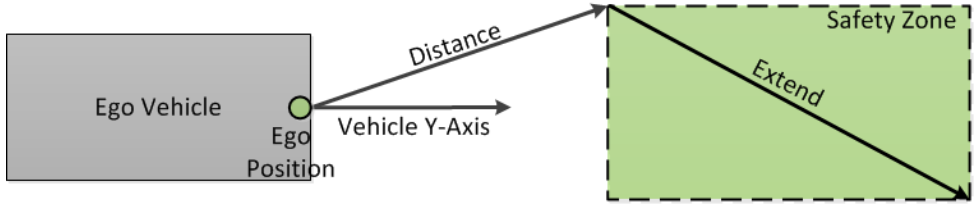


Figure 4.11: Definition of a "Safety Zone" relative to the ego vehicle position. Through the "Distance" vector the area can be defined at any place in the environment of the car. Later application puts the "Safety Zone" below the car. Other positions like in front of the car (see figure) are possible. With help of the "Extend" vector the rectangular size of the area is defined.

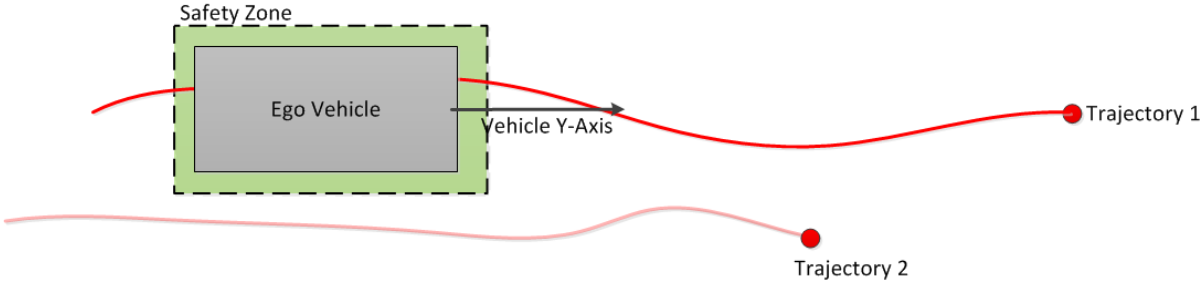


Figure 4.12: Selecting trajectories by investigation of one "Safety Zone" (green) below the car. Trajectory 1 is chosen. Because it has positions inside of the "Safety Zone".

From this reference point on, a "Distance" vector defines the position of the lower left corner of the rectangular "Safety Zone". Thus this point can be located at any place of the environment relative to the ego car. The left lower corner of the zone is the second reference point. The size of the zone is defined with a second vector "Extend". It points from the left lower corner to the right upper corner of the rectangular zone. The definition of a "Safety Zone" is visualized in 4.11.

In the simplest implementation, the safety zone is exactly that area of the environment which is covered by the shapes of the autonomous car on the ground (see Figure 4.12). A swarm member trajectory, which contains points at the current ego position of the car, is advantageous if selected. The ego vehicle takes immediately that trajectory for swarm plan generation. It is expected to be good because of the fact that the car is already at one position of the trajectory (at least one position is lying inside the green "Safety Zone"). It is very safe because no position changing manoeuvres have to be made. The already contacted trajectory is continued. Thus this approach has a very strong safety aspect.

One problem may occur in this context. Only few or no trajectories are selected because of the very strict definition of the "Safety Zone" below the ego vehicle. For that case the approach is extended to a more generalized idea: Different zones are defined and evaluations for each zone are happening after the same idea. Each zone gets a confidence value. Selections are made after priority of the different safety zones. So only if no trajectory is found in the zone located directly below the car, a search takes place in the next preferable zone and so on. See visualizations in Figure 4.13.

That was implemented and a toolkit for "Safety Zones" evolved which can be defined generically and checked. In that approach degrees of safety can be defined. It is a generic approach. Very "safe" zones can be created. More relaxed zones can be defined for the case no trajectory

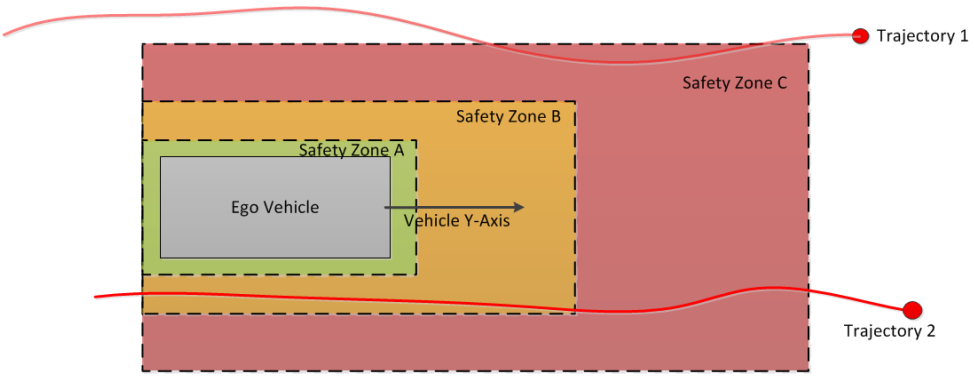


Figure 4.13: Selecting trajectories by using prioritized "Safety Zone"s: Per example three different "Safety Zones" are defined. "Safety Zone A" is below the car. Tests for "Safety Zone B" and C are applied, if no trajectory is found in the previous area. In the example Trajectory 2 is chosen because it lies in the closer area B (instead of Trajectory 1, which lies in area C).

is found in the optimal area. By the described definition with the vectors for "Distance" and "Extend" - see Figure 4.11 - a rectangular "Safety Zone" can be located at any place in the environment of the ego car with any size. This creates a powerful tool for building new heuristics based on this concept.

The algorithm is more complex. Dependant on the situation, more calculations have to be made. In a worst case for all trajectories all positions have to be examined. And further for all of this points all zones have to be checked if the point lies inside. With logged data, at very crowded situations (e.g. Ernst-Reuter-Platz roundabout in Berlin) the approach with three zones located around the car, still showed real time calculated plans for the autonomous car.

First real-life tests have been made with constellations like in Figure 4.13. Three areas with a increasing degree of relaxation have been used. Results are convincing. Live test with the test carrier showed good results. Further more application-oriented heuristics are possible with the described approach. An example is the additional consideration of the trends of trajectories. In that case defining "Safety Zones" in the directions of curves have to be made. Complexer zones can be created through definition of smaller zones of different size which lie close to each other. Sets of zones can be combined for different priorities. Experiments have not been applied in such far applications, yet.

An application of the different "Safety Zones" takes the different zones (described by the vectors for "Distance" and "Extend") and iterates over them as long as either a track is found within an area or no track can be found. The basic idea can be seen in Algorithm 1. For the checking if a point lies in a "Safety Zone" a specialized method is used which uses the dot product for x and y direction for efficient checking.

Complexity of the Algorithm 1 depends on the number of "Safety Zones", the number of trajectories and the number of stored positions in the trajectories. The algorithm stops as soon as one point is found. As searching takes place from the safest zone to the unsafe zones, this brings the best solution. In worst case (e.g. no trajectory in any zone) for each zone all trajectories with all stored positions are checked. Tests in real-life showed still real time Swarm Plan generation.

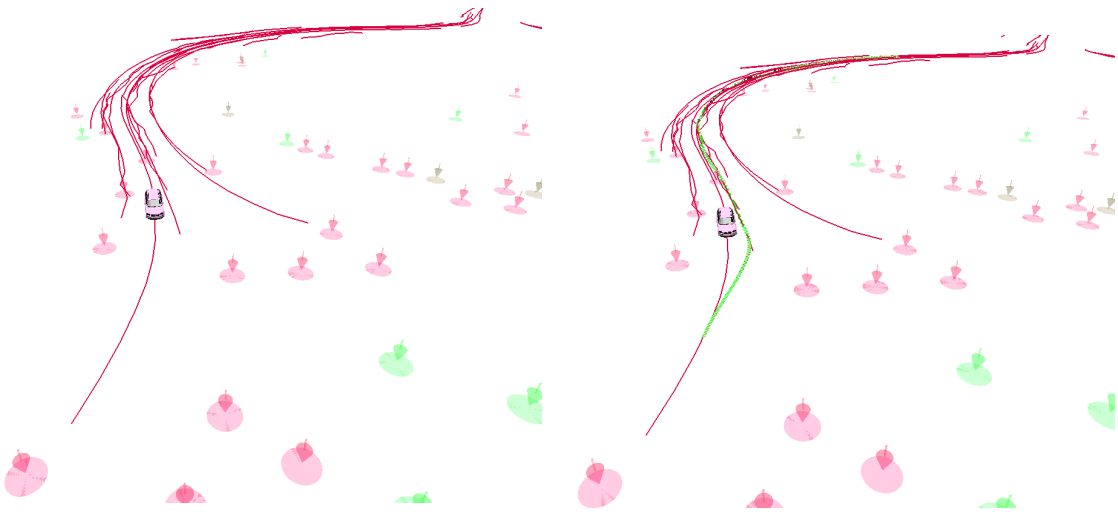
```
Current Safety Zone is the most restrictive one;
while not all Safety Zones checked AND no Swarm Member Trajectory for Swarm Plan
found do
    get vector descriptions for current Safety Zone;
    // check all Swarm Member Trajectories with current Safety Zone:
    while not all Trajectories checked AND no Point Found in current Safety Zone do
        get current Trajectory;
        // check all stored Positions in current Trajectory
        while not all Points of Trajectory checked AND no Point Found in current Safety
        Zone do
            get current Point;
            if current Point in Safety Zone then
                set Point Found in current Safety Zone;
                return current Trajectory for Swarm Plan;
            else
            end
            set next Point in Trajectory to current;
        end
        set next Trajectory to current;
    end
    set next Safety Zone to current;
end
```

Algorithm 1: Trajectory Selection Algorithm: to select usable swarm trajectories by using different "Safety Zone"s

Trajectory Merging and Plan Generation

For all described heuristics one question is still open. What happens if in the selection process more swarm member trajectories are relevant? Here further fine granular ideas can be used to further prioritize trajectories. Again the first one found can be chosen which is currently implemented because of less calculations (timing aspects). But if enough time or calculation power is available, possible further prioritisation should be done: take the longest trajectory or take the trajectory with the most far away last position. In both situations it has to be considered, that most trajectories in traffic situations are evolving. So calculations are made on a current "Snap Shot" of the environment and only the "Current Best" can be chosen. Further selection ideas under consideration of more information are explained in the following sections.

One approach for generating Swarm Plans by using "Safety Zone" Heuristics, is described in Algorithm 2. It is a generic Swarm Plan generation process, which is reusing the old generated Swarm Plan of the last iteration step. A "Fixed Planning Horizon" is defined. This is a certain distance in front of the ego vehicle. The current Swarm Plan, up to that distance, is fixed and will not be changed. At that distance, again new swarm member trajectories are searched. Therefore, again the "Safety Zone" Heuristics or others can be applied. If a new last part for the Swarm Plan is found, a new assembling is done: The old Swarm Plan is cut at the "Fixed Planning Horizon" - only the first part is relevant. The new found trajectory is cut at the closest position to the "Fixed Planning Horizon", too. But here the last part is relevant. Now both parts are stuck together and a new actualized Swarm Plan is generated. Consequently, at each step dynamic changes in the environment are taken into account to enhance the last part of the current Swarm Plan. This is one advantage of this method. Further the car is not "jumping" around because of harsh Swarm Plan changes. The "Fixed Planning Horizon" keeps a minimum plan constant. This leads to robustness.



(a) Swarm member trajectories in a roundabout for plan generation (Berlin - Ernst-Reuter-Platz)

(b) Generated plan (green) from trajectories in a roundabout based on logged data (Berlin - Ernst-Reuter-Platz)

Figure 4.14: Plan generation based on trajectories of swarm members

if *Swarm Plan is not available OR Swarm Plan is not long enough* **then**
  // take a safe basis swarm trajectory if available
  rebuild Swarm Plan (e.g. with one Safety Zone below the car);
else
  // given Swarm Plan from last step is used and extended:
  1. find closest point on Swarm Plan to ego position;
  2. find next point on Swarm Plan in forward direction in planning distance (Reference Point);
  3. find a swarm trajectory from this Reference Point on, which is most suitable (e.g. use Heuristics with Safety Zones at Reference Point);
  4. process found trajectory: get last part behind Reference Point (new Swarm Plan part);
  5. resize old Swarm Plan: Discard part behind Reference Point;
  6. stick new Swarm Plan part onto the old Swarm Plan at end;
  7. return;
end

Algorithm 2: Trajectory Selection Algorithm: to select usable swarm trajectories and stick them together after certain planning distance

As soon as the plan generation is completed the controller of the autonomous car is able to use it. Autonomous driving in the environment is possible. In Figure 4.14 a scene is visualized: A plan (green) was generated on basis of the swarm data.

Solution for the Velocity Matching Problem

For solving the velocity problem described in Section 4.3.2 the processing pipeline (see pipeline in Figure 4.9) was extended. Positions of the observed obstacles, which were used for the swarm data, are stored. Additionally to their trajectory data, to each position the current velocity vector of that position is stored. The velocity is stored in that way, that it includes the movement

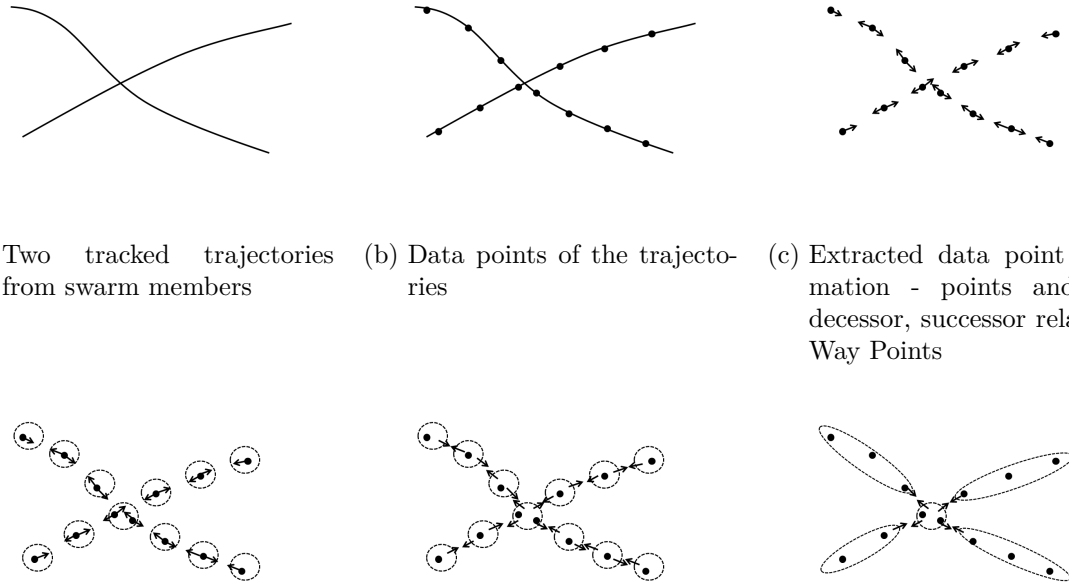
direction of the vehicle, which was observed at that point. Thus for each observed and used trajectory, not only the position is retrievable, also information about the possible speed and direction at a certain point is available. Consequently the movement direction of each stored point is retrievable - trajectories have a given direction. The processing pipeline is in principle as in Figure 4.9. In the application, the swarm based velocity, the autonomous ego car wants, is read out from the stored position. To give back the wanted velocity to the autonomous car hardware it is taken the ego position of the car. For that position the closest point on the selected swarm trajectory is searched and the velocity at that point of the swarm member, which produced that trajectory is given back to the car's controller.

4.3.5 Clustering of Swarm Member Trajectories

Merged information of swarm based data brings further gain. Storing of advanced data and further processing through using redundancy is helping for higher approaches. As discussed in Chapter 3 one basic advantage of swarms is that the relatively "simple" habit of different agents can lead to a globally good "complex" habit. Comparable with pheromones from ants, reused ways can be stored. So some kind of higher information about usable ways is stored in this work.

Concerning the data available from the current framework, a swarm approach can bring further gain if a clustering takes place. That means redundant information is merged and clustered. Thus structures of usable ways evolve during the application of this processing. In this case again the data of trajectories of objects is taken as a basis. The trajectory of an object can be seen as a sequence of points. Those points were successively reached by that object over some time. Consequently the points and their relations among themselves provide possible driving data: From which point can be reached a certain other point in the environment. Further information can be deduced, if additionally more trajectories are available, which are subtending other trajectories or which are locally very close to some other trajectories in certain points: This can be seen as general possible connections between different trajectories.

Therefore in the context of clustering, in this work, the above described information, stored in the given trajectories, is extracted and stored in a new data structure (see Figure 4.15 for the schematic idea and Figure 4.16 for the processing pipeline). In Figure 4.15a two possible trajectories are shown. They can have its origin from swarm members and they can be perceived. As discussed above a trajectory is represented through reached points in the environment - see Figure 4.15b. The data points can have different distances, depending on the sensor which tracked them, the sampling rate and the speed of the objects. In a first extraction phase (see Figure 4.15c) that points are stored separately - each one in a so called "Way Point". To preserve the information about connections between points, contained in the trajectory, predecessor and successor point relations are stored - shown in the pictures through arrows pointing to the next neighbouring Way Point. Further information like the speed of the objects that was observed at this position and an identification number of the trajectory that Way Point belongs to, is stored. In a next step different Way Points are merged in a merging process after certain criterions. A spatial checking algorithm is used to identify Way Points which are lying close by each other - see Algorithm 3 and Algorithm 4 and explanations below. Possible merges in the example are shown with dotted circles in Figure 4.15d. The two points in the middle (close to the crossing point of the two trajectories) are possible candidates for merging because they are of a relatively small spatial distance. In Figure 4.15e the output of the merging process is shown - the new "Merged Way Points". The two points in the middle have been merged in one new Merged Way Point while all other Way Points are building a separate new Merged Way Point. Merged Way Points store the information of all of their included Way Points. So predecessor and successor



(a) Two tracked trajectories from swarm members

(b) Data points of the trajectories

(c) Extracted data point information - points and predecessor, successor relations: Way Points

(d) Possible merge of Way Points located close by each other

(e) Way Points located close by each other are merged with predecessor and successor relations: Merged Way Points

(f) Clustered Merged Way Points with final predecessor and successor relations: Clusters

Figure 4.15: Schematic idea of the clustering process

relations and trajectory ids are further used. With help of all stored Way Points advanced processing is applied. Different merging techniques are used e.g. the mean for the position or velocity of all containing points is build to find a representative value for the Merged Way Point.

```
while not all Way Points assigned do
    take a not assigned Way Point;
    if at least one Merged Way Point does exist then
        while unchecked Merged Way Points AND current Way Point is not assigned do
            calculate distance to unchecked current Merged Way Point (e.g. to mean of
            Merged Way Point), consider area with lateral and forward distance;
            mark the unchecked Merged Way Point as checked;
            if distance is smaller than Threshold then
                assign current Way Point to current Merged Way Point;
                mark current Way Point as assigned;
            else
                do nothing;
            end
        end
    else
        create a new Merged Way Point for the current Way Point;
    end
end
```

Algorithm 3: Spatial Checking Algorithm

As marked in Algorithm 3 different distance checking methods for the merging process can

be applied. Through testing with logged data it was found out, that good results are obtained if a representative value of the Merged Way Point is used. In a first approach the distance of an unassigned Way Point is calculated to all Way Points of a Merged Way Point. Distance checking is implemented by testing if one of the points lies in an area defined by lateral and forward extension around the new point. If the distance to one of the Way Points is smaller than the threshold, the new Way Point is assigned. In certain cases this leads to a blurring effect. In these cases distances successively become longer. E.g. a Way Point is added which lies in the threshold distance. In the next step again a Way Point is added which lies in the threshold distance of the last added point. In this way in worst case in each step the merging area is extended by the threshold distance. That leads to bad results - an accumulation of far distributed points. This has the effect of imprecise Merged Way Points. So solutions were searched to cope with that blurring effect.

Thus the second approach is to calculate a representative value for the Merged Way Point every time a new Way Point is added. In the implementation the mean of all current Way Points is taken. Distances of new Way Points are checked to that representative mean value. That lead to far better and clearer results. This method has still the disadvantage that once assigned Way Points have influence to the Merged Way Point, even if the mean value of the Merged Way Point is wandering out of an assigning distance (through distant new points) to recently added Way Points over the time.

Therefore a another method for further improvement is implemented. It works with a pre calculation of representative points: D. Guo et al. introduce an algorithm for "Extracting representatives of GPS points" [GLJ10]. In this method a "circular window" is used to find representative values for data points. An assignment of all data points to that representative points takes place. The representative values ("centroids") are pre calculated via a special method (see algorithm below) which considers unassigned points. The assignment of points to a new "centroid" considers already assigned points: It is checked if the new "centroid" fits better. Through the related problem an adaptation of the algorithm for the context of the clustering problem of this work is implemented - see Algorithm 4:

```
for all Way Points wp do
    if Way Point wp is NOT assigned to any representative centroid then
        currentWPsForCentroid;
        store wp in currentWPsForCentroid;
        for all Way Points wp2 do
            if Way Point wp2 is NOT assigned to any representative centroid then
                if Way Point wp2 is close enough to wp (inside euclidean distance) then
                    store wp2 in currentWPsForCentroid;
                end
            else
                do nothing;
            end
        end
        calculate centroid (mean of all positions which are in currentWPsForCentroid);
        for all Way Points wp3 do
            if Way Point wp3 is NOT assigned to any representative centroid then
                if Way Point wp3 is close enough to centroid(inside euclidean distance) then
                    assign wp3 to current representative centroid;
                end
            else
                find representative centroid to which wp3 is assigned to;
                compare distances of wp3 to old and current representative centroid;
                if distances is smaller then
                    delete wp3 from old representative centroid;
                    assign wp3 to current representative centroid;
                else
                    leave current assignment;
                end
            end
        end
    end
end
```

Algorithm 4: Spatial Checking Algorithm Through Representatives - adaptation of the "Extracting representatives of GPS points" algorithm (see [GLJ10, p. 7 f.]) to the context of this work

After building Merged Way Points, in a last step "Clusters" are built. Therefore all Merged Way Points are compared and joined if certain criterions are fulfilled: Merged Way Points contain the information about the trajectories they are based on. In a situation in which different Way Points were inserted into one Merged Way Point, these Merged Way Points store the trajectory ids of each Way Point. Successive Merged Way Points are stored in one Cluster if they are belonging exactly to the same original trajectories. If at least one trajectory id from two different Merged Way Points is different, then that Merged Way Points are belonging to different Clusters. The idea of this constraint is, that a Cluster has only parts of exactly the same trajectories. A further criterion is that all Merged Way Points in a Cluster have to be successive. That means a predecessor or successor relation has to exist between the Merged Way Points in that way, that a connection from the first Merged Way Point of the Cluster to the last Merged Way Point of the Cluster (possible via other Merged Way Points of the Cluster) does exist - if its size is bigger than one. A Cluster consequently stores related information of paths. Thus a Cluster contains information about a drivable structure. In Figure 4.15f the example of the two crossing trajectories shows five final Clusters:

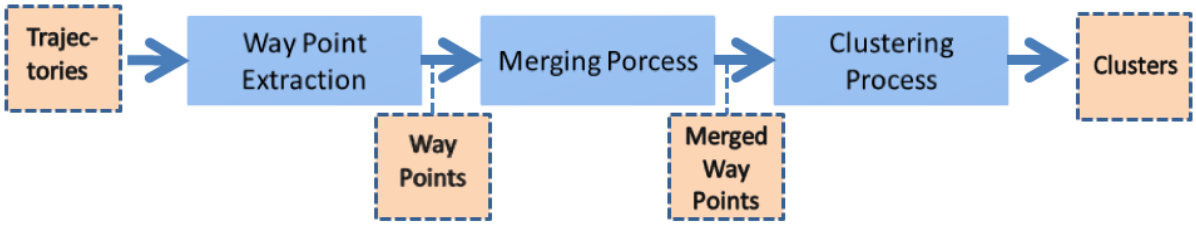


Figure 4.16: Pipeline of the clustering process: Trajectories are refined to "Clusters"

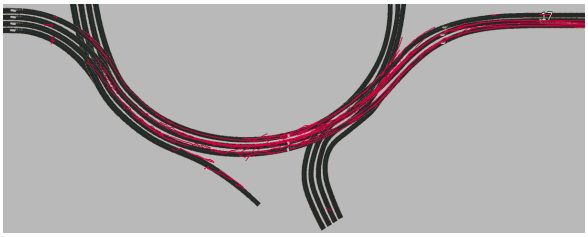
- Four Clusters containing successive Merged Way Points with their fundamental Way Points and
- One Cluster with the Merged Way Point of the two basic Way Points in the crossing area of the trajectories.

A Cluster stores predecessor and successor relations at the Cluster level. Clusters can be merged according to their front and back relations. If two Clusters have a predecessor/ successor relation they can be stuck together. That means their original trajectories have a direct spatial connection to each other. Those paths have more fine granular information than the original trajectories. This is because the clustering of different Way Points from different trajectories was performed to build the Cluster. And further the connections to other Clusters are stored. So connections between Clusters are usable for further processing. E.g. Clusters are connectable for a swarm plan generation or for a map generation. The clustering processing pipeline is summarized in Figure 4.16. The blue boxes show the different processing steps. The red boxes are showing different data states of the processing and where the input and output happens. The trajectory data of all relevant objects is the basic input and the refined Clusters are the output.

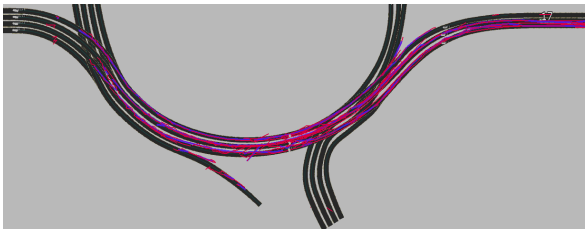
Through the Clustering pipeline a tool is created to refine the "simple" swarm data, which can be redundant and exhaustive. As input the trajectories of different swarm members comes unrelated into the pipeline. The combination of the different data leads to the following advantages:

- Confidence: The clusters in some cases base on one trajectory, but in the other cases they base on more trajectories. If more vehicles take the same way this means more confidence in terms of a good usable way for the ego vehicle. Additionally the velocities are calculated more appropriate because e.g. a mean of all vehicle velocities, which are relevant for the own velocity is built. This is done per Merged Way Point. This information is retrievable from the Clusters.
- Degree of Detail: A detailed graph of accessible paths and connections between them is built. The Clusters contain information about different possible ways through the storage of the predecessor/ successor relations. Thus different way options are available.

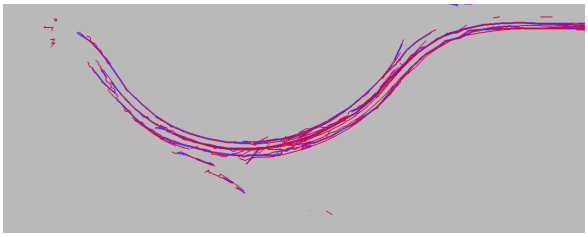
These advantages of the Clustering idea are usable for different applications. Two applications, which bring gain to the AutoNOMOS Project are explained in the following parts. A visualization of results of the current implementation can be seen in Figures 4.17, 4.18, and 4.19. The underlying road map model (black) is visualized to allow a comparison. In the roundabout scenarion (Figure 4.17) the basis red trajectories (see Figure 4.17a) are shown together with the generated Clusters with and without the road map (see Figure 4.17b and 4.17c). The Clusters alone show different traces of the roundabout with possible connections (see Figure



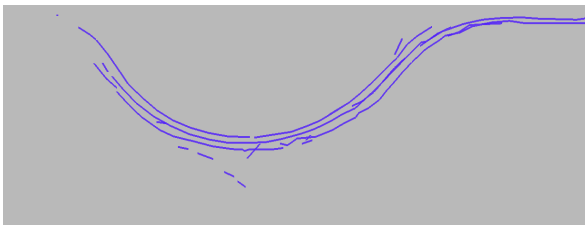
(a) Captured trajectories (red) of objects in a roundabout scenario with underlying road model



(b) Generated "Clusters" (blue) based on the captured trajectories (red) with underlying road model



(c) Blue "Clusters" and red trajectories without underlying road model



(d) Only blue "Clusters" without underlying road model - drivable parts of tracks are visible

Figure 4.17: Generation of "Clusters" from tracked position data of swarm members with comparable underlying road model

4.17d). On some positions connections between different roundabout traces can be observed. Here are possible lane changes because a tracked object did a lane change or because Way Points of different Clusters are close by each other.

4.3.6 Building a Local Map From Clustered Swarm Member Trajectories

The Clusters are used to build a "map", which is used for path planning. The map contains the data of the current situation in the surroundings of the car and shows driving position and velocity possibilities. From a swarming perspective, many vehicles mean better conditions. The more vehicles are detectable in the environment, the more swarming data is produced, which can be used for further processing. In general traffic scenarios, vehicles are on the streets surrounding the ego car. In daily situations other vehicles are in front of the ego vehicle. All of these traffic participants are used in the clustering process to get information about the environment. Thus, the information is not restricted to only one trajectory or one velocity. Through the suggested algorithms, which cluster close by trajectories, this redundancy is processed and stored. So a local map of the current surroundings of the ego vehicle is built. The latest data is restricted to the sensor range. But recent stored data gives a map of the whole stored past. So a situation based map is generated over the time about the observed environment. That map is dependant on the swarm members, which were detected during that time. The current implementation is at the state that the "map" is the set of currently stored Clusters.

Following ideas are not implemented but show how Clusters can be used. The Clustering proceeding can be used to generate general maps of long-term relevance. First very actual maps can be generated. A new unknown street can be taken by the autonomous test carrier. Through the storing of the cluster based map the information about lanes and speeds can be used for following drives. This information can be stored, extended and updated through new drives at other times on the same street. Applied over different days more redundancy is used. Further if applied massively, statistics about streets can be generated. Therefore the processing on different days and times is applied successively. So on the one hand a more robust map can be built.

On the other hand very precise maps for different times can be produced via massive redundant data. For example, a main traffic connection into an industrial area of a city is highly frequented only at certain daytimes. At that times congestions may occur and accidents are more likely than on other day times because of more traffic. Through a time-based statistic that data can be stored. Pattern recognition can be used to find relations. Local- and time-based maps can be generated and used for later path planning. Implementations are at the Cluster level and such advanced ideas are still open. This was further not tested and is left open for future work.

Further short-term relevance of the map is given. A such generated map is storing all current situations. If accidents are happening or road works are taking place, such new dynamic events lead to changes in the driving possibilities of the environment. Even with pre known static maps this cannot be stored in such a time close way. The timespan reaches from seconds (sudden accidents) to minutes (barriers) and to a few hours (roadworks) and even days (prolonged works). The cluster based local maps contain that information. So accurate current maps for such timespans are available. That maps can be used by the autonomous car itself to make it very reactive. Further such maps can be propagated to other traffic entities (e.g. C2C). Map propagation was not part of this work and is left for future work.

4.3.7 Cluster Based Path Planning

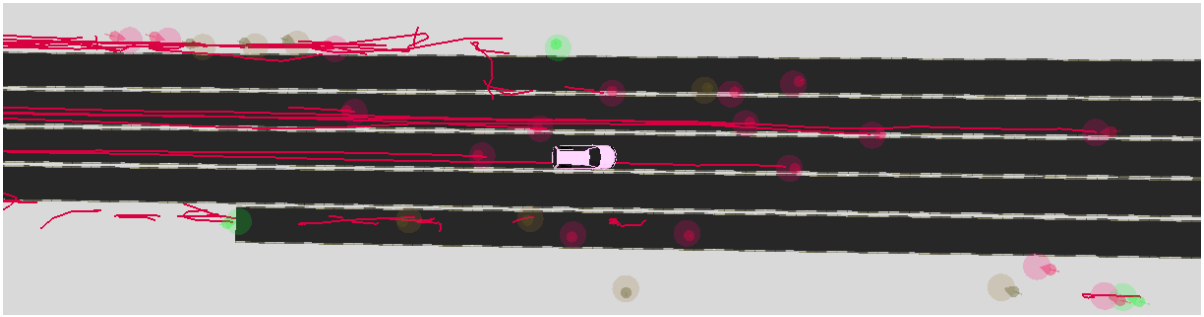
The generated Clusters, described in the last sections, are used for path planning. Clusters give possible ways through the environment of the autonomous car. These basic ways (Way Points) and their connections (successor and predecessor relations) are stored in the Clusters and are used as a basis for a plan. Further Clusters bring gain to the swarm based path planning because of the redundant data.

Through the predecessor / successor relations, information about possible connection between the Clusters are stored. So joining of Clusters is used to generate usable ways. Given one Cluster, a following Cluster has to be found considering some selection criterion. A decision has to be made, if more than one succeeding Cluster is available. Different Cluster heuristics are applied in that way. Here different heuristics have been implemented and tested. A description follows:

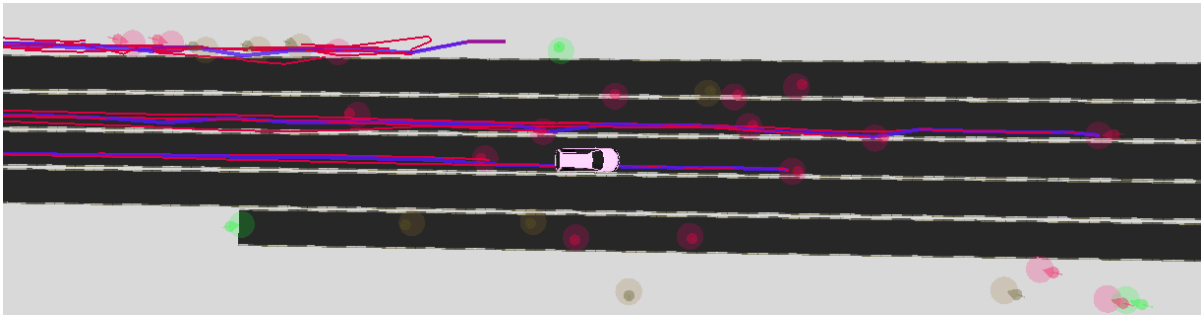
Longest Successor

A preferable long plan is intended in context of plan generation. The planned autonomous drive should be long enough to allow a comfortable driving. For that reason the selection of the longest possible succeeding cluster is implemented and is called the "Longest Successor" heuristic. To reach that aim, different methods were applied and tested. One approach is to choose the succeeding Cluster which has the most number of containing Merged Way Points. This is retrievable fast from the Clusters. It has to be read out the size of the set of Merged Way Points in the Cluster. It is mostly right to generate long plans. Another tested approach which is cheap in terms of calculation, is to calculate the euclidean distance between start and end point of a Cluster. Then that one with the longest distance is taken. Both approaches showed similar habits. So that one with less calculation steps is taken for this heuristic - thus the current implementation prefer the Cluster with most Merged Way Points.

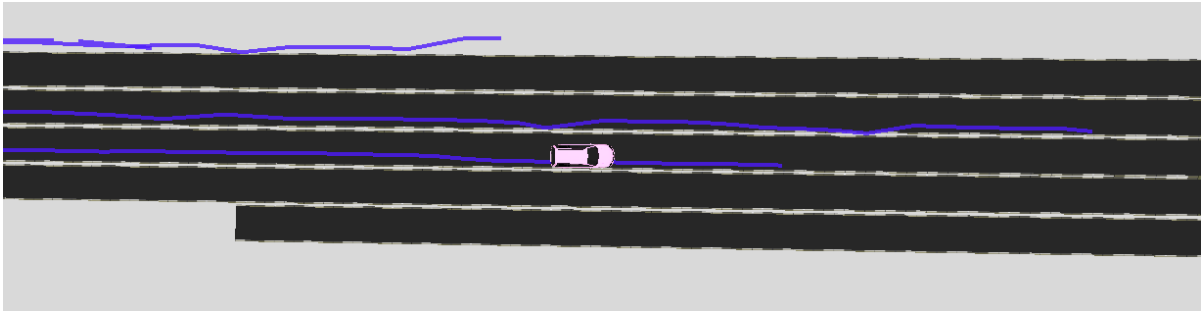
The "Longest Successor" is a heuristic approach because the longest local Cluster does not necessarily mean that the global generated plan is the longest possible plan. But through the fact that a long Cluster often leads to other long succeeding Clusters it generates long plans.



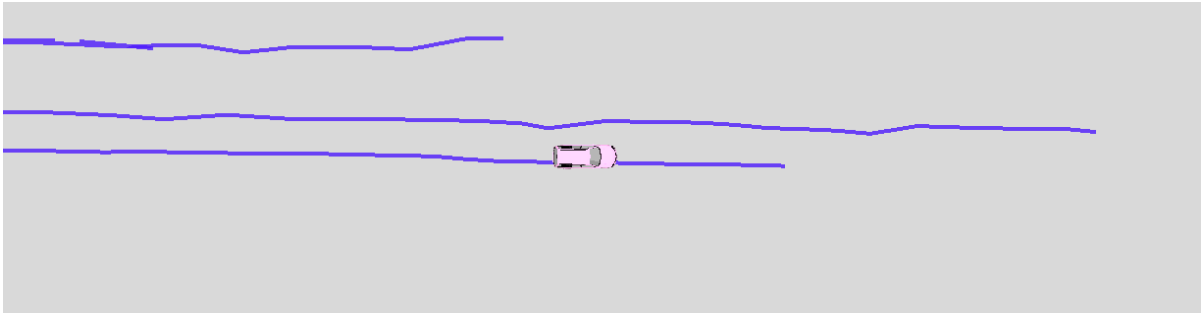
(a) Captured traces of swarm members on a straight lane with traces of swarm members (red)



(b) Generated "Clusters" of way points (blue) and their connections together with the swarm data and a road model

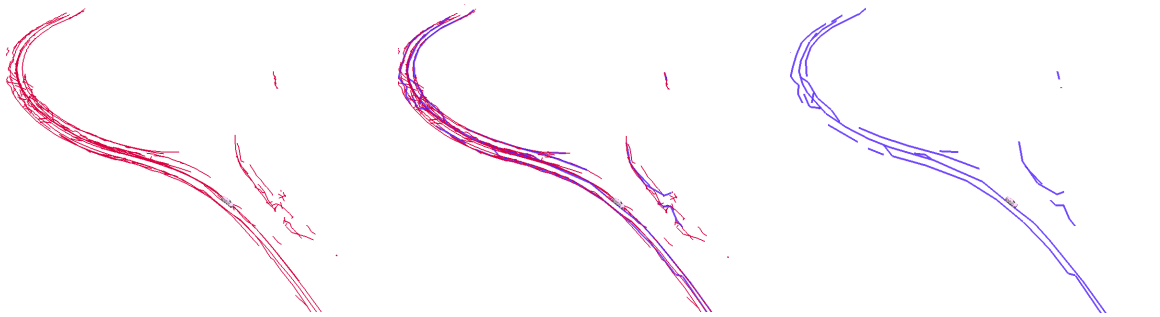


(c) Generated "Clusters" of way points (blue) and their connections together with a road model



(d) Only Information of "Clusters" without road model

Figure 4.18: Generating connected "Clusters" from tracked position data of swarm members



(a) Tracked data of swarm members in a roundabout (b) Tracked data together with generated "Clusters" (c) Generated "Clusters" of roundabout

Figure 4.19: "Cluster" generation with swarm based data from a roundabout

Most Confident Successor

A plan in autonomous driving context has to be safe. In the swarming context, a path is preferable which is taken by more individuals than others. This signalizes safety and confidence. In traffic context, a lane, which is taken by more vehicles, signalizes to be more manageable then lanes, which are only taken by less vehicles - in extreme case only one or no vehicle. Here the swarm is an indicator for confidence and safety. Concerning difficult situations like roadworks, or narrow curves this is very helpful to drive in a safe way.

The confidence information is retrievable from the Clusters. Each Cluster stores the ids of the trajectories it is based on. Thus a heuristic for a most confident succeeding Cluster is to take that succeeding Cluster, which has the most stored distinct trajectory ids. More trajectory ids are representing a way, which is used by more swarm members which were driving at that positions and their Way Points were merged.

The "Most Confident Successor" is also only a heuristic because the stored number of based trajectory ids differs in special situations e.g. when occlusion appears. Further a swarm is wrong in some situations. Because of limited sight in some situations the most swarm members take a more difficult lane than others. But in most situations the heuristic is right. In tested situations this heuristic showed good results.

Minimal Direction Change Successor

A problem of driving plans are lane changes and in general not continuing the driving habit respectively harsh interruptions of the driving continuity. An approach is to keep the change of direction of the driving plan as small as possible. This heuristic selects succeeding clusters after this criterion. The driving direction of the last point in the current cluster is taken. Then the absolute value of the deviation from this direction to the direction of the last points of the succeeding clusters is calculated. The cluster which has the smallest absolute deviation in its last point is taken as the succeeding Cluster.

The "Minimal Direction Change Successor" is a heuristic selection because deviation of direction of the last cluster point depends in some cases on the size of the cluster: Clusters with long distances in some situations have more curved parts than shorter Clusters. So the success of the heuristic depends on the size and the curve habit of the Cluster. The heuristic showed good results in tests with the simulator.

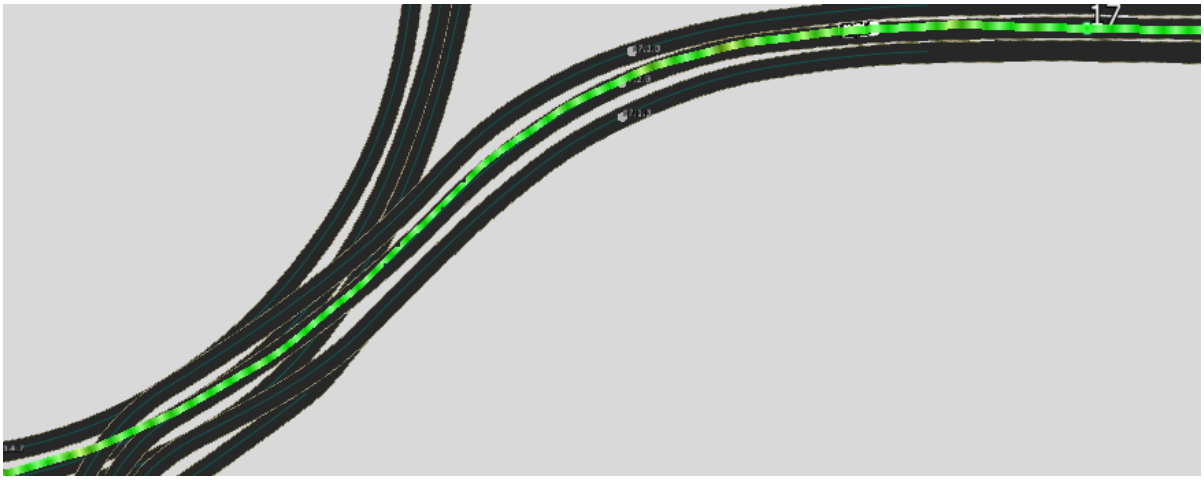


Figure 4.20: Smoothed swarm based plan, based on swarming data (Cluster based with selection of most confidence)

Advanced Heuristics

The implemented heuristics give a basic solution for swarm behaviour for path planning. Trajectory based heuristics can be used for accurate path planning. Further the Cluster based heuristics are usable for advanced path planning. These ideas can be extended, combined and further improved to advanced heuristics as described in Chapter 6.

4.3.8 Smoothing the Swarm Plan Data

Further action has to be done to generate smooth driving plans for the autonomous car. Current Swarm Plan Data is based on many different points. Either these points are positions, which are extracted from trajectories. Or these points are positions stored in clusters. In both cases they are originally from sensors which produce many points in small distances to each other. Respectively imprecision of the sensors and produced outlier points, this leads to a current Swarm Plan Data state which is not usable to generate smooth driving plans.

In that context, redundancy of data points is a positive aspect. This is exploited in a smoothening way. Through inaccuracy around real positions, the redundant data together gives a good approximation for the real positions in a trajectory. Smoothening is reached with help of linear regression. Position data points of a part of the Swarm Plan Data is taken. Then a model for that part is created with linear regression methodology. The model is used to sample all points of the taken part and get corresponding values from the model. These values are smooth because they are basing on a polynomial. The values are further used for generation of a smooth driving plan. Furthermore an algorithm is applied which uses redundant data to delete outliers for smoothing the driving data. Here an adaptation of the RANSAC method with linear regression was used (see [FB81] and application of the RANSAC method in the project [Zei13]).

One problem arises in that context. To get an usable model for linear regression the data points have to be in a coordinate system in that way, that no clustering of most points at small x-value distances is happening. This means, in an extreme case all y-values are located along one x-value. For a good model a distribution along the x-axis is needed. The Swarm Plan Data is appearing along the road. All data points in the project are given in a world coordinate

system, so different from the car perspective. Through the fact that a road can run along the y-axis direction of the world coordinate system, exactly that problem occurs. All y-values of the data points are clustered along x-values of small deviation. In such a case a good polynomial approximation to the data points is not possible. To cope with this problem a transformation of all relevant points into the car coordinate system is done. This helps because the car's direction in general is going into the direction of the street (at least a few meters). Further curves can happen, but even concerning a 90 degree curve, some distance is between the coordinate origin at the car's position and the data points which are distributed in 90 degree to the cars direction. Further if the car is following the course of the curve that problem is disappearing the closer it comes to the problematical data points. So this method helps to get at least in the immediate surrounding of the car data points in a representation which helps to create an usable linear regression model. And through the fact that the car is following the direction of the street an always latest transformation into the car coordinate system is keeping this constraint for the immediate surroundings of the car upright. Transformations in the implementation are done with help of a affine transformation and with help of the C++ library "Eigen" (see [Eig14]).

After the transformation of the data points into the car coordinate system is done, the linear regression model is built. Here a method was implemented to test different degrees for the used polynomials. For the described small distances (because of possible narrow curves) polynomials of degree two or degree three are good applicable. With help of the model a sampling in the relevant area for which the model was created is done. The new data points, based on the sampling with the model, have to be re-transformed into the world coordinate system. This is done with the inverse matrix from the first transformation.

In Figure 4.20 the resulting driving plan based on the smoothing with linear regression is visualized with help of the simulator. The basic heuristic for swarm plan generation is based on the clustering method with a merging size of 2 meters into the front and 3 lateral meters. The succeeding cluster selection is based on the most confidence criterion - means the cluster which has most basic trajectory ids. The linear regression model is based on a polynomial of third degree. A sample rate of four meters was applied on the model. Additionally for local plan generation only the closest data points in a distance of a maximum of 60 meters to the front and the back of the car were considered. This lead to a consideration of data points in a range in which a good approximation via a polynomial of third degree is possible. Further the successive consideration of the area behind the car leads to a smoother application of the plan for driving. Jumping plan positions below the car are avoided. In that way, old data points which influenced the current plan have impact on the plan generation of the current situation.

4.3.9 Interface to the Controller Module

The planned positions and velocities have to be handed over to the car's hardware. Therefore the basic tasks and pipeline of Figure 4.21 is applied. The dotted black line is signalizing the interface to the existing project modules which are abstracting from the vehicle hardware. Basic ideas for planned positions and velocities are described in the following.

To apply the wanted swarm based plan, generated by the heuristics, to the autonomous car hardware, a communication between the swarming modules and the car controller is needed. Plan data contain that information which is used by the car's controller to reach positions with velocities. So the main data is a sequence of positions and corresponding directions (an alignment of the car). Further in the swarming context, wanted velocities at certain points are relevant. So a new data structure for managing all of this relevant data is used. It further provides specialized methods to manage the swarm plan data. Methods for adding new data

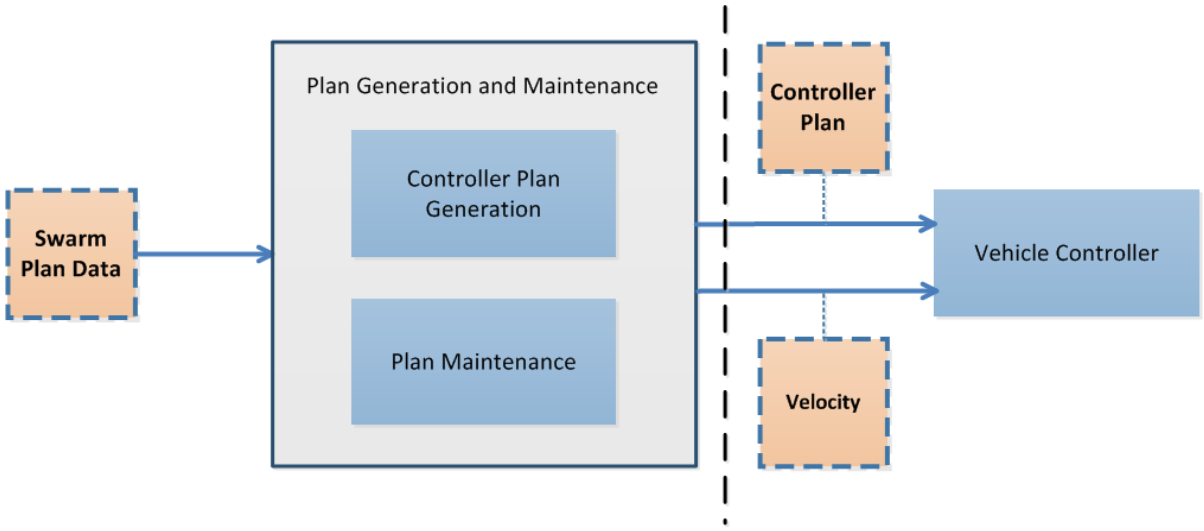


Figure 4.21: Pipeline for building a plan from Swarm Plan Data and handing it over to the vehicle controller. The interface to the next abstraction level is marked by the dotted black line. Once a special plan for the vehicle controller is generated. Second the velocity is extracted. Both is handed over.

or integrating new planned data into an old existing plan (new planned parts of the plan) are provided.

To get the autonomous car to drive to the planned points, generated by the heuristic implementations, a communication between the swarm modules and the hardware is needed. Here the fundamentals of the current project were useful because the communication to the controller can run via a given data type which is sent over a module connection. The new data structure provides a method which generates data for the controller and hands it over. The controller is responsible for calculating parameters to reach the plan.

Additionally the velocity calculated via the velocity matching is given to the controller via a new module connection which was established. So parallel to the position data a way was implemented to get the controller to try to obtain a wanted speed. This is sent in real time. Therefore the work of the velocity matching was used, which stored a wanted speed for every position of a planned trajectory (see Section 4.3.2). For each step for getting a wanted speed out of the stored planned Swarm Plan Data, the following idea is applied: The closest point on the planned trajectory to the current position of the ego car is searched. Therefore the euclidean distance is taken. Then the stored velocity of that point is used. It is sent via the established new module connection to the controller of the vehicle. The controller tries to obtain this velocity with respect to safety aspects (centrifugal accelerations, obstacles, etc.).

5 Evaluation - Experiments and Tests

5.1 Test Cases

Different aspects for test cases are interesting in the context of this work. The general idea is to evaluate the approaches of this work. Two different general kinds of tests were applied:

- Evaluations based on the simulator of the project
- Evaluations based on test drives with the autonomous test carrier of the project

These tests are described in the following sections. Different ways of generating driving plans for the autonomous car are introduced in this work. The best heuristics (trajectory based path planning with angle, "Safety Zones" and Cluster based path planning) were used in tests with the simulator to compare their success rates after special criterion. Therefore different standard traffic situations were selected. First, it is important to be able to generate swarm based plans on straight areas. Second, curves on streets have to be managed. And third a combination of both: A roundabout traffic scenario. Here straight parts (e.g. at the exit) are combined with curvy parts.

The tests in the simulator were applied with logged data. The behaviour of a simulated autonomous car with the swarm behaviour module was observed. All situations were tested with logged data, stored from real traffic. In all situations swarm members were available. Heuristics are compared with help of the roundabout scenario as it represents a combination of the different situations. The simulator from the existing project was used for accomplishment.

Further it is important to evaluate, if the swarming approach is applicable in real-life scenarios. Therefore an experiment with the test carrier (introduced in Section 2.1.2) in combination with real traffic participating cars in a test area is designated. Here the general applicability of the Swarm Behaviour module is evaluated against real sensor input and real hardware output.

5.2 Evaluation of Different Heuristics in the Simulator

An evaluation was carried out with help of the simulator of the project. Success between the different heuristics was measured. The object of comparison is a driving plan. The general idea behind all approaches is to be able to generate a plan which is sent to the autonomous car's hardware. Consequently the generated plan directly effects the behaviour of the autonomous car. So it affects the quality of autonomous driving. Thus the generated plan of the different approaches is compared (also see ideas in [Wan12] Chapter five for evaluating plans). Different aspects have been taken into account as a criterion for a good plan:

1. Length and continuity: The possibility to drive through a certain traffic situation without stopping. A stop is connected with a replanning or an intervention of the safety driver. A stop is connected with a plan of smaller length. The longer a autonomous drive, based on a plan, without intervention of the safety driver is, the better is the plan.

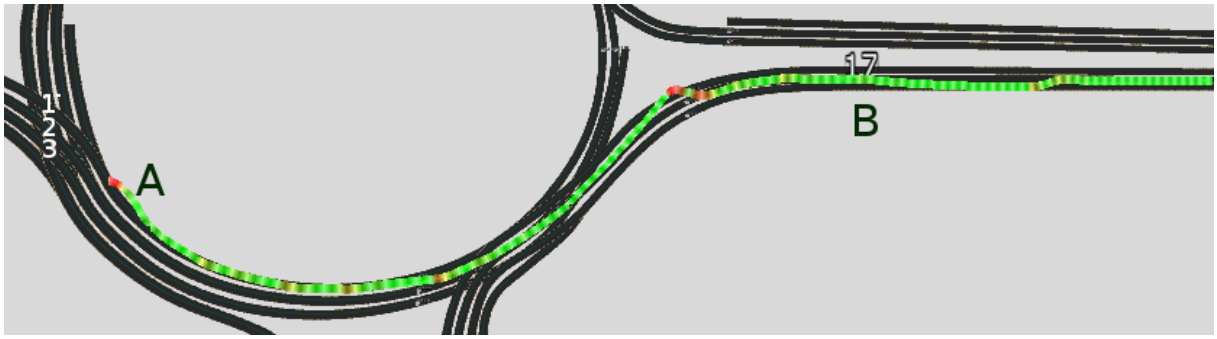


Figure 5.1: Evaluation in roundabout scenario in the simulator of the project. A generated example plan is visualized in green and red.

2. Small number of changes of continuity: If the plan makes relatively sharp curves which are not necessary. Comparable with a lane change in a situation were the current lane is good and has not be changed.

As a basic traffic situations which covers all difficulties which were discussed in this work (straight lanes, curves, and combinations of both cases) a roundabout is used. In Figure 5.1 the used scene in the simulator is visualized. The evaluation measurements start from the position of the beginning of the green line (Point A) at the left side till the number 17 at the end of the roundabout (Point B). Logged data from a live test drive with the test carrier was taken for the scenario. The data is from the Ernst-Reuter-Platz Roundabout in Berlin and was logged at date 14.11.2013. That data was applied with the simulator. The input form the logged data was taken by the "Swarm Behaviour Module". It was processed. Plans and velocities were generated by the "Swarm Behaviour Module". The plans were forwarded to the simulator. The simulator of the project used a such created plan to steer a virtual car with the simulated behaviour of the real test carriers hardware. Plans and a road map were visualized. This visualization was used as a basis for the above described evaluation points. Each lane change of the plan was penalized with one point - in the example in Figure 5.1 in the considered segment three lane changes are visualized. This equals three penalty points. Further a replanning and a replacement of the car in the simulated environment was penalized with one point. A replanning was carried out, when the simulated car was not continuing with driving, but the tested scenario segment was not driven off. When replanning was not helping to continue the drive, an replacement of the car was done in the simulator. This also counted one penalty point. In real both, replanning and replacement means, an intervention of the safety driver is necessary to continue the drive. For each started test a replacement to the start position of the scenario segment and a replanning was carried out to start planning from comparable positions. This is equally counted for all heuristics with one penalty point for replacement and one penalty point for replanning. Three different lanes were used as a starting point for each heuristic. So an evaluation for data with different frequented lanes was carried out. Success is measured with the sum of penalty points. An approach is more successful than another one, if its sum is smaller than the sum of the other approach. Less penalty points equals a better plan. In Figure 5.1 the referencing numbers of the lanes are visualized on the left side. The inner roundabout lane is number 1, the middle number 2 and the outer roundabout lane is lane number 3. The Tables 5.1 till 5.6 show the counted evaluation of this scenario.

In the following the different evaluated heuristics are specified in more detail. The term "lane" is used in the following for comparability. In the swarming context driving can be considered detached from marked lanes on the road. Nevertheless lanes are suited as a measure for comparison and as a fundamental term for discussion. As discussed before the greedy approach

Different lanes ========= Different Criterions	1	2	3
Number of Replacements	4	5	2
Number of Replannings	4	4	2
Number of Lane Changes	4	4	5

Table 5.1: Evaluation of the "Angle Based Trajectory Selection" heuristic

Different lanes ========= Different Criterions	1	2	3
Number of Replacements	3	1	2
Number of Replannings	1	1	2
Number of Lane Changes	1	0	1

Table 5.2: Evaluation of the "Trajectory Selection by Safety Zone Below the Ego Vehicle" heuristic

of trajectory selection is not further used. Because it showed no applicability in daily traffic situations. So it is not appearing in the following evaluation.

Angle Based Trajectory Selection:

As described in Section 4.3.4 - "Selection of Trajectories by Concerning Reachability" an angle based checking of trajectories is applied. An opening angle of four degrees in the y-direction of the vehicle is used. As depicted in Table 5.1 compared to other approaches many replannings, replacements and lane changes happened. One main problem of the approach is to find an initial trajectory in a curvy area. Further, as soon as the ego vehicle is driving a curve the reference checking area defined by the angle in forward direction is looking to side lanes. This results in lane changes, if other trajectories are discovered in these areas. Or a stopping of the car if no trajectories were in that area. Through curves this happens often and declares the high penalty values.

Trajectory Selection by Safety Zone Below the Ego Vehicle:

This heuristic selects trajectories by considering a defined area below the car - see explanations in Section 4.3.4 - "Selection of Trajectories by Different 'Safety Zones'". In the tests, in some cases, no trajectories can be found for selection. This is explainable through the very precise definition of the area below the car. It is a very strict definition and if no trajectory data of swarm members is available for this area, an intervention by replacement and replanning has to be done - see values in Table 5.2. This is the cost of the "safety" of this method. Otherwise, few lane changes are happening. The fact that a once taken trajectory (which already is located below the car) is followed to the end, leads to the consequence, that a realistic (human like) drive is happening. So less lane changes according to the drive of the selected trajectory is performed. Best results are achieved by initially taking the middle lane (number 2). That is the location were most vehicles produced trajectories. Consequently an ending trajectory is more likely located to other close by located trajectories than this is the case on other lanes. In that case no further replanning and replacements (except the initial ones) has to be made.

Different lanes ========= **Different Criterions**	**1**	**2**	**3**
Number of Replacements	1	1	3
Number of Replannings	1	1	1
Number of Lane Changes	1	1	0

Table 5.3: Evaluation of the "Trajectory Selection by Three Safety Zones in the Ego Vehicle Area" heuristic

Different lanes ========= **Different Criterions**	**1**	**2**	**3**
Number of Replacements	1	1	1
Number of Replannings	1	1	1
Number of Lane Changes	1	2	2

Table 5.4: Evaluation of the "Closest Cluster - Longest Successor" heuristic

Trajectory Selection by Three Safety Zones in the Ego Vehicle Area:

In this heuristic again "Safety Zones" are applied - see explanations in Section 4.3.4 - "Selection of Trajectories by Different 'Safety Zones'". Here not only one area below the car is defined. Three areas are used: The first "Safety Zone" is defined exactly below the car. It is comparable to the heuristics described before and represents the "safest" zone. The second "safest" zone is an extension of that area to each side. This means that the lateral respectively the forward and backward boundaries of that zone is at distances of about double distance to the ego car position than the boundaries of the first zone. A third zone is defined in the front of the car and afterwards to the front of both other zones. This is the "unsafest" defined zone because it lies in a farther distance than the other zones. But still it covers an reachable are, because it is in some distance to the front of the car. With that application of the "Safety Zones" results are as depicted in Table 5.3. Again comparable good results for lane changes were reached. Here the explanation is as above for the usage of one zone. Once selected a good trajectory and followed, this is comparable to a human drive related to less lane changes. Further, better results, concerning replanning and replacement, were reached than in the "Trajectory Selection by Safety Zone Below the Ego Vehicle" heuristic. This is explainable through the more relaxed definition of further "unsafer" zones which are applied if no appropriate trajectory could be found in the safest zone. So a way is described how to define better trajectory selection based heuristics with the usage of zones: A fine enough arrangement of the number and positions of the "Safety Zones" have to be applied.

Closest Cluster - Longest Successor:

This cluster based heuristic showed relatively good results in the test scenario - compare table 5.4. In Section 4.3.7 the "Longest Successor" heuristics was introduced. The closest cluster to the ego position is initial selected. Succeeding Clusters are distinguished by length. The longest is taken as successor. In all cases good results were reached. After starting no replanning and no replacement - so no intervention of the safety driver - has to be done. Few lane changes are happening. This is explainable through the kind of selection: If a longer cluster was detected on a close by lane then this is preferred. Through following long clusters, only fewer opportunities for changes are existing.

Different lanes ========= Different Criterions	1	2	3
Number of Replacements	1	1	1
Number of Replannings	1	1	1
Number of Lane Changes	1	1	1

Table 5.5: Evaluation of the "Closest Cluster - Most Confident Successor" heuristic

Different lanes ========= Different Criterions	1	2	3
Number of Replacements	1	1	1
Number of Replannings	1	1	1
Number of Lane Changes	1	0	0

Table 5.6: Evaluation of the "Closest Cluster - Minimal Direction Change Successor" heuristic

Closest Cluster - Most Confident Successor:

The cluster based heuristic, which is selecting the most confident successor, even showed better results (see 5.5 in the scenario. Again, once taken the closest cluster no replanning and no replacement has to be done. This time less lane changes happened than in the test before. This is explainable through the definition of confidence in this context. Always the succeeding Cluster which represents most trajectories is taken. Once found such a Cluster it is probable that following clusters with most confidence are at the same lane. In the roundabout scenario the second lane (middle one) is highly frequented. So once taken a Cluster which leads to that lane, it can be stayed on it and continued. Thus in the current consideration the most confidence heuristic idea is evaluated as very good usable for daily traffic situations.

Closest Cluster - Minimal Direction Change Successor:

The cluster based heuristic selecting succeeding Clusters, which have the minimal direction change, showed very few lane changes and no need for intervention. In the results of the test shown in Table 5.6 only one lane change was carried out if started on the inner lane of the roundabout scenario. The explanation is that the direction change of Clusters of other lanes are so different from the direction change from the current Cluster that concerning this heuristic it is mostly better to stay on the lane of the current Cluster and take a following Cluster on that lane.

Comparison of Different Applied Heuristics

A comparison of the different results from the test is depicted in Table 5.7. The results of the different heuristics of the previous evaluation tables are taken. Per lane the sum of the penalty points in the tests are listed. The result column is showing the sum of all penalty points per heuristic in all tests. Angle based trajectory selections has a very high penalty sum. So this approach is compared to the other approaches very weak. Cluster based selection approaches have best results (small penalty sums). Future work should focus on that ideas. Further the application of different "Safety Zones" show good results. Approaches should lead to a finer definition of "Safety Zones" if a clustering is not trusted and a exact following of trajectories is required.

Different test ========= Different Heuristics	1	2	3	Result (Sum)
Angle Based Trajectory Selection	12	13	9	34
Trajectory Selection by Safety Zone Below the Ego Vehicle	5	2	5	12
Trajectory Selection by Three Safety Zones (Ego Vehicle Area)	3	3	4	10
Closest Cluster - Longest Successor	3	4	4	11
Closest Cluster - Most Confident Successor	3	3	3	9
Closest Cluster - Minimal Direction Change Successor	3	2	2	7

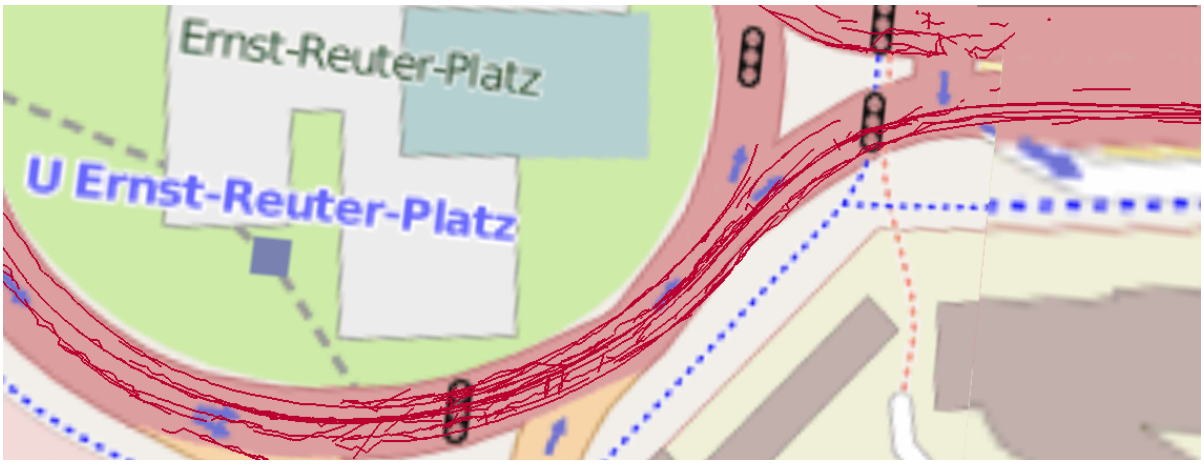
Table 5.7: Comparision of the different heuristics - per lane sum of points from evaluations and result (sum of points over all lanes)

5.3 Evaluation of the Clustering of Swarm Member Trajectories

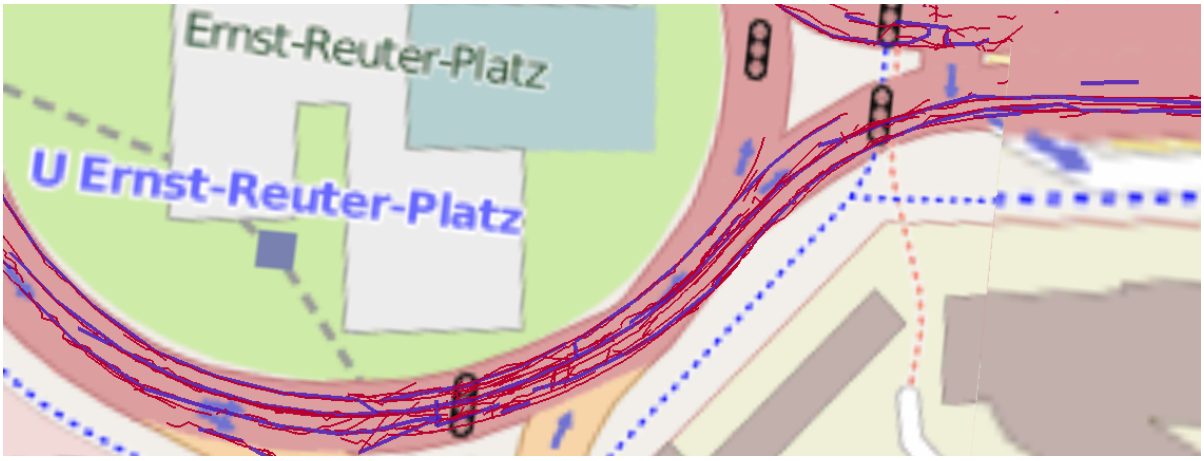
Clustering of Swarm Member Trajectories is usable to generate a Possible driving map. This map can be used for path planning. To evaluate the generated clusters in a map context, logged data were used. For this a test drive with the test carrier was logged. The logged data of the obstacles were stored together with its GPS data. This was usable to match map data with the obstacle data and the data of the clustering output. Data from a roundabout in Berlin was used: The Ernst-Reuter-Platz. In Figures 5.2 and 5.3 the results are visualized. A good approximation of the different lanes of the Ernst-Reuter-Platz roundabout is reached.

To show the different steps of the clustering process compared to a map, in Figure 5.2a the logged data is visualized. The red lines are the trajectories of tracked obstacles. Under the data the GPS matched data of the map is shown. So the part of the Ernst-Reuter-Platz in Berlin is in the figure. In the second Figure 5.2b the output of the clustering module is shown together with the basic logged obstacle trajectory data. The last Figure 5.2c shows the generated clusters alone. They are matching the lanes of the roundabout in most areas. It has to be considered that the clusters were generated based on the current situation of the logging process. So this lanes which are seen are showing a kind of "snap shot" of that situation, how the lanes (defined by the swarm members) were located at that time. If no traffic participants were at that time at a certain lane, that lane is not detected. It can be seen that a good approximation of the basic lanes of the Ernst-Reuter-Platz are taking place. On some parts are lane changes. Based on the matching of GPS data of the Cluster positions and the map data, a good result can be seen. The visualized results are based on the clustering process which uses a merging area with forward and lateral area definition. For comparison, Figure 5.3 has to be considered. Here the implementation of the described adaptation of the "Extracting representatives of GPS points" [GLJ10] method was used.

First using the method described in Section 4.3.5 was applied with using a continuously adoption of the representative value each time a point is added to a Merged Way Point. Here a merging distance of seven meters in forward direction and three meters of a total lateral distance (a bit less than a lane width) showed good results (compare Figure 5.2). So the lanes of a traffic scene were re-creatable by using the swarm based trajectory data. By using a very high lateral distance for merging (e.g. ten to 15 meters of total lateral distance and forward distances of about 6 meters) a good approximation of the middle of the street was obtained. Through the distinction between forward and lateral merging distances this was possible and showed good



(a) Raw tracked data of swarm members

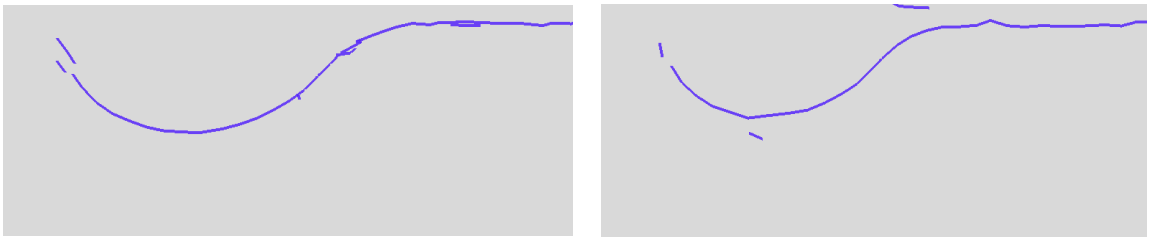


(b) Raw tracked data of swarm members and generated "Clusters"

(c) "Clusters" generated from the tracked swarm data

Figure 5.2: Evaluation of the Clustering Process: Generated "Clusters" based on swarm data at the Ernst-Reuter-Platz in Berlin

Figure 5.3: "Clusters" generated from the tracked swarm data using the described adaptation of the "Extracting representatives of GPS points" method from [GLJ10]



(a) Application of a merging of Way Points with a lateral and forward defined area for building Clusters

(b) Application of a merging of Way Points with an adaptation of the "Extracting representatives of GPS points" method from [GLJ10] with a "circular window"

Figure 5.4: Approximating the course of the road with different methods and high merging values

results - compare 5.4a. This method can be used if a general course of the road is wanted to be extracted from swarm data.

With the adopted method based on the approach of D. Guo et al. "Extracting representatives of GPS points" [GLJ10] good results were reached with application of a "circular window" of a size of 1.8 till 2.2 meters (radius) to extract relevant lanes. It showed better and clearer results than the previous method in cases of overlapping trajectories - see 5.3. This is explainable through the more precise selection idea of representative points. Points are assigned in a clearer way to get Merged Way Points in this method. An application of this method with a high value (six to ten meters) for the "circular window" showed relatively good approximations for the general course of the road - compare 5.4b. Nevertheless some inaccuracy at points in curves were observable. The other method showed better result in terms of accuracy but also some noise (parallel close by lane parts) was detected. Both is explainable through the distinction between forward and lateral merging distances in the above method compared to the "circular window" of the current method. It is left open for future work to combine both ideas and evaluate an application of forward and lateral distances to the second method.

(a) Test area Tempelhofer Feld

(b) Test area Tempelhofer Feld with test carrier

Figure 5.5: Testarea - Tempelhofer Feld in Berlin - area, obstacles and test carrier

5.4 Live Experiments with the Test Carrier

During development of the Swarm Behaviour Module in addition to tests with logged data in the simulator as well testing in real life took place. The special test area Tempelhofer Feld was used for this purpose. The autonomous test carrier of the project (see Section 2.1.2) was used as the autonomous ego vehicle. The test area is a big field with obstacles. Some areas have lane markings. So suitable to simulate traffic scenarios. Other vehicles were used to get data about obstacles and possible swarm members. The test area can be seen in the pictures of Figure 5.5. Different experiments were carried out to simulate real traffic situations were the implemented swarming approaches were applied. Tests were performed till speeds of 30 km/h. Failures and unexpected habits of the implemented software were discovered during the tests. This was used for improvements through out the development of this work. Different implemented developments are basing on the insights of the live tests. E.g. improvements of the swarm based plan like smoothing before handing it over to the vehicle controller. Further a range of improvements were done to stabilize the habit of the software and reaching a good maintainability.

Different test scenarios with swarm members were performed. In the simplest test configuration the autonomous test carrier was located behind one other car - the leading vehicle. The leading car performed different driving manoeuvres. The test carrier should detect the leading car, and percept all of its relevant values: the trajectory (positions) and velocities with direction at this positions. Additionally with the current ego state this was the input into the swarm module as described in the previous Chapter. Swarm algorithms were performed and the test carrier followed the leading car. The different manoeuvres included straight drives, average curves and sharp curves. Accelerations and brake applications were tested.

In further test scenarios two vehicles were used as swarm members. In one case both vehicle started in front of the ego car. Again the autonomous car had to perceive the relevant swarm information. The swarm behaviour was performed and the habit of the ego vehicle was observed in the situations of straight drives, curves and speed differences. A good performance was accomplished. In a further case the two swarm member cars were performing manoeuvres in a more unpredictable way. So their trajectories were crossing over. Occlusions of the cars happened. So parts of the trajectories were vanishing for the ego vehicle's point of view. So only one trajectory was usable. In this case again a good swarm behaviour was observed. In a third case at the beginning only one car was detectable as a swarm member. A second car was appearing after some time, overtook the ego car and provided swarm data which was as good as the first swarm member's data. Again in this tests good swarming results were observed.

Further a test was accomplished to find out how accurate the autonomous car can follow another leading car. Therefore a test lane was used with several curves and straight parts. The leading car was accelerating at different positions. The autonomous car was following the leading car and was keeping the velocities of the leading car at the appropriate positions. Through the lane markings the accuracy of the actual reached positions of the autonomous car were comparable. The result was very good. A good swarm based driving performance over a larger distance (several straight and several curvy parts with a roundabout similar situation at the end) was achieved. Velocity and positions were accurate. Thus the swarm based autonomous driving with the implemented approaches in the tested traffic situation is evaluated as possible.

6 Conclusion and Future Work

6.1 Conclusion

Swarm behaviour for path planning is object of this thesis. With this work swarm based approaches for path planning are implemented. To get a context to the topic, an introduction to swarm based ideas is given. The AutoNOMOS Project is introduced. Further, a transfer of swarming ideas to the autonomous driving context is discussed. Implementations with focus on the topics swarm member selection, velocity matching, processing of swarm member trajectories, trajectory based path planning, further processing of swarm member trajectories to get abstracted Clusters, path planning based on Clusters, smoothing of a swarm based plan and handing the processed swarm based plan to the vehicle controller are described and discussed.

With the usage of this approach it is not only possible to generate better autonomous driving solutions in unknown or dynamic areas. It is also usable to generate better street maps concerning current situations like roadworks, if swarm data is available. These maps are further usable for autonomous path planning. So this work helps to bypass limitations in current approaches for the map based planning of driving through swarm approaches. It also suggests an improvement to generate maps appropriate to current situations. These maps are basis for further swarm based path planning. Advanced implementations around this topic are still open. Implementations are at the state of Clusters and Cluster based heuristics. In the following a detailed explanation of the fulfilled requirements of Table 1.1 is given:

REQ01 Swarm Based Extension of Current Software Solution

Throughout Chapter 4, a description of the implementations of this work is given. It describes the software which was developed in this work. Swarm based ideas are introduced - see Chapter 1 and Chapter 3 - and the current AutoNOMOS Project is described - see Chapter 2. Swarm based ideas are further used as basis for implementations. A basic idea is given how to integrate swarm based ideas into the current state of the software of the AutoNOMOS Project. First a swarm member selection is introduced. Further different applications and their implementations of swarm member based trajectories are described. So swarm based path planning is possible. Further an abstraction of swarm based trajectory data is introduced - the Clusters. An description is given how these Clusters can be used for swarm based maps which are a foundation for advanced swarm based path planning. Different heuristics and their implementation for such swarm based path planning are given. With the smoothing of the swarm based plan and the implemented connection to the vehicle controller of the current AutoNOMOS Project an integration of swarm based driving plans is given. Thus a swarm based autonomous driving is possible. Consequently a swarm based extension of the current software solution for the autonomous test carrier is reached.

REQ02 Swarm Based Ideas

A transfer of swarm based ideas towards traffic is given at different parts of the work. All implementations and described ideas were examined under the consideration of swarms. Thus in a traffic situation swarm members are extracted. Therefore moving obstacles are considered. They are considered as swarm members, which are giving valuable information for the

ego autonomous car. With help of their trajectories swarm based data is given. That is fundamental for implemented algorithms and data structures. Implementations allow a swarm based autonomous driving. Consequently this aim is reached.

REQ03 Implementation of Swarm Based Algorithms

In Chapter 4 implemented ideas are described. Processing pipelines are given to reach a swarm based behaviour of the autonomous car. Implementations start with object detection and swarm member selection in the context of traffic and the autonomous vehicle. Velocity matching is implemented and described. Implemented ideas of the processing of trajectories of swarm members are described. Further the different ideas of a swarm trajectory based path planning are given: a greedy approach, a more advanced approach working with a reachability area, and well suited approaches with "Safety Zones" with algorithmic described ideas. Further algorithms for a clustering of the swarm data is given. Different implemented ideas are described using different ideas to merge data. Different implemented heuristics for swarm Cluster based path planning are given: "Longest Successor", "Most Confident Successor" and "Minimal Direction Change Successor". With further described implementations an autonomous driving with that swarm based algorithms is realized.

REQ04 Implementation of Swarm Based Data Structures

Throughout the work different implemented data structures are mentioned. They were necessary to reach the swarm based autonomous driving. Besides the algorithms described before that is necessary to maintain and store current data. So data structures like "Swarm Object Tracks" and the data structure of "Clusters" which contains "Merged Way Points" and "Way Points" are implemented. Further a data structure for managing "Swarm Objects" with "Swarm Members", "Swarm Static Obstacles" and "Swarm Unclassified Obstacles" and a data structure for a "Swarm Based Plan"s are implemented.

REQ05 Embed Software into Current Project

Section 4.1 gives a basic idea how the "Swarm Behaviour Module" can be integrated into the current architecture. See especially Figure 4.2. Detailed names of the used existing project modules and connections are given. Further Section 4.2 gives a more detailed idea, which existing project modules are connected with which processing swarm tasks as input. And further how the processing is applied to generate the output which is given to the vehicle controller module of the existing project. See the Figure 4.3, describing the general architecture with its connections to the existing project. In more detail in Section 4.3.1 and Figure 4.4 and further in Section 4.3.3 and Figure 4.7 the input interfaces are described and how data of the existing project is used for further processing in this work. The output data of the "Swarm Behaviour Module" is given to the vehicle controller of the autonomous car. This implementation and interface is described in Section 4.3.9 and visualized in Figure 4.21. To make a drivable swarm based plan possible, a smoothing of the generated driving plan is integrated - see Section 4.3.8.

REQ06 Integrate Data of Current Project Modules

As described under REQ05 the interfaces to the existing implementations of the AutoNOMOS Project are implemented and described. In this way, the input data of the existing module "Obstacle Fusion" is used to get data about potential swarm members. Further existing modules providing data about the current ego state are used. All processing of this work is based on this data. So REQ06 is fulfilled.

REQ07 Simulation Tests

Throughout the work testing was done. Therefore the simulator of the project was used. The autonomous car was simulated. Input data was given to the "Swarm Behaviour Module", processing was done and output was generated for the simulated hardware. Observation of the habits of the "Swarm Behaviour Module" was done through the simulator. For detail see Chapter 5.

REQ08 Visualization

A visualization of data is done. This is done with help of the simulator. Swarm Members, their trajectories and generated swarm based driving plans are visualized. Further the generated Clusters are visualized. See figures throughout this work.

REQ09 Real Live Tests with the Test Carrier

The test carrier of the AutoNOMOS Project of the Freie Universität Berlin was used to test the "Swarm Behaviour Module" in real live. Experiments and results are described in Section 5.4.

6.2 Future Work and Outlook

A starting point is set with the current work. Basic data structures for swarm members, trajectories, swarm based plans and clustered trajectories are implemented. At each step of the processing pipeline new ideas can be implemented and tested. The processed data of previous steps can be used. The swarm member selection process can be improved to allow more detailed distinction of swarm members. For the swarm based path planning, the basic following ideas can be extended. The cluster based map building process should be of main interest. New maps can be easily built and propagated. Situation based applications of swarm based solutions have to be analysed. Further ideas are given in the following:

6.2.1 Advanced Velocity Matching

Swarm members give information about the possible velocity in an area. In combination with special traffic scenarios like crossroads with traffic lights advanced usage of the swarm based velocity data is needed. Currently the stored velocity of the past situation is stored at certain Way Points. Even that data is from a timespan of seconds to minutes, in some situations it may be outdated. An example is the scenario with a crossroad and with traffic lights. In the case of a switched light to red, but the stored velocity is from a time where the traffic light was green. In such situations it is helpful to orient the ego vehicle on the direct surroundings in addition to the orientation on the stored velocity at a Way Point some time ago. The closest cars in the front, back and lateral give additional information. Both values, the current immediate surroundings and the stored velocities of the past, can be considered in future approaches to calculate the own velocity.

6.2.2 Improved Static Obstacle Avoidance

Static obstacles can be used for further advanced heuristics. It has to be investigated if trajectories which are more far away from static obstacles are more preferable than others. This is interesting in different traffic situations, e.g. in cities: Parking cars which start driving change from static to dynamic obstacles. So a planned driving trajectory for the ego vehicle, which considers such kind of uncertainty, can be preferable. Traffic scenarios with high velocities may include other necessities. Therefore advanced experiments has to be made.

6.2.3 Improved Dynamic Obstacle Avoidance

Current implementations are considering (dynamic) obstacle avoidance only in a very basic manner. The plan is given to the controller and there are basic implementations which check if obstacles are on the plan. A break is accomplished if the controller is detecting a possible crash. A consideration of fully dynamic obstacles can lead to an improvement. These obstacles are objects which are currently not on the plan but through their movement can touch the plan in any manner in the future. Through observing dynamic obstacles and through trying to recognize their intention, gain can be reached. An example application is to take all dynamic objects (in this case obstacles) and calculate/predict their positions into the future. This can be reached by observing their trajectories - e.g. the last observed ten meters - and extrapolate them into the future. Through the current implementation the velocity is stored in the points of the trajectories. Thus direction and speed can be extracted. In further use Clustered maps of future situations can be generated. So Clusters of different time states can be built. That Clusters could store time based information. A suggested time classification of the Clusters:

- currently real observed
- a few seconds ago observed - maybe outdated
- possible future extrapolated

That information can be used for advanced path planning. Implementations and experiments in that context have to be analysed.

6.2.4 Building Advanced Maps

The implemented Clusters are providing data about positions, velocities, possible driving ways and connections. This data can be used for building advanced maps. See the ideas in Section 4.3.6.

6.2.5 Propagating Swarm Based Data

Further it would be interesting to investigate if and how propagation of swarm data is bringing a gain for traffic situations. Here ideas like Car2X (Communication between cars and other objects) especially Car2Car (Communication between cars) are becoming interesting. Scenarios where cars are propagating their detected swarm based maps and trajectories to following cars are interesting. So the scope sight of a single car can be extended. Current information can be propagated over distances more than a few hundred meters and around corners. Current sensor restrictions which lead to a very local and reactive approach can be overcome. Interesting is the question if it is better to keep the information local (a defined relative small area) or to propagate it over far distances to give the possibility to make good global decisions. On the one hand a good point for keeping it local is the fact, that swarm data is good in reactive and very dynamic scenarios (like current trajectories in a roundabout). So propagating this data over longer distances would not be advisable because the data can already be outdated if relevant for the receiver. On the other hand swarm data can lead to higher decisions. E.g. if the traffic is very crowded at one place or if the mean driving velocity is very low it can be advisable to avoid a certain zone on the streets. Therefore the swarm data can be used if it is propagated over longer distances. In this context it is interesting how far this data can influence high level planning of driving. In general experiments and tests in this context has to be made.

6.2.6 Intention Recognition with Swarm Based Data

The framework, especially the clustering part of this work gives a tool to the AutoNOMOS Project which clusters in a very basic way the data which is obtainable. The clustering process can be improved with further advanced ideas. One point would be an intention recognition. Here we can combine current data like position, velocity and direction of obstacles to a situation recognition. The data is already stored in the Clusters and retrievable per Way Point (via the Merged Way Points). This is illustrated by the following example: A cross-road or two lanes on the autobahn are recognized. This is connected to a set of possible actions. If data like acceleration of other cars (calculable through the successive observation of the velocities, stored in the Way Points) in the current situation is known, we can detect if the car is speeding up etc. With this information we can extract further information, for example if a car wants to overtake another one. This data can be stored in a Cluster. The Cluster data structure is appropriate to be extended for processing and storing data like this. This can influence the decision making process. E.g. a certain lane, respectively a certain Cluster, may not be interesting when an overtaking process is taking place at positions connected to that Cluster. For implementing this idea the framework described in this thesis can be extended, e.g. the Way Points can be extended with information like intentions. This can lead to more complex data structures. e.g. enriched Clusters with intention data (e.g. stored in each single Way Point and further abstracted to the Cluster). One problem connected with that idea is how to cope with the time component. Information like described above, is relatively fast outdated (overtaking processes are fast and intentions can vary over the time). Time has to be stored in such a data structure. Further, an extension of the current Cluster idea is connected to advanced managing algorithms. So data has to be managed via time and id of the data producing obstacle. That algorithms are responsible for keeping stored intentions up to date and deleting old ones. Surrounding intentions in such an approach can be extracted and restricted through knowledge about the own position. Ideas like this can be inserted into the current implementations. Further tests have to be made. The work around intention recognition is left open for future work.

6.2.7 Advanced Heuristics

Further advanced heuristics can be built like calculating the mean of the velocity in each cluster. Through selection of the cluster with the highest mean value a heuristic is built which gives the swarm based "fastest" way through the environment. A selection of the Cluster with the highest number of successors stands for a way with most opportunities connected with likely changes of the driving direction. Implementations are left open for future work. The advantageous result of such Cluster based advanced heuristics is that the solution of a plan bases not only on one trajectory. It is based on the best parts of trajectories (according to the used heuristic) of all known parts of trajectories. All kind of retrievable information can be used and combined to build advanced heuristics. Through the appearing redundancy, coming with the swarming aspects, gain in confidence and possibilities is reached.

All described heuristics show good results in the test scenarios. Nevertheless some heuristics are better suitable for special use cases: In situations with long steady parts the, "Longest Successor" is appropriate. In difficult situations like in road work areas, safety and confidence is important. So a selection of a "Most Confident Successor" is preferable. Selecting "Minimal Direction Change Successors" is convenient on straight parts in the traffic habit. Unnecessary lane changes in such cases are inconvenient. A situation specific selection of heuristics is not part of this thesis and is left open for future work. A combination method for above described heuristics has to be found. A weight function has to be found to combine the heuristics. Machine learning methods can be applied to get good results.

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I hereby confirm, that I have written this thesis on my own, that it has not been submitted for a degree at this or any other university and that I have not used any other sources and materials and citations than the ones referred to.

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