ReliablE in-Vehicle pErception and decisioN-making in complex environmenTal conditionS

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Executive Summary

This document reports the initial work done for Tasks 4.1 (Motion Planning) and 4.2 (Behavioural decision making) of the EVENTS project. It contains the preliminary designs of the decision-making and motion planning modules of the project. Note that both tasks are work in progress and the final results will be reported in the following deliverables, due in month 24. Not every experiment in the project has the goal of handling the decision making of the vehicle. Therefore, only the ones for which a full navigation system will be designed are mentioned here. Being the first approach to the motion planning problem inside the project, this document contains mostly initial architectures and algorithmic designs with few, or none results depending on the experiment.

Final development and results of the motion planning and behavioural planning algorithms will be explained in the D4.2 and D4.3 deliverables respectively.

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Abbreviations & Acronyms

Abbreviation / acronym	Description
ACC	Adaptive Cruise Control
AD(F)	Autonomous Driving (Function)
AI	Artificial Intelligence
AL	Alert Limit
AV	Automated Vehicle
BP	Behavioural Planner
CA	Consortium Agreement
CAM	Cooperative Awareness Message
CAV	Connected Automated Vehicle
CPM	Collective Perception Messages
DDT	Dynamic Driving Task
DENM	Decentralized Environmental Notification Message
DM	Decision Making
EC	European Commission
EXPs	Experiments
FIS	Fuzzy Inference System
FoV	Field of View
FTP	Fail-degraded Trajectory Planning
GA	Grant Agreement
IR	Integrity Risk
ISO	International Organization for Standardization
I/O	Input(s) / Output(s)
LiDAR	Light Detection and Ranging
MDP	Markov Decision Process
MPC	Model Predictive Control
MRM	Minimum Risk Manoeuvre
MOP	Moving Object Prediction

Abbreviation / acronym	Description
MOT	Multi-Object Tracking
ODD	Operational Design Domain
PE	Position Error
PL	Protection Level
PP	Perception Platform
RADAR	RAdio Detecting And Ranging
REQs	Requirements
RL	Reinforcement Learning
SAE	Society of Automotive Engineers
SMD	Safety-mode Decision
SoTA	State of the art
SPaT message	Signal Phase and Timing message
SPECs	Specifications
TOR	Take Over Request
TP	Trajectory Planner
TSs	Target Scenarios
UCs	Use Cases
VRU	Vulnerable Road User
WP	Work Package

1. Introduction

1.1 Project aim

Driving is a challenging task. In our everyday life as drivers, we are facing unexpected situations we need to handle in a safe and efficient way. The same is valid for Connected and Automated Vehicles (CAVs), which also need to handle these situations, to a certain extent, depending on their automation level. The higher the automation level is, the higher the expectations for the system to cope with these situations are.

In the context of this project, these unexpected situations where the normal operation of the CAV is close to be disrupted (e.g., ODD limit is reached due to traffic changes, harsh weather/light conditions, imperfect data, sensor/communication failures, etc.), are called "events". EVENTS is also the acronym of this project.

Today, CAVs are facing several challenges (e.g., perception in complex urban environments, Vulnerable Road Users (VRUs) detection, perception in adverse weather and low visibility conditions) that should be overcome to be able to drive through these events in a safe and reliable way.

Within our scope, and, to cover a wide area of scenarios, these kinds of events are clustered under three main use cases: a) Interaction with VRUs, b) Non-Standard and Unstructured Road Conditions and c) Low Visibility and Adverse Weather Conditions.

Our vision in EVENTS is to create a robust and self-resilient perception and decision-making system for AVs to manage different kind of "events" on the horizon. These events result in reaching the AV ODD limitations due to the dynamic changing road environment (VRUs, obstacles) and/or due to imperfect data (e.g., sensor and communication failures). The AV should continue and operate safely no matter what. When the system cannot handle the situation, an improved minimum risk manoeuvre should be put in place.

1.2 Deliverable scope and content of the Document

In the EVENTS project, WP4 is tasked with developing the decision-making systems, including motion planning, behavioural planning, and fail-safe control. This Deliverable (D4.1) is an intermediate report on the WP4 progress. The purpose of this document is to report the initial designs and objectives for the behavioural decision-making (T4.2) and motion planning (T4.1) algorithms being developed in Tasks 4.1 and 4.2 and which will be implemented and tested in some of the experiments defined in deliverable D2.1 [1] of the project EVENTS, as such this deliverable is heavily focus on state of the art, and initial test done in each of the experiments. The final status will be reported in the Deliverables D4.2, for the Task 4.1, and D4.3, for the Task 4.2, where algorithm descriptions and results will be explained.

T4.1 involves the motion planning in the control architectures. In the context of this project motion planning is understood as the group of algorithms that generate trajectory references for both, the longitudinal and lateral control.

T4.2 involves the supporting techniques to the motion planning. Behavioural planning should provide the motion planning methods with enough information to compute the trajectories. Here methods like collision risk assessment or manoeuvre selection are contemplated. The information flow does not necessarily go only from the behavioural planner to the motion planner. After all, some methods generate motion candidates, which are evaluated by the behavioural planner.

This information flow is represented in the Figure 1 using specific terminology for the shared information, such as, Occupancy grids and Time to collision values that feed the motion planning model, or the trajectory candidates that can be sent back to the behavioural planning. The output of the models developed in the WP3 in the project are used as input for the behavioural planning as obstacle information. Additionally, more information of the surroundings can be obtained from the communication modules.

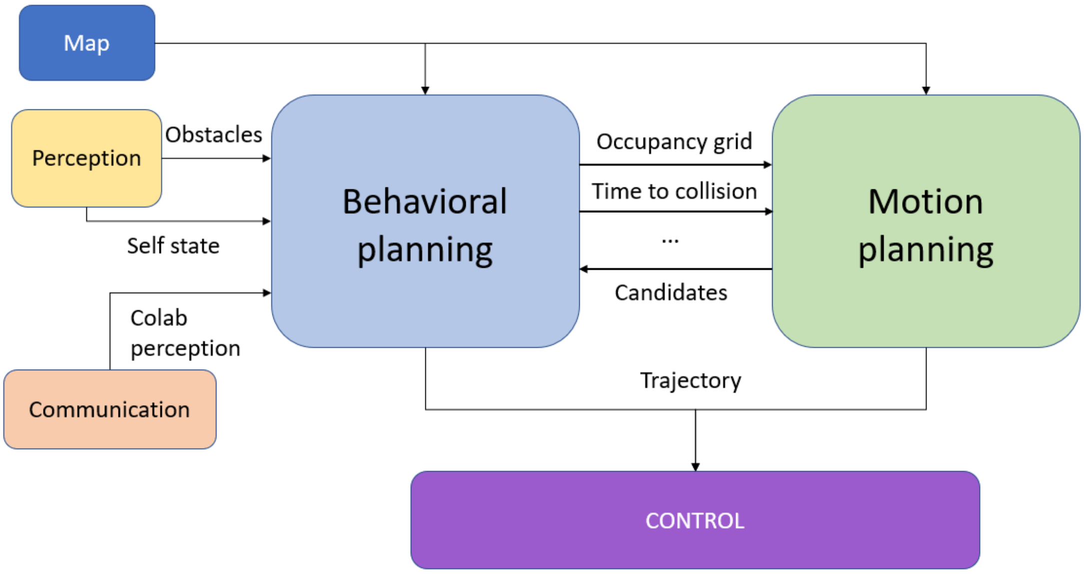


Figure 1: Behavioural Planning and Motion planning generic information flow

In this document not every experiment is discussed in the project EVENTS. After all, the development of both motion and behavioural planning depends on each experiments focus. Motion planning will be developed and tested for EXP1, EXP2, EXP4, EXP5 and EXP8. Behavioural planning will be developed and tested for EXP1, EXP2, EXP3, EXP4, EXP5, EXP7 and EXP8.

The document is structured as follows:

- Chapter 2 describes the research and progress made in motion planning for each of the relevant experiments, as well as future works to be included in following deliverables.
- Chapter 3 addresses behavioural decision making in the same manner, including the state of the art and algorithmic approach followed by future works.
- Finally, Chapter 4 presents the conclusions of the progress mentioned in the previous chapters as a summary of the document.

2. Motion Planning

Motion planning is a critical aspect of the intelligence of an Autonomous Vehicle (AV). As these vehicles navigate through dynamic and often unpredictable environments, the ability to plan and execute precise motions is of paramount importance to ensuring safety and efficiency. The primary goal of the motion planning system is to generate a feasible and comfortable path for the control to follow, based on the information provided by the perception, the communication and the internal acquisition and self-assessment modules as represented in EVENTS architecture (Figure 2) [2].

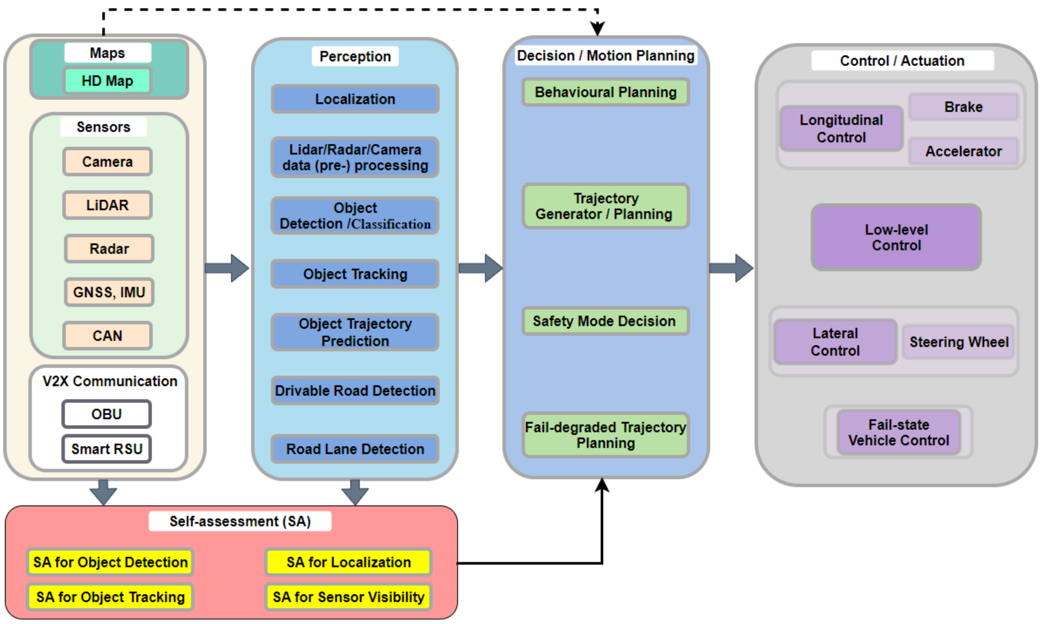


Figure 2: EVENTS high-level Full Stack Architecture and Interfaces ("Master Architecture")[2] .

The architecture of the motion planning module may vary from application to application. Sampling-based methods such as Rapidly Exploring Random Trees (RRT) or A-star (A*) algorithms can combine both, behavioural planning and path planning in one single method, being able to guide the vehicle along a lane change manoeuvre without even having defined a specific behaviour, but they use to need an additional speed planner. This is not the case with optimization-based trajectory planning such as Model Predictive Control (MPC) or Linear-quadratic regulator (LQR), which are also able to perform lane change or avoidance manoeuvres and use to include an intrinsic speed planning. These types of algorithms usually work better on unstructured roads where there is no other information on the map and the constraints of the path are limited to the bounds and the obstacles.

On the other side, there are techniques that are designed to handle complex interactive scenarios by planning for each specific case. Here the motion planning system is separated into several modules. First a behaviour is specified, saying if the vehicle must avoid an obstacle, wait or maintain the velocity to name some common examples. The most common methods to determine this are Finite State Machines (FSM) and Behaviour Trees (BT). The complexity of this methods lies in the definition of these states and the design of the conditions to be met so the behaviour planner chooses a reliable solution. They also rely on information about the roads, centrelines, borders and signals. Other methods use potential fields to evaluate the following of the lane centre and the collision risk with other vehicles. They are usually complemented by parametric or geometric curves for path planning such as Bezier or Spline curves, along with other speed planning methods.

Finally, Artificial Intelligence based methods can fit in both techniques. End-to-end solutions have proven they are able to substitute the entire control pipeline. Some people use them to assess the risk of some manoeuvre inside the behavioural planner and there are applications that substitute trajectory planning algorithms to save computational time.

2.1 EXP1

Experiment 1 (EXP1) focuses on the "Interaction with Vulnerable Road Users (VRUs) in a Complex Urban Environment". The objective is to achieve safe, comfortable, and time-efficient automated driving in a complex urban environment while engaging with VRUs such as pedestrians and cyclists.

The experiment unfolds as the ego-vehicle navigates a two-lane road, with potential scenarios involving VRUs entering its path (e.g., crossing, walking longitudinally, swerving), possibly emerging from behind obstructions like parked vehicles. The motion planning targets to provide collision-free trajectories in the presence of possibly unbounded and Gaussian uncertainties.

2.1.1 Architecture

Overall structure of motion planner with decision making is shown in Figure 3. The explicit differentiation of various driving manoeuvres due to the presence of obstacles can also be accomplished by employing the concept of homotopy classes. This concept is embraced to segment the non-convex trajectory space, facilitating continuous optimization [3]. The guidance planner computes various homotopy different trajectories within the free space. The generated guided trajectories are evaluated by multiple local planners simultaneously. Each local planner optimizes the trajectory, ensuring that it is both dynamically feasible and correspond to any imposed constraints. Ultimately, the selection of the optimal trajectory is determined through a minimal cost decision in decision-making block.

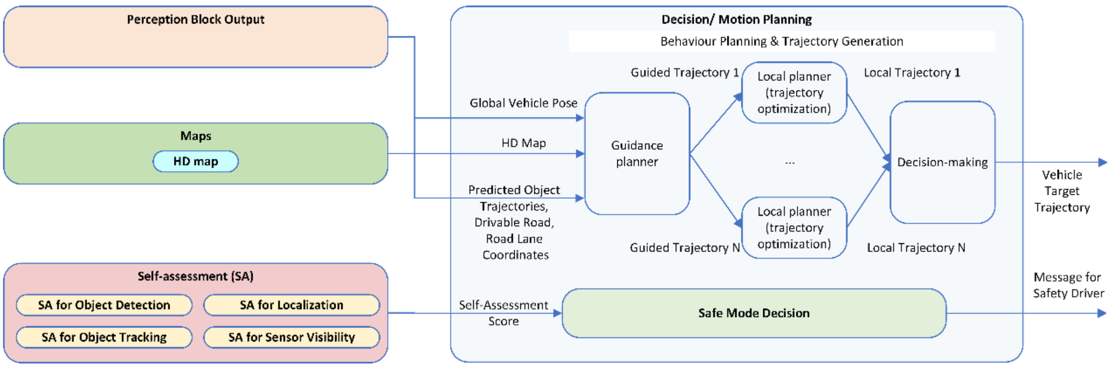


Figure 3: Structure of motion planner with decision making.

2.1.2 Algorithmic approach

Motion planning methods based on optimization effectively prevent collisions by incorporating constraints into the optimization problem. Traditional approaches operate under deterministic assumptions, meaning they don't consider uncertainties in obstacle predictions. This lack of consideration for uncertainties can compromise safety since it overlooks the potential range of outcomes.

Leveraging local optimization enables to plan locally optimal trajectories. Model Predictive Control (MPC) is a frequently employed technique in this regard, aiming to optimize planning performance, such as speed and comfort, while satisfying constraints (e.g., collision avoidance, vehicle model, actuator limits). MPC provides a flexible and safe framework, accommodating features such as path following [4] and dynamic collision avoidance in both deterministic [5] and uncertain [6], [7], [8] scenarios.

Alternatively, global planners like Randomly exploring Random Trees (RRT*) [9] and motion primitives [10] adopt a different approach. They generate numerous feasible trajectories, assessing safety and performance for each. However, they may produce numerous redundant and suboptimal trajectories, resulting in low-quality motion plans within stringent computational constraints. This challenge becomes particularly pronounced in highly dynamic environments where the rapid computation of trajectories is essential, e.g., driving in a complex urban environment with multiple VRUs such as pedestrians and cyclists.

In the EVENTS project, the planning framework is used that concurrently optimizes trajectories across multiple distinct homotopy classes [3]. It leverages the strengths of global planners (guidance planner) and optimization-based planners (trajectory optimization or local planner).

This global planner considers both static obstacles and the overarching route to the goal, thereby preventing potential deadlocks for the local planner. To further improve performance, dynamic obstacles can be integrated into the global planner. Planners of this nature, taking dynamic obstacles into account, are referred to as 'guidance planners.

In the EVENTS project, the proposed topology-guided planner encompasses the following features:

- Consideration of homotopy classes within the dynamic collision-free space [11], accounting for the motion of dynamic obstacles.
- No assumption of a structured environment [11].
- Independence from a structured environment.
- Capability to address scenarios where its goal is obstructed, considering multiple goal positions.

The planning problem over a horizon of N_L steps is formulated as:

$$\min_{u\in U, x\in X} \sum_{k=0}^{N_L} J\left(x_k, u_k\right) \quad (1a)$$

$$\text{s.t.} \quad x_{k+1} = f\left(x_k, u_k\right), \forall k \quad (1b)$$

$$x_0 = x_{init} \quad (1c)$$

$$g\left(x_k, o_k^j\right) \le 0, \forall k, j \quad (1d)$$

where x_k and u_k are the state and input at instance k, o^j_k is the position of obstacle j, N_L is the prediction horizon. In equation (1a), the cost function J represents the planning objectives, such as adhering to the reference path. The simplified vehicle dynamics are defined by (1b), while (1c) enforces initial conditions. Additionally, collision avoidance constraints are imposed by (1d).

The guidance planner rapidly calculates multiple homotopy distinct trajectories within the free space. In the process of refining the trajectories produced by the guidance planner, multiple local planners operate concurrently. Each local planner refines a specific guidance trajectory, with the responsibility of ensuring that the final trajectory is not only dynamically feasible but also complies with any other imposed constraints.

The formulation of local planner is as:

$$J_i^* = \min_{u\in U, x\in X} \sum_{k=0}^{N_L} J\left(x_k, u_k\right) \quad (2a)$$

$$\text{s.t.} \quad x_{k+1} = f\left(x_k, u_k\right), \forall k \quad (2b)$$

$$x_0 = x_{init} \quad (2c)$$

$$g\left(x_k, o_k^j\right) \le 0, \forall k, j \quad (2d)$$

$$g_H\left(x_k, o_k^j, \tau_{i,k}\right) \le 0, \forall k, j \quad (2e)$$

where τ_i are the guidance trajectories. Homotopy constraints are imposed by (2e). It should be noted that more advanced model of vehicle dynamics can be used in (2b).

Finally, the selection of the best trajectory is performed based on minimal cost decision.

The presented approach has been applied to a mobile robot, which has less constraints with orientation and low speed [11]. The results are shown in Figure 4.

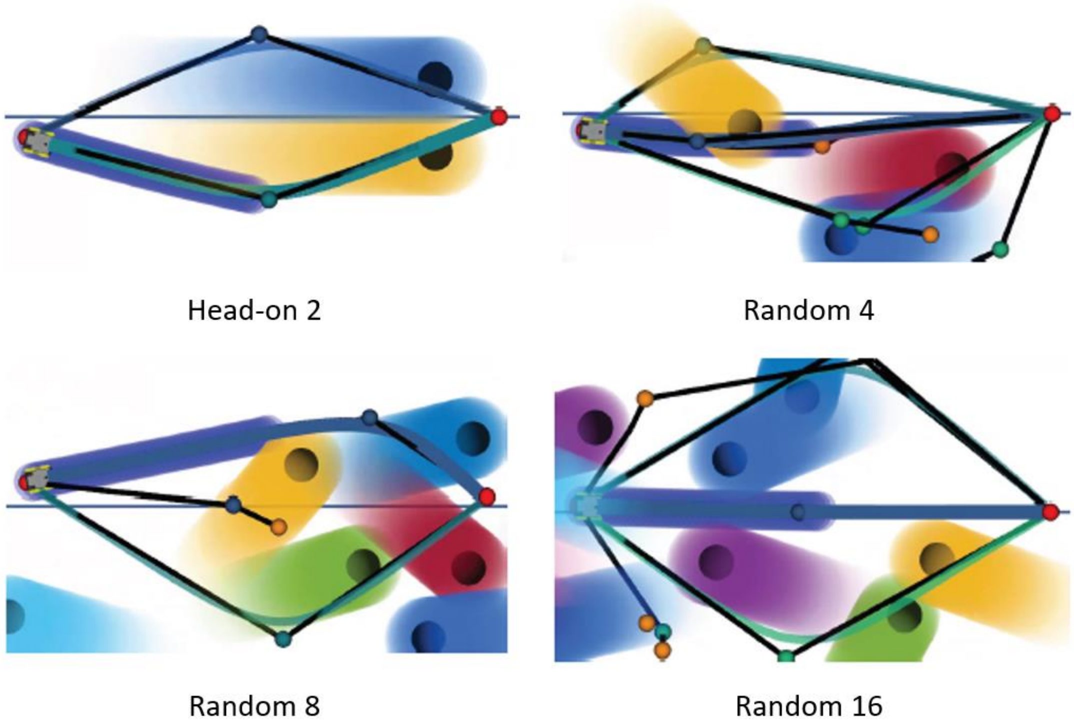


Figure 4: Snapshots of the simulations. Pedestrians, depicted as black discs, are presented alongside their predicted areas represented by coloured discs, which are inflated to account for the robot area [8].

2.1.3 Outlook and future works

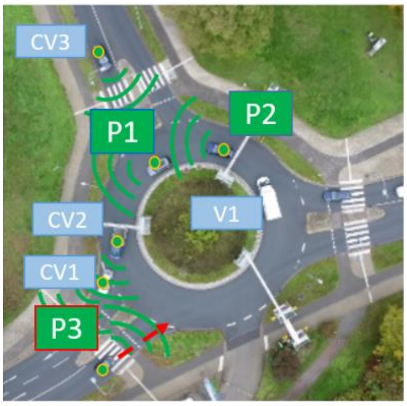
The described above topology-guided planner will be extended for automated vehicle driving in a complex urban environment with multiple VRUs such as pedestrians and cyclists. The guidance planner will incorporate the mass-point vehicle model, while local planners will consider the kinematic bicycle model. The cost terms will be broadened to encompass comfort considerations.

2.2 EXP2

Platooning is a technique that was born to improve traffic flow and reduce the fuel consumption of vehicles in highways by reducing the inter-vehicle distance and, therefore, the air drag. Since then, platooning has been thought to be used in other scenarios such as logistics for restricted and urban areas. Here, some complex scenarios can happen where vehicles must interact with each other to avoid collisions, so is the case with roundabouts.

In the EXP2 a platoon formed by a leader and its follower must cross a roundabout safely. Motion planning plays a major role in the end goal of the experiment since the followers should be able to determine whether it is safe for them to follow the leader or not.

Each follower will receive information from their surroundings through V2X and perception. This information will be composed by Moving Object Detection (MOD) and Prediction (MOP). To maintain the platoon a V2V communication is required and the information of the obstacles inside the roundabout will come from the perception inside each follower. Additionally, the perception information from every source in the use case will be combined and verified externally (aka 'collective perception' approach) and given back to each vehicle through V2X communication (Figure 5).



- Green dot denotes V2X capability of the traffic agent

P1: CAV platoon leader
P2: CAV platoon follower #1
P3: CAV platoon follower #2
(←this is the subject vehicle which tries to reconnect with the platoon via merging into the roundabout right after/before P1, P2, details of P1, P2, P3 choreography so that a platooning reconnection is realized to be specified later)
CV1, CV2, CV3: Connected vehicles able to share CAM, DENM, CPM info
V1: not connected vehicle

Figure 5: EXP2 Graphical Representation

Let's assume the platoon has been split due to another vehicle stepping in. When both the preceding and the following vehicle exit the roundabout will have a gap that is bigger than the desired platoon distance or even experience communication loss between them. Therefore, the behavioural planner will need to identify the best course of action, whether it is possible to reunite or replan to continue travelling on their own.

2.2.1 Architecture

The architecture of a vehicle for this experiment can be seen in the Figure 6. This detailed architecture builds on the general architecture for EVENTS project and was initially presented in [2]. Reading left to right, first, there is the acquisition module, which gathers some sensors, the map information, and the communication submodule. The perception module receives data from the acquisition module and uses it to process the localization of the vehicle as well as the object detection and classification, which feeds the information to the third module. In EXP2 the behavioural planning algorithm must choose when and how to enter the roundabout safely. While the Motion planning module is composed by a local planner, speed planner and fail-safe trajectory. The local planner generates the trajectory that will use the control module as reference. The self-assessment and the collective perception modules will provide more accurate information about the obstacles and the state of the vehicle in the experiments.

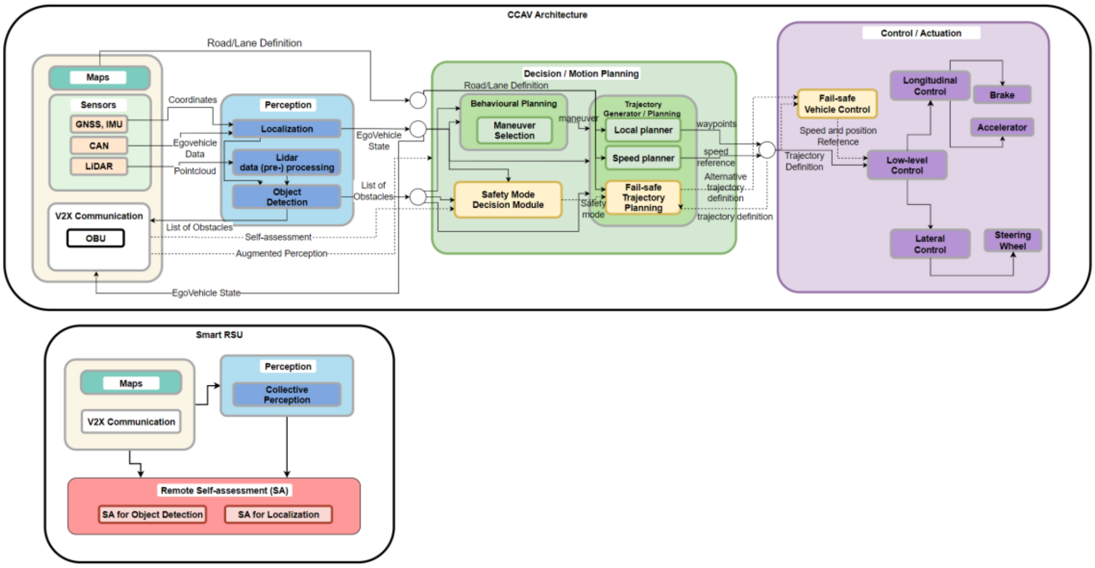


Figure 6: EXP2 Detailed Full Stack Architecture and Interfaces [2]

The speed planner may vary depending on the speed reference decided by the behavioural planner. Four cases are possible:

- Platoon follow: The speed profile is calculated so the vehicle can maintain the specified time gap between the two consecutive platoon members.
- Vehicle follow: If a vehicle in the roundabout steps in between to following platoon members, the speed reference will change to maintain a safety distance to the preceding vehicle. In this case, since there is no communication between the two vehicles a higher distance should be maintained (such as in ACC mode).

- Lane follow: In this case it's assumed there is no preceding vehicle, so the speed reference will come defined in the map, along with the information coming from the observations of the environment.

- Stop: If a collision is detected in the near future the speed profile should stop the controlled vehicle.

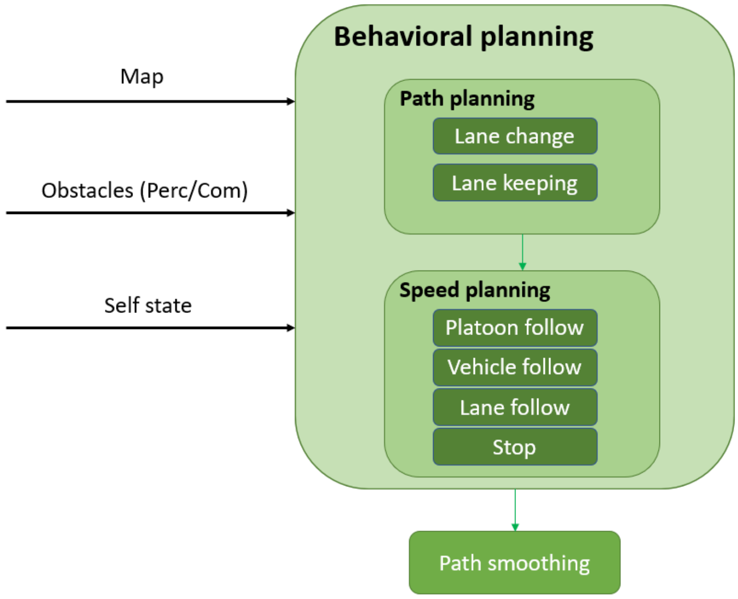


Figure 7: Motion Planning specific architecture

Finally, a path post processing sub module is added to smooth the path and ensure comfortable driving. This last process can be time consuming, therefore, its use needs to be properly justified.

2.2.2 Algorithmic approach

As mentioned in the introduction of motion planning in this same document, the isolation of the motion planning from the behavioural planning, or Decision Making (DM) can be hard sometimes. After all, the DM can be dependent on the path that is generated in the motion planning system.

It must be noted that the motion planning can also be separated in two different problems. A trajectory needs to be specified in the space by geometrical points and each point should have attached a speed value. The array containing these speed values is known as the speed profile.

Since motion planning can be such a heterogeneous problem the contribution from Tecnalia in the EXP2 will be on testing a benchmark of trajectory generation options that consider obstacles and try to improve the comfort of the ego vehicle. Until now the main contribution to the task 4.1 in the EXP2 has been research in the SoTA, which will be presented in the following section.

Trajectory generation SoTA

A motion planning SoTA research have been made using [12] as base line. Here, a qualitative comparison study is made among a big amount of trajectory generation and DM algorithms. Since it would be rather difficult to implement every method in a single project, a selection needs to be made. The literature review shows that parametric curves along with mathematical optimization methods are the most interesting regarding computational efficiency, vehicle safety considerations, capabilities of integrating vehicle kinematics and road obstruction constraints in the modelling pipeline [12].

Bezier curves offer several advantages in the context of path planning. Their mathematical definition ensures that trajectories will be tangential to the initial and last control points, and, therefore, will have a smooth curvature. Incidentally, this characteristic of Bezier curves is usually associated with driving comfort, but the SoTA lacks in depth quantitative analyses of this matter. Bezier curves are also regarded as computationally easy to implement and efficient.

In previous studies, the authors use Bezier curves in addition to a repulsive potential field collision risk assessment for both path and speed profile generation [11]. Results regarding comfort and computational time looks promising in simulation. The authors in [13] used a trajectory generation based on Bezier curves that was chosen using a nonlocal optimization method named BOBYQA with computational time results between 50 and 500ms for 50m trajectories. In [14] the authors present a methodology to generate a safe corridor of control points for Bezier curves. In [15], a comparison of the curvature influence on the accelerations of a vehicle is given for a set of Bezier curves that have the same control points and different parametrization.

B-Splines are also used in the SoTA for trajectory generation instead of Bezier curves. In [16] the authors presented a B-splines based trajectory planning for roundabout scenarios, although the path planning method did not consider obstacles. They are also used for specific manoeuvres, like in [17], where the goal is to create an efficient lane change path planning method. They are also used as smoothing method to complement other coarser planning methods like RRT [18], [19].

Finally, mathematical optimization methods such as MPC, or LQR are sometimes used for trajectory planning thanks to their ability to use constrains both in the input and control variables, such as, throttle, brake and steer in the case of autonomous vehicles. In [20] the authors used Model-Predictive Motion Planner (MPMP) to generate a trajectory that would follow a human driver.

Metrics

Since the motion planning implementations are situational most of the time, there are no previous works that compare vastly different motion planning approaches with the same KPIs. In this work, those different approaches are going to be evaluated in roundabout scenarios while following a platoon and compared to each other by measuring three key parameters:

- Computational time: Time consumption of the whole process.
- Jerk: Usually used to measure ride comfort in autonomous vehicles along with the curvature of the trajectories.
- Situation solving time: Under the same conditions how fast can the vehicle with different motion planning complete the scenario proposed.

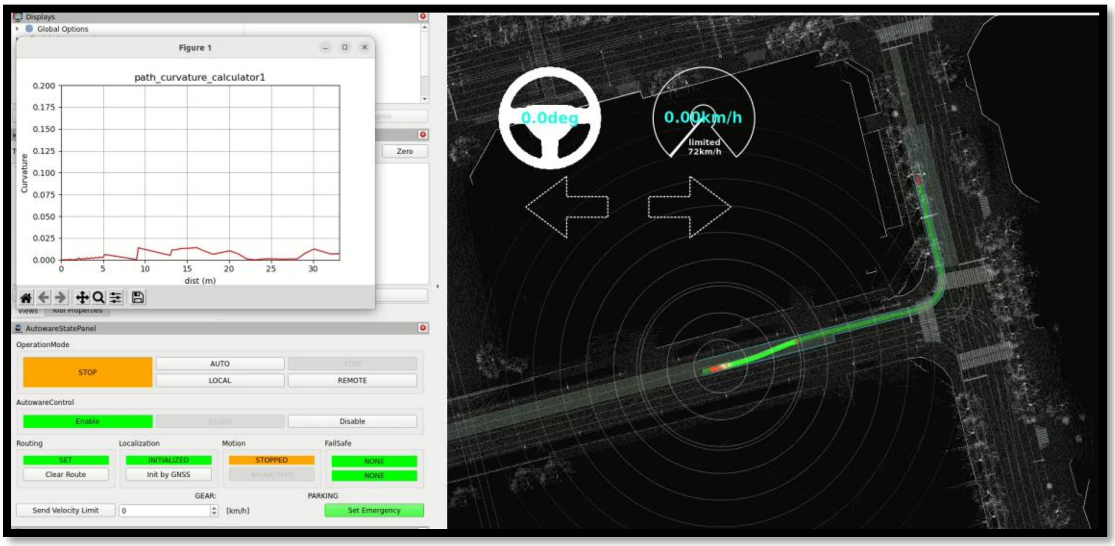


Figure 8: Lane change trajectory with curvature graphic, simulation for EVENTS using EXP2 motion planning architecture with curvature calculation.

2.2.3 Outlook and future works

As stated before, the future work regarding the motion planning on Tecnalia's' side for the EXP2 is the study of a trajectory generation benchmark for lane following. Although a thorough study has been made the specific benchmark has not been decided yet. Nevertheless, the tests will be performed using Carla simulators vehicle model.

2.3 EXP4

Some roads do not have clearly defined lanes and drivers must navigate through a chaotic scenario where they must read the intents of other vehicles and act accordingly to avoid collisions. In these situations, the traffic is slow and traffic jams are more common than on other structured roads.

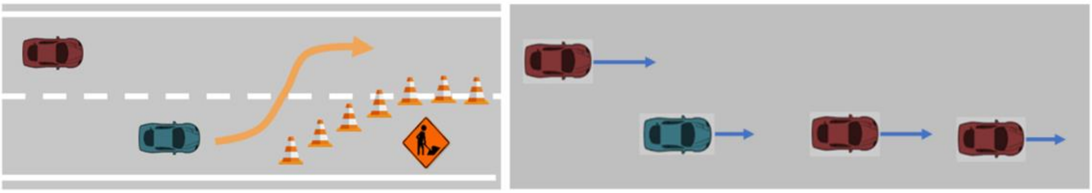


Figure 9: Graphic description of EXP4

In this experiment the goal is to have an autonomous vehicle drive safely with the fastest speed that is allowed in the road following comfortable trajectories without using V2V communication. It's an end-to-end experiment starting with the precise vehicle localization, by defining a semantic representation of the environment, and the MOP in the scene. The ego-vehicle will perform a self-assessment by deciding whether to trust the perception. After that, the motion planning will have to define the MRM with computation times able to cope with real time simulation scenarios.

2.3.1 Architecture

The architecture for the EXP4 is like the architecture in the EXP2, with the same 4 modules: acquisition, perception, motion planning and control. However, there are notorious differences between most of them. First, on an unstructured road there are no defined lanes, so the information given by the map should only be used for global planning purposes. Regarding the behavioural planning, these types of roads can be treated as a single wide lane. The need to identify the boundaries of the road through semantic segmentation makes it a requirement to add a camera to the set of sensors, and a radar is added too.

The perception, then, is completed with drivable road detection, road lane detection and traffic sign detection and classification.

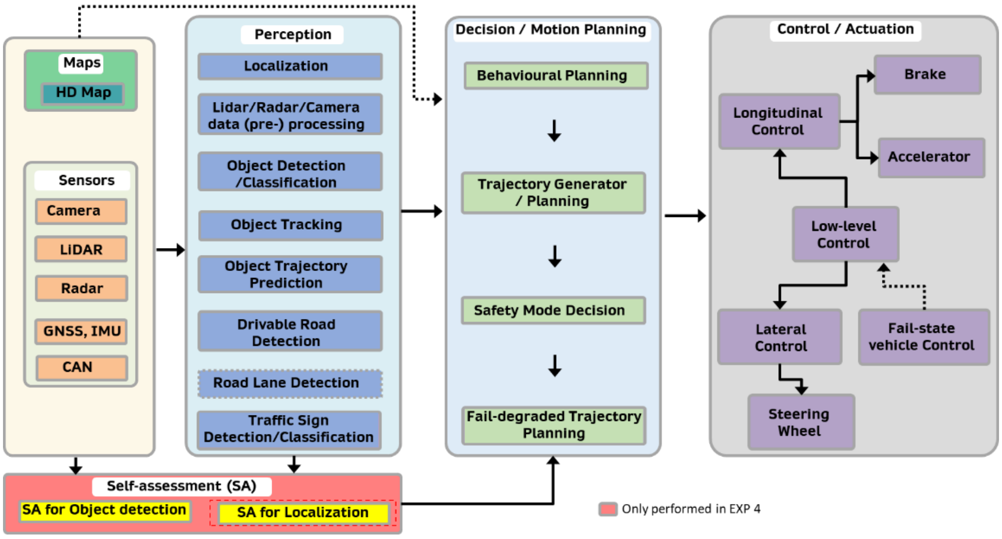


Figure 10: High level architecture of EXP4

The motion planning module is designed as it is shown in the Figure 11. Since there are no lanes defined in the road, a dynamic discretization of the driveable space around needs to be done. This will allow the generation of control points for the path planning algorithms. An evaluation of the collisions should give as a result whether it is necessary and possible or not to avoid an obstacle. In the case the obstacle needs to be avoided the local planner (path planning and speed planning) generates first a rough trajectory. That rough path is then considered inside the collision detector to get viability feedback. Finally, a smoothing algorithm is used to ensure the comfort of the vehicle and this path is validating again checking the collisions.

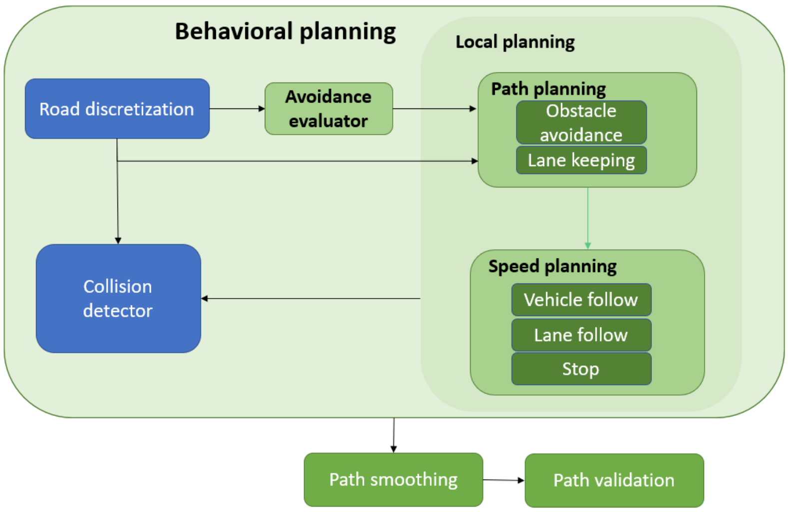


Figure 11: Detailed Motion Planning EXP4

2.3.2 Algorithmic approach

Within the EVENTS project, EXP4 & 5 aims also to develop reliable, safe, and efficient autonomous driving when faced with road works, narrow roads and merge and yield situations, for complex urban autonomous driving. Particularly, addressing problems related to localization in GPS denied environments, predictive perception of dynamic objects and smooth/safe vehicle motion planning.

Motion planning on unstructured road requires to be able to consider constraints due to the lack of defined lanes. Here, optimization methods and heuristic approaches for trajectory generation have been mostly used in the literature since they are not usually tied to trajectories generated based on the lane centres.

Also, an essential component for such reliable and safe software functionalities is high definition (HD) maps. Such maps are used by autonomous vehicles as the primary ground truth description of the surrounding environment and road characteristics (**Error! Reference source not found.**).

Figure 12: Example of HD Map [24]

Trajectory Generation SoTA

Based again in [12], it is possible to identify the predominant motion planning methods on unstructured roads. Optimization based methods are usually expressed as the minimization of a cost function in a sequence of state variables under a set of constraints. This is generally used in two ways. The first is to choose the "best" trajectory among several candidates [18] and the second one is finding an optimal path itself [21]. MPC based algorithms are specifically popular due to their replanning ability and the incorporation of constraints.

Pathfinding methods are a subpart of graph theory in operational research used to solve combinatorial problems under a graph representation. Although their main use is for route planning, they can be adapted for local planning too. Their main drawback is their dependency on the graph size and therefore the road discretization method.

This makes them slow in big areas. Nevertheless, there is an effort made to speed up the computation of these methods. In [18] RRT* based method is used in combination with Artificial Potential Fields (APF) to improve the convergence time. Results are shown for 100 and 120 m sections with average running times above 1s, which is still very slow for real-time applications, but it could be improved using shorter distances. Other authors [22] are able to show improved computation time up to 19ms using RRT to discretize the space on an occupancy grid map, generating trajectory candidates with a Dijkstra based method formulating a cost optimization problem. However, this approach only considers static obstacles. In [19] dynamic obstacles are considered with under 0.7s computational times in curve scenarios of 180m.

Machine Learning based methods have also received some of the spotlight among the SoTA. [23], for example, proposed a Receding-Horizon Reinforcement Learning approach for motion planning with good results even comparing with RRT*, MPCC and Safe RL methods (29ms).

HD Maps SoTA

Currently HD maps are not publicly available, and it can be quite expensive to produce them. Motivated from these limitations, the main objective of this work is to demonstrate the creation of cost-effective, lightweight and scalable HD maps by leveraging the merits of openly accessible geodata and software tools. Furthermore, and in the context of the EVENTS project's EXP4&5, such HD maps can be used for localization, perception and planning functionalities.

The Early Days & Future Market Opportunities

The concept of HD maps for autonomous driving applications has emerged from the early DARPA challenge days (i.e., Grand Challenge and Urban Challenge). As part of these trials, contenders were given a Road Network Description File (RNDF) which contained geometric information on lanes, lane marking, stop signs, parking lots and special checkpoints, in GPS coordinates [25] (Figure 13)

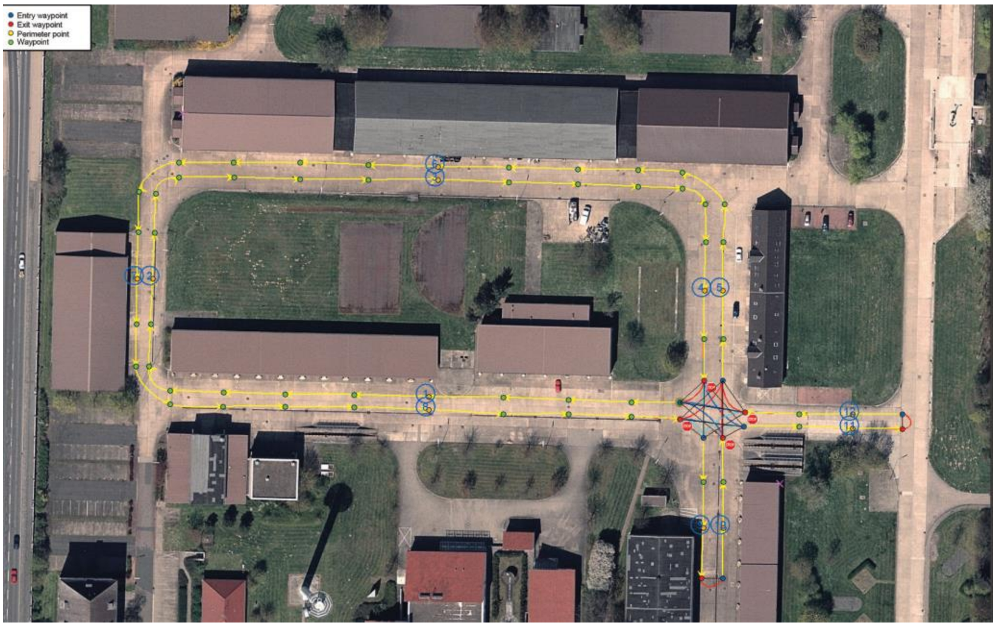


Figure 13: Example RNDF used in DARPA urban challenge.

By fusing the available RNDF information and the real-time sensor readings (e.g., laser/radar scans, camera images, inertial measurement units etc.), robo-vehicles were able to achieve centimetre level localization, real-time object detection and prediction, and safe path planning and vehicle control. The RNDF content forms the basis of all modern HD maps for autonomous vehicles and is the key information that is not available within Standard Definition (SD) maps e.g., Google Maps, OpenStreetMap (OSM) etc.

Since the early DARPA challenge days, the HD maps have evolved significantly and have now become a promising global market which is projected to reach USD 20.4 billion by 2030, at a Compound Annual Growth Rate (CAGR) of 36.2% from 2020 to 2030 [26] (Figure 14).

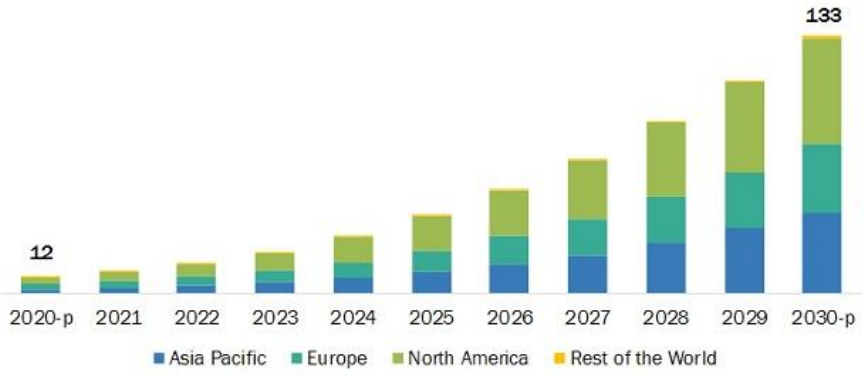


Figure 14: HD maps market for autonomous vehicles by region (USD billion) [26]

HD Maps Today

Modern HD maps are structured in a multilayer fashion with distinct layers to describe the basic road network (SD Map), the lane network (similar to RNDF) and finally the surrounding 3D environment which is used to increase the accuracy and reliability of localization and perception functionalities. There are numerous companies that create and maintain commercially available HD maps in a standardized format for automotive grade applications. Two of the most dominant market players are TomTom [27] and HERE [28].

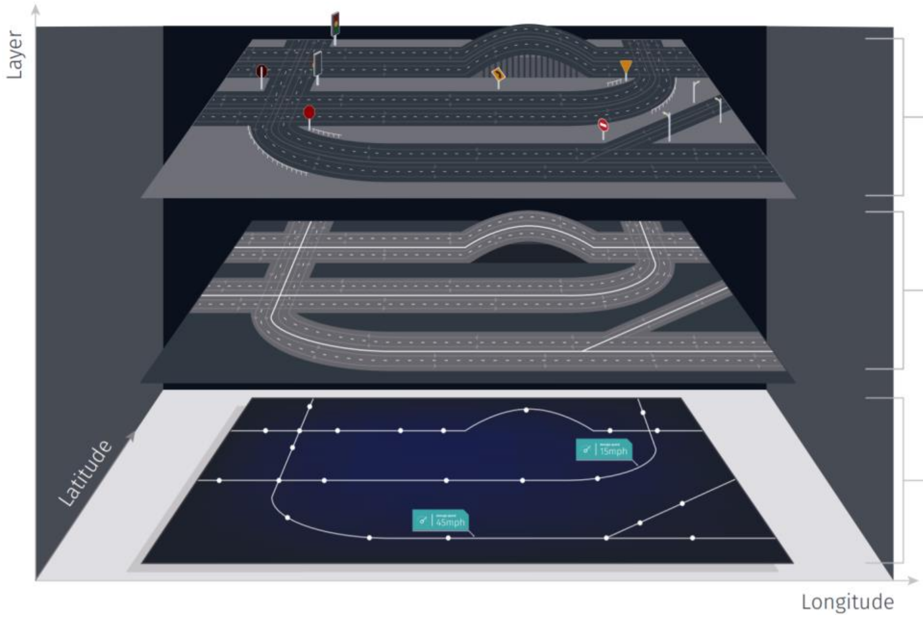


Figure 15: HERE HD map layers. Road Model: SD Map used mainly for route planning – HD Lane Model: Lane level features used for localization and path planning – HD Localization Model: 3D environment used for localization and perception [29]

Why Light-weight HD maps

Despite the recent advancement in the creation and maintenance of HD maps, one key limiting factor that slows down the faster adoption of autonomous vehicles is that HD maps are not publicly available. This makes it difficult for early startups and new innovators to exploit the benefits of HD maps as applied to autonomous driving functionalities. Additionally, the creation of HD maps is a labour-intensive activity making it difficult to scale at low cost. The research community is currently investigating alternative methods to reduce the cost of creating HD maps by utilizing AI solutions that can automate repetitive tasks such as annotating lane topology [30] and crosswalks [31].

Objective

The primary goal of this research activity is to develop a toolchain for creating a lightweight HD-map visualisation functionality using openly accessible geodata and software libraries. Previous approach relied on rasterising the entire HD-Map. This led issues related to runtime memory being excessively utilised.

The visualisation functionality processes lanelets to generate markers as lanelets represent important information via a graph like data structure (which is quite space efficient).

It should be highlighted that this toolchain does not provide solutions for 3D mapping (i.e., point cloud registration) but could be incorporated in future. Following the development of the toolchain, the aim is to test the accuracy of the resulting HD maps as applied to localization, perception and path planning software modules using real-world experimental data. This research should hopefully contribute towards the faster adoption of autonomous vehicles in urban environments.

Methodology

Openly Available Geodata & Software Libraries

As mentioned earlier, the proposed methodology seeks to exploit the merits of openly accessible geodata and software libraries to generate lightweight HD-map visualisation functionality for automated vehicles. The core open-source data and tools that are employed are shown in Figure 16:

- OSM, is the main source of geodata and satellite imagery and can be interpreted as the SD map layer. The user may decide to use different OSM editors such as JOSM or ArcGIS.
- Lanelet2, is the main software library used to annotate the road network such as lane boundaries, direction, markings, stop signs etc.
- ROS, stands for Robot Operating System and it serves as the main middleware for interfacing with vehicle sensors e.g. LiDAR, cameras etc. and low-level control systems i.e. steering and speed control systems.

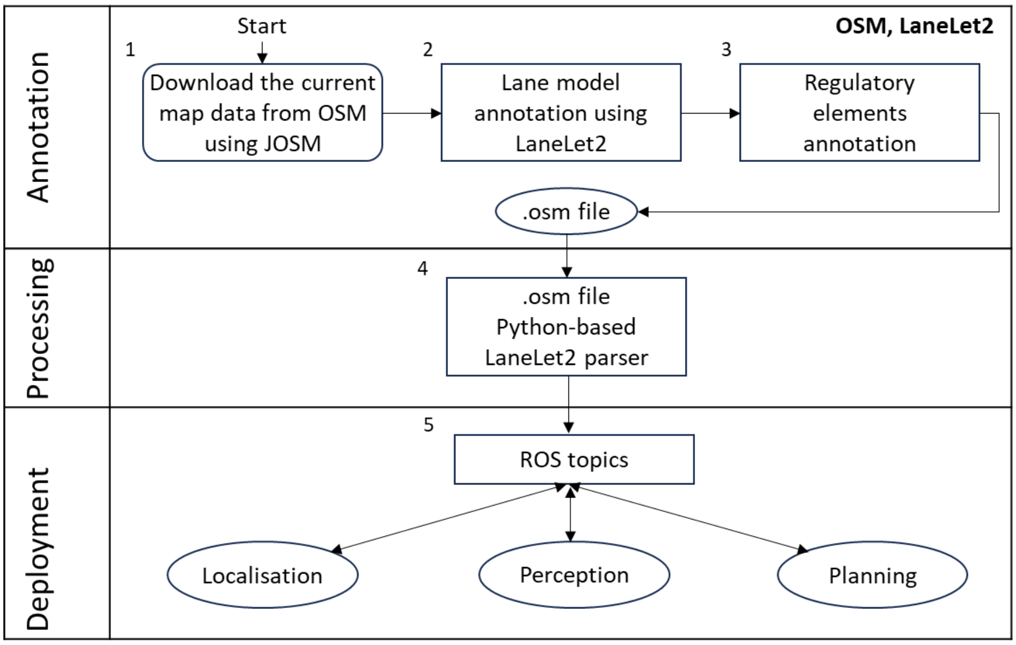
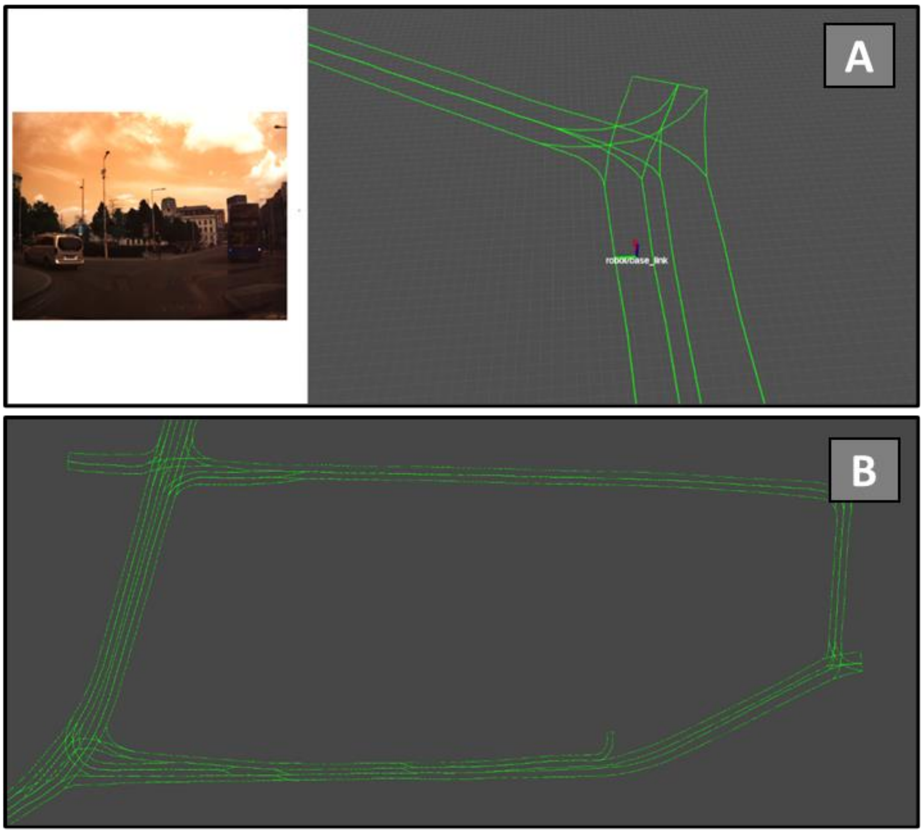


Figure 16: Process flow diagram

Figure 17 (a, b, c and d), shows some screenshots of generated lane markers which, as can be seen, provide useful information for AD functionalities such as path and motion planning.

These lane artifacts are light and are easily queries by LaneLet in real-time adding no processing overhead to AD function needing them.



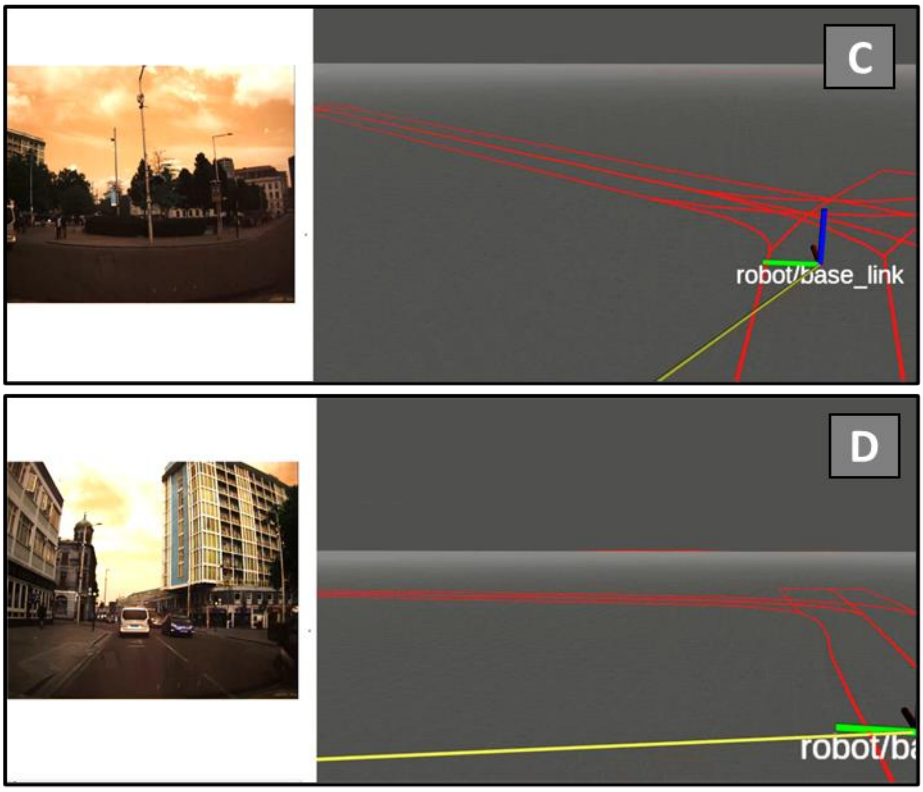


Figure 17: Screenshots of Lane artifacts generated by LaneLet2 running in ROS2.

2.3.3 Outlook and future works

The goal of the motion planning task in EXP4 is to implement an efficient method that uses the input provided by the WP3 results. After the SoTA analysis the discussion remains to choose a suitable motion planning method.

The final method will be tested in Carla simulator using a custom map with unstructured roads.

2.4 EXP5

The most challenging driving scenarios are those where the vehicles must consider the actions of the others to make a safe decision to travel along the road. This is the case of the high-speed lane incorporation situation. Whether the controlling vehicle is entering this lane or is already inside, a decision must be taken so the manoeuvre is smooth and safe.

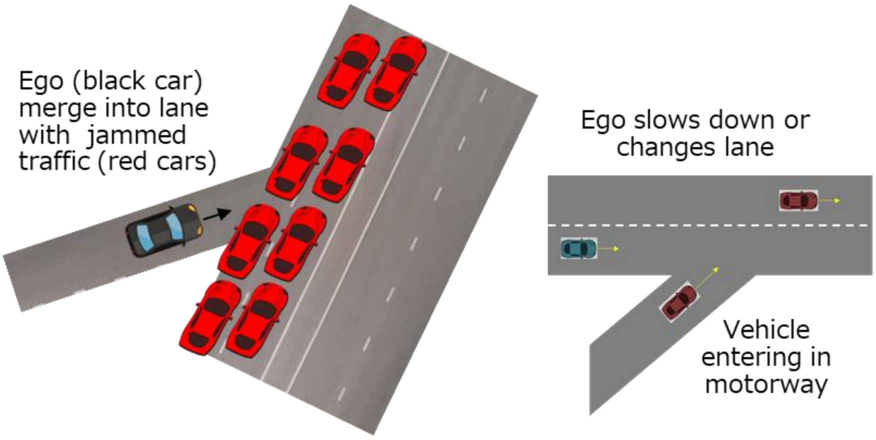


Figure 18: Graphic description of EXP5

There are two different cases then (Figure 18):

- The ego vehicle needs to merge into the high-speed lane.
- The ego vehicle needs to change its behaviour to let another vehicle merge into the high-speed lane.

In this experiment the goal is to manage the situation with no collision for any initial conditions of the actors. There is no communication between vehicles. Therefore, the information of the obstacles will be received from the perception system. From the motion planning view, the challenge lays in the generation of dynamic trajectories (dimensional path and an added speed profile) in real time to guarantee there will not be any collisions.

2.4.1 Architecture

The global architecture for this experiment is the same as the one used in the EXP4. After all, both experiments need to deal with heavy traffic scenarios without communication. Although, in this experiment, there is no self-assessment and the information of the road centrelines is available for the motion planner to use.

2.4.2 SoTA

On-ramp merging areas are typical bottlenecks for the traffic flow since the merging vehicles may cause great disturbances due too conservative or too risky decisions. According to [32] the study of this scenario, specifically for the case in which there is a single AV, can be split into two problems: Low level control and high-level control. In the EVENTS project, these two problems are solved by the motion planning module and the behavioural planning module respectively.

Most of the related work reviewed in [32], combines low- and high-level planning by formulating an optimization problem. Other works create a virtual platooning with the vehicles in the main lane to ensure a smooth merging [33], [34]. However, the efficiency of the manoeuvre is limited due to the dependency to the chosen vehicles speed. Others described the problem as an interaction of two vehicles, where the trajectory is the result of an optimization problem [35]. Other authors [36] used a set of candidate trajectories and then evaluated them to select the optimal one based on a cost function incorporating merging progress, comfort and risk. MOP were considered in this work.

After reviewing the literature and considering the EVENTS project task structure (No V2V connection, motion prediction available in the architecture) a trajectory candidacy approach is going to be implemented using Bezier curves for the lane change manoeuvre.

2.4.3 Outlook and future works

Currently the work on the EVENTS project regarding the task 4.1 in the EXP5 has been exclusively related to SoTA review. However, trajectory generation for the lane change manoeuvre literature overlaps with the one described in the section 0. Future work in this task consists of the integration of the compared trajectories for the lane merging scenario. The end results will be tested in the Carla simulator environment, using custom maps crafted to replicate the merging scenario.

2.5 EXP8

According to US Department of Transportation data, the 10-year averages for weather-related accidents break down by condition as follows [37] :

Snow/sleet	210,341 crashes, 739 fatalities
Icy pavement	151,944 crashes, 559 fatalities
Snow/Slushy pavement	174,446 crashes, 538 fatalities
Rain	**573,784 crashes, 2,732 fatalities**
Wet pavement	**907,831 crashes, 4,488 fatalities**
Fog	28,533 crashes, 495 fatalities

Table 1: Crashes and fatalities due to weather conditions

It is noticeable that rainy and wet pavement conditions are more often in weather related accidents compared to snowy, icy, or foggy conditions.

Therefore, Experiment 8 (EXP8) focuses on the " Emergency evasion manoeuvre on slippery road under rain conditions". The objective is to perform collision avoidance (e.g., pedestrian or cyclist) in poor weather condition on slippery road.

2.5.1 Architecture

Overall structure of collision avoidance controller is shown in Figure 19. The presented controller integrates motion planning, path tracking, and vehicle stability objectives, with a primary focus on obstacle avoidance in adverse weather conditions. It incorporates dynamic adaptation of friction constraints through enhanced slip detection using radar-based vehicle odometry. Additionally, the controller takes into account uncertainties from the perception module, incorporating them into the optimal problem for a more robust decision-making process.

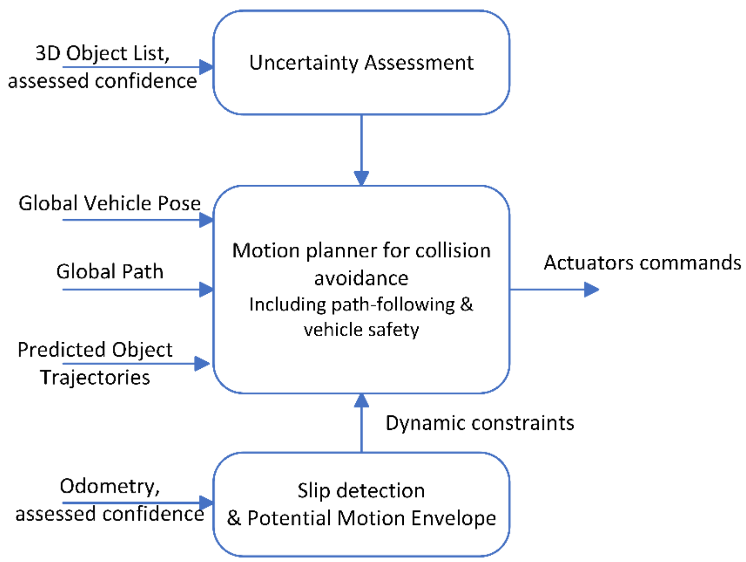


Figure 19: Structure of collision avoidance controller on slippery roads.

2.5.2 SoTA

The capacity to navigate around obstacles during evasive manoeuvres is crucial for the safety of automated vehicles. Various studies address this issue of vehicle control for obstacle avoidance in automated driving. Broadly speaking, controllers for obstacle avoidance can be classified as either hierarchical or integrated.

In hierarchical controllers, the obstacle avoidance task is split into three distinct controllers: motion planning, which generates a free obstacle trajectory; path tracking, which computes the desired steering angle and longitudinal acceleration / force; and vehicle stability, which modifies the previously computed inputs to keep the vehicle within stability boundaries. Each controller optimizes its performance independently, without analysing potential conflicts in their objectives [38], [39]. Notably, the vehicle stability controller can adjust inputs computed by the path tracking controller, leading to an increase in tracking error and a potential collision with an obstacle, despite achieving stability objectives [40]. Consequently, modern approaches integrate path tracking and vehicle stability objectives into a single controller [41], [42], [43]. For example, the integrated controller computes two expected yaw rates in the Model Predictive Control cost function—one based on the steering angle and the other based on measured vehicle lateral acceleration [44]. The MPC dynamically prioritizes either path tracking or vehicle stability during online execution by adjusting the cost function weights of the two yaw rate errors, considering the estimated yaw rate-sideslip angle phase portrait. Vice versa, an alternative approach, also based on MPC with the same inputs, ensures stability solely by constraining the sideslip angle and does not prioritize tracking or stability [41]. The cornering stiffness modelled via Dugoff tyre model is treated as an external parameter in each iteration, with its dynamics not included in the prediction model to reduce computational time. While this assumption has minimal impact when the controller accurately follows the reference trajectory and relies on the predicted solution from the previous time step, it becomes problematic at slippery conditions, resulting in inaccurate predictions and limiting MPC performance. Furthermore, neither of these approaches considers the impact of inaccurate tracking on the reference trajectory due to stability constraints or trajectory unfeasibility.

The integrated controllers fuse motion planning, path tracking, and vehicle stability into a unified controller [45], [46]. This approach addresses potential path-tracking errors by factoring them into trajectory re-planning, allowing the controller to prioritize collision avoidance and temporarily deviate from stability constraints in emergencies. For example, using Model Predictive Control for optimal steering in obstacle avoidance and a simple feedforward-feedback longitudinal controller for braking/acceleration [41]. In this way, the highly non-linear coupling between longitudinal and lateral dynamics can be discarded, and the single-track vehicle model used in the MPC can be linearised into an affine time-varying model. This simplification enables real-time operation, demonstrated in successful experimental validation. However, limitations arise due to neglecting longitudinal and lateral coupling vehicle dynamics, prompting an alternative approach optimizes steering angle, longitudinal force, and brake distribution simultaneously, overcoming the non-linearities [45]. Due to the high non-linearities involved, the prediction model cannot be linearised anymore, so a non-linear interior point solver is implemented to solve Nonlinear Model Predictive Control (NMPC). The Frenet reference system is employed for kinematics, though it can lead to an overestimation of distances in emergency scenarios, affecting the controller's effectiveness. Thus, the controller can start prioritising collision avoidance when the vehicle is too close to the obstacle, limiting its effectiveness.

For this reason, a different formulation of MPC has been recently introduced to perform motion planning [5] and lap time optimization [47], [48] called Model Predictive Contouring Controller (MPCC). It consists of an approximation using the Cartesian coordinates of the typical MPC formulation with the Frenet reference system, introducing a lag and contour error in the cost function. The MPCC integrating motion planning and tracking has proven to reduce the lap time of a hierarchical structure consisting of a path planner and an NMPC for tracking [47]. Despite the promising lap time reduction, the controller does not consider any explicit vehicle stability constraints, and it requires a longer computational time.

Our recent study [49] demonstrates the integration of motion planning, path tracking, and vehicle stability constraints in the MPCC framework for high-speed collision avoidance near the handling limits. The terms of the cost function cover various aspects, including tracking a reference longitudinal and lateral position, sustaining a desired velocity, dynamically adjusting the indicated trajectory to maintain a safe distance from obstacles while ensuring stability, and ensuring the physical feasibility of input signals. The cost function, denoted as *J*, is as follows:

$$J = \sum_{i=1}^{N} \left(\begin{array}{l} q_{eCon} e_{Con,i}^2 + q_{eLag} e_{Lag,i}^2 + q_{eVel} e_{Vel,i}^2 + q_{\dot{\delta}} \dot{\delta}_i^2 + q_{\dot{F}_x,i} \dot{F}_{x,i}^2 + \\ + \sum_{j=1}^{N_{obs}} \left(q_{e_{V2O}} e_{V2O,j,i}^2 \right) + \sum_{j=1}^{N_{edg}} \left(q_{e_{V2E}} e_{V2E,j,i}^2 \right) \end{array} \right)$$

where *N* represents the length of the prediction horizon, N_{obs} is the count of obstacles on the road, and N_{edg} stands for the number of road edges. The parameters $q*$ denote the weights assigned to the corresponding quadratic errors.

The reference trajectory is tracked through the introduction of the contouring error e_{Con} and the lag error e_{Lag} [47], Figure 20. The contouring error, denoted as e_{Con}, represents the projection of the vehicle position onto the desired trajectory calculated based on the distance travelled by the vehicle in relation to the reference line θ_s.

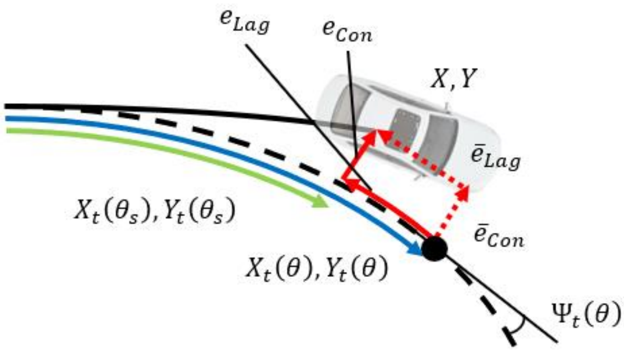


Figure 20: A representation of the contouring eCon and lag error eLag. ϑ and ϑs are the vehicle travelled distance and the distance with respect to the reference line [49]

The controller dynamically adjusts the reference trajectory to maintain a safe distance from obstacles, achieved by assessing the Vehicle-to-Obstacle (V2O) distance. The error function, denoted as e_{V2O}, is computed as the difference between a user-defined parameter representing the safety distance between the vehicle and the obstacle $D_{Sft,O}$ and the V2O distance D_{V2O} calculated as:

$$D_{V2O} = \sqrt{(x - x_{obs})^2 + (y - y_{obs})^2} - r_{veh} - r_{obs}$$

where X_{obs} and Y_{obs} are the longitudinal and lateral position of the obstacle centre, and r_{veh} and r_{obs} are the radius of the vehicle and obstacle circles. Thus, the vehicle and the obstacle collide when the D_{V2O} is lower than zero.

A similar error is introduced to prevent the vehicle from approaching the road edges. D_{SftE} signifies the safety distance between the vehicle and the road edge, and D_{V2E} represents the distance between the vehicle and the road edge. Additionally, costs are incorporated to limit the steering angle rate and the longitudinal force rate.

Vehicle stability is maintained by constraining the total available tire force at each axle based the tire friction circle Including the safety margin which serves to limit the available longitudinal force and accounts for uncertainties in road conditions.

Figure 21: Controller performance in high-friction conditions .Figure 21 illustrates the performance of the controller in high-friction conditions [49]. Both described above and baseline state-of-the-art controllers demonstrate the ability to successfully avoid collisions during a double-lane change manoeuvre. However, it is noteworthy that the baseline controller struggles to maintain the vehicle outside the unsafe area in proximity to obstacles or road edges.

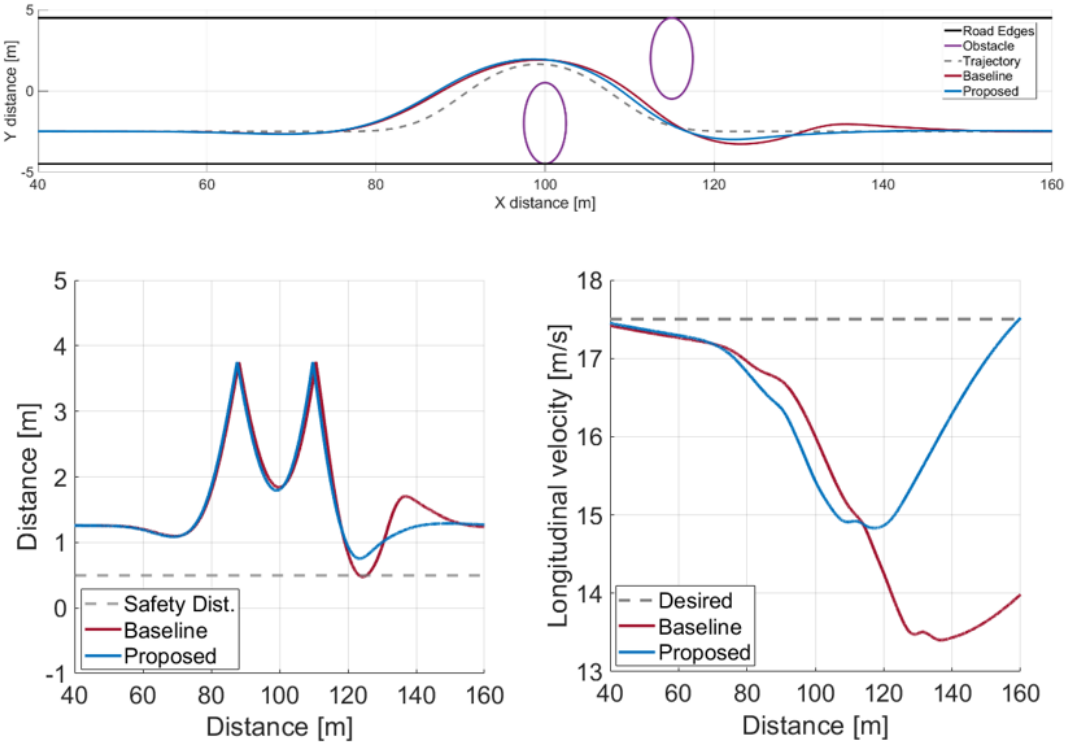


Figure 21: Controller performance in high-friction conditions [49].

2.5.3 Outlook and future works

Our recently developed controller requires several adaptations to operate effectively in slippery conditions. Firstly, it is needed to replace the Fiala tire model with a more sophisticated model, such as the Pacejka model, to accurately represent combined slip conditions. Secondly, enhancements should be made through the integration of a model-based estimator for motion capability and dynamic adaptation of friction constraints based on enhanced slip detection via radar-based vehicle odometry. Thirdly, the cost function needs to be extended by comfort terms avoiding abrupt vehicle behaviour. Lastly, to account for uncertainties from the perception module, it is crucial to incorporate the integration of these uncertainties into the optimal problem formulation.

3. Behavioural decision-making

As aforementioned, the main objectives of WP4 are to design, implement and test on a lab environment (or prototype vehicle), the on-board decision-making and control algorithms of EVENTS use cases, considering complex traffic and environmental conditions, especially around critical zones where potential contradictions to existing traffic rules can emerge, or the environment is unstructured. In this perspective, T4.1 deals with the “behavioural decision-making” (hence the name of the task); in particular, thanks to the inputs provided by WP3 (e.g., tracked objects and their associated forecasted short term trajectory, lane marking detection, self-assessment of the perception, etc.) the goal is to ***generate behavioural decisions***, that is, the “**best action**” to perform (e.g., lane-keeping / car-following, lane-change, return to the left lane, etc.). The following figure shows the different connections among the tasks in WP4:

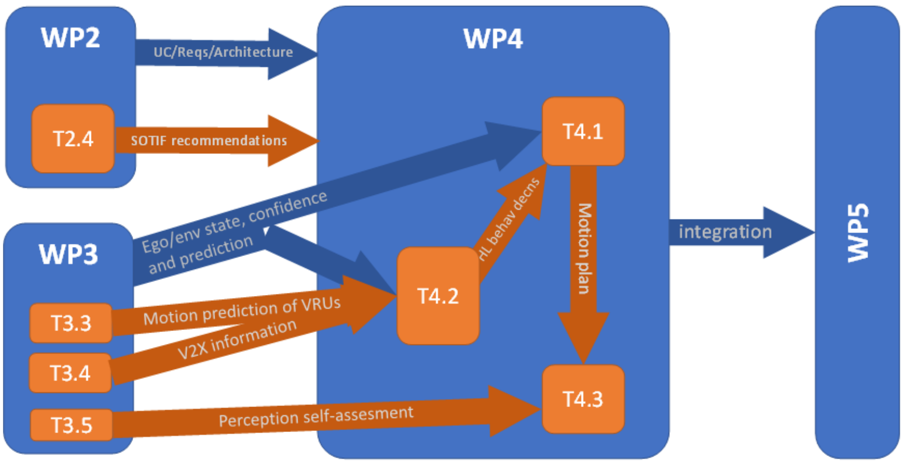


Figure 20: sketch of the WP4 interactions (in a graphical way).

This type of outputs can be used by a human driver or an automated system, to significantly reduce the number of accidents in traffic, as well as to increase comfort, efficiency and create new solutions for individual transport in cities.

In addition, the ego-vehicle behaviour will be considered when other road users’ trajectories are estimated in a cascaded integration approach in which the prediction estimation (other vehicles, VRUs, etc.) feeds the ego-vehicle’s behavioural decision-making, and vice-versa.

The algorithms used in Task 4.2 are based on the state-of-the-art (SOTA) of the machine learning (ML) and probabilistic methods (such as, [50], [51]). Still, classical state-machine-based algorithms along with collision checking (considering space-time propagation) can be deployed to benchmark more innovative approaches during conflict or risky situations [52] which can emerge in the EVENTS use cases. In addition, since the goal is to provide high-level decision-making strategies in uncertain and complex environments and to estimate the most likely manoeuvre in each situation, probabilistic approaches and non-linear approaches) are considered as well. The first ones are related to the Markovian Decision Process (MDP), while the second deals with the Fuzzy Inference Systems (FISs), possibly in combination with Neural Networks (ANFIS) [53]. At the moment of this deliverable, the investigation is still in progress, to determine the best solution.

Under this point of view, it is important to consider that various technical challenges which need to be taken into account. Firstly, the perception of an AV is uncertain due to noise of data and to the range limitations of sensors, as well as to the occlusions/blocks in the environment. Secondly, in order to generate safe trajectories for the ego vehicle, the motion of the other traffic participants (TPs) need to be predicted, by taking into consideration the uncertain information of their current state, including hidden variables (such as unknown goal and destinations). Thirdly, since the motion of the ego vehicle must be collision-free, the probabilistic optimization framework has to meet its kinematic and dynamic constraints and follow the traffic rules [54]- [55].

One of the most interesting solutions is represented by the Partially Observable Markov Decision Process (POMDP) algorithm for autonomous driving, because this technique is able to incorporate all the aforementioned uncertainties in the planning problem. It provides optimized solutions for the behaviour generation on different situations, with an arbitrary road layout and a variable number of traffic participants with unknown manoeuvre intentions. By planning in the belief state, it integrates the prediction and planning problem into a single, combined problem. Furthermore, this approach considers that during the execution of a trajectory, the ego vehicle will continuously gather more information about its surrounding [48]. Hence, the algorithm expects that the intention estimation of the other traffic participants becomes more precise at a certain/estimated point in time and incorporates this into the decision making. The result is a sequence of actions, that can be directly used as controller inputs or as goal states for a trajectory planner [56] , [10]. In other terms, formulating a problem as a POMDP, allows to model interactive behaviour and uncertain motion with a probabilistic transition model. The solution to this formulation is an optimal policy, given the various uncertainties [48]. Several publications pursue this direction and consider different forms of uncertainty in the planning model [57] [58].

However, POMDP has also some disadvantages, among which one of the most relevant for our real-time and online applications is represented by the computational time complexity, of the problem so formulated. Computational latency and storage considerations could be investigated in the project at a future stage, but it is not sure if it can be adopted.

3.1 EXP1

The detailed description of the experiment is presented in Section 2.1. The architecture of the proposed motion planning algorithm with behavioural decision making is described in Section 2.1.1.

Regarding the decision making, the automated vehicle can execute only a single trajectory. As the cost function of the local planners aligns with that of the guided global path optimization, the effectiveness of the guided plans can be directly compared based on their optimal costs (J^* defined in Eq. 2a in Section 2.1.2). As each local planner minimizes an identical cost function, the most optimal trajectory with the lowest cost is considered the best trajectory according to the specified objective.

As the next step, from the practical point of view, frequent switches in the homotopy class of the executed trajectory can diminish the performance of motion planning and result in collisions. Even if, at each time instance, the chosen trajectory achieves the lowest cost, there may be a degradation in overall effectiveness. As a solution, a generalization of the decision-making process will be considered, giving precedence to the previously selected trajectory. This is feasible by maintaining a consistent set of trajectories in different homotopy classes, with the marked designation of the previously executed trajectory.

3.2 EXP2

The goal in the EXP2 is to solve the situation where a platoon needs to drive safely through a roundabout. Regarding behavioural planning, the challenge falls under the decision to enter or not enter the roundabout. More detail about the experiment conditions have been explained in the section 2.2.

3.2.1 Architecture

The global architecture of this experiment has been explained in the 2.2.1 section. There, the motion planning is explained to be divided in several steps for path planning and speed planning. In the behavioural planning a collision risk assessment needs to be made with the MOP information, so the speed planner can avoid collisions with the vehicles inside the roundabout. This, of course, is highly dependent on the reliability of the information available of the surrounding vehicles. In traffic heavy scenarios like roundabouts there might be occlusions. Therefore, an external collective perception module will be used to improve this information.

3.2.2 Behavioural planning SoTA

The main contribution to the behavioural planning module in the EXP2 is the implementation of a collision risk assessment method that considers confidence of object detection (which is extended to an area greater than the FoV when T3.4 is considered) and predictions for surrounding vehicles.

There are several methods used in the SoTA but most approached only consider static objects as obstacles. Potential Field Methods [59] define a virtual potential field around obstacles, and the vehicle navigates by moving through the field, avoiding regions with high potential (indicating obstacles). They are very used on static obstacle situations with good results in simulation, but the use to have high computational costs. Analytical methods [60] define occupancy grids and calculate using physical equations a time to collision for a certain path. These methods usually need to have a path precomputed to work, so the behavioural planning and the motion planning have a loop architecture. Finally, some authors use AI based collision risk assessment [61] known as collision prediction models.

3.2.3 Outlook and future works

Currently the advances in the behavioural planning task for the EXP2 is only theoretical and will start developing using the information provided by the development in the work done in the task 3.3 of the EVENTS project.

The success of the collision risk assessment method will be measured by the number of simulations that is able to run without collisions.

3.3 EXP3

EXP3 aims to demonstrate safe automated driving in complex urban environments with occlusion. This can be achieved by using self-assessment methods in the onboard perception system making reliability assessment outputs and additionally using V2X data from an infrastructure pilot site. EXP3 is described in detail in Deliverable D2.1 "User and System Requirements for selected Use-cases" [1]. In the context of EXP3 not only the perception is an important part but also the following components like the behavioural decision-making and the trajectory planning. So, the behavioural decision-making reacts on various influences, e.g., on the environment or internal states and is able to control the vehicles actions. The trajectory planning calculates the vehicle's path on the outcome of the behavioural decision-making. In the following, the focus is set to the behavioural decision-making in the context of EXP3.Architecture

3.3.1 Architecture

The system architecture for EXP3 is designed in Deliverable D2.2 "Full Stack Architecture & Interfaces" [2], which is a subset of the project's master architecture. Figure 22 shows the overall architecture of EXP3, which defines the internal data flow between the modules, as well as the input and output. The onboard sensor data of the vehicle is processed, and a tracking algorithm associates and filters the objects over time. As a novel innovation and the main focus in EXP3, the onboard object tracking is extended with a self-assessment procedure. The object list obtained from the onboard tracking and a self-assessment score are handed over to the behavioural decision-making to determine and plan the vehicles behaviour. Additional to the object list of the vehicle based on onboard sensors, the behavioural decision-making gets an object list from the infrastructure pilot site, wherefore the V2X communication is used to send the data in form of CPMs to the vehicle. The object list of the infrastructure has in contrast to the vehicle's object list no self-assessment score. With all this information, the behaviour decision-making of EXP3 is performed. Then, the behaviour is realized into a trajectory in the following trajectory planning step.

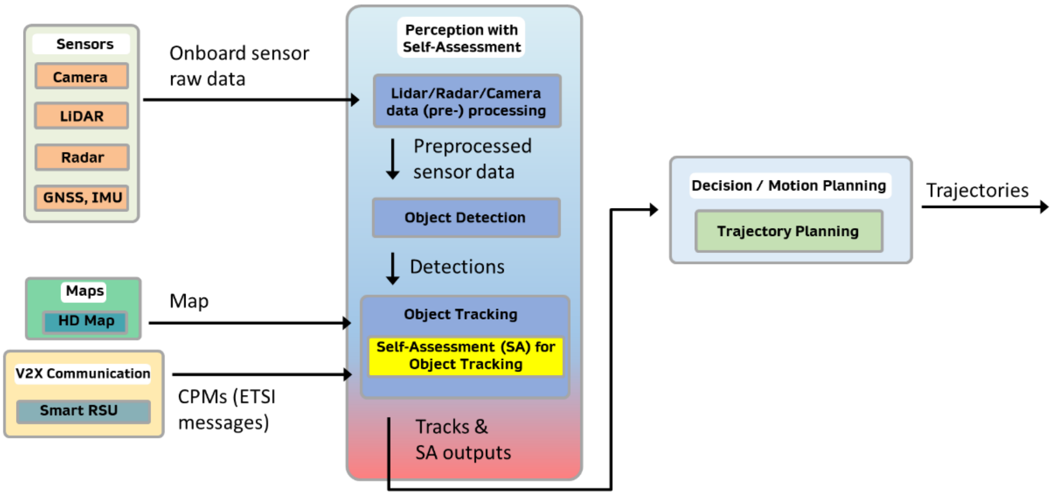


Figure 22: Architecture of EXP3 showing the data flow between the modules. The behavioural decision-making gets the data from the perception of the vehicle and the infrastructure. Taken from [2]

3.3.2 Algorithmic approach

The behavioural decision-making gets as input the onboard object list with the corresponding self-assessment outputs from the vehicle and the object list from the infrastructure, which has no self-assessment module available. Depending on the content of the data and the information, the vehicle's behaviour is determined by the decision-making module. One example of data-dependent behaviour in the scope of EXP3 is entering the intersection. Here, the vehicle can enter the intersection without stopping, in the case infrastructure data is available in order to resolve the occlusion at the intersection. However, without the infrastructure data, the vehicle must drive slowly into the intersection until the vehicle's sensors can resolve the occlusion.

3.3.3 Outlook and future works

So far, only high-level considerations have been made in the behavioural decision-making part. Further considerations and algorithmic realizations will be done in the direction of how the self-assessment score calculated in the tracking on the vehicle can be integrated into the behavioural decision-making and what impact this will have on the behaviour of the vehicle.

3.4 EXP4

As explained before, the objective of the EXP4 is to navigate in an unstructured road wide enough for at least 2 vehicles driving in parallel and with occasional disturbances, like roadworks. The challenge regarding behavioural planning is the selection of a collision free path within the boundaries of the roads in real time.

3.4.1 Architecture

The architecture has been explained in the section 2.3.1.

3.4.2 Algorithmic approach

State-of-the-art

Nowadays many institutions have conducted research on behavioural planning (BP), intended as the "best action" to perform in a given situation. This topic is also correlated with the driver intention recognition, where the goal is to infer the intention of a driver to perform a given manoeuvre. There are two main approaches commonly used to decide which is the action to perform: Probabilistic Graphical Models (PGMs) and the Artificial Neural Networks (ANNs).

Probabilistic Graphical Models

They can be further divided into Bayesian Networks (BNs), Dynamic Bayesian Networks (DBNs) and Hidden Markov Models (HMMs) [62]. DBNs and HMMs, with their variants, are the most used methods [63]- [64]. Examples can be found in [65] and [66], in which this algorithm has been suitably applied for driving behaviour or other human behaviour studies.

As a Bayesian nonparametric alternative for standard HMM, HDP-HMM is used without fixing the number of assortments of hidden states [67]. Others approaches combine HMM with Support Vector Machines (SVM)s [68] or with Fuzzy Logic (FL) [69].

Artificial Neural Networks and Machine Learning

Different Machine Learning (ML) – and more specifically Artificial Neural Networks (ANN) algorithms – have been applied for learning and modelling driver's decision, such as Support Vector Machines (SVM), Fuzzy Logic (FL), Random Forest (RF), Convolutional neural network (CNN), and so on. In particular, recent studies rely often on deep neural networks (DNNs) for recognizing driver intentions [70], [71], [72]. The usage of deep learning (DL) methods to recognize driver intentions rose from 2017 onward. Since 2016, 70% of the turn manoeuvre studies and 50% of the lane change manoeuvre studies applied a deep learning method to infer the driver's intentions (examples can be found in [73] and [74]). In particular, for the behavioural and planning systems, the core of the solution is a multiple input/output Recurrent Convolutional Neural Network (RCNN) that is responsible to imitate and predict the human driving behaviour in terms of future yaw rate and speed demands.

Technical Background and Method

As aforementioned, BP is mainly concerned with the prediction of a best action to perform in the immediate future (e.g., change the lane for an overtaking, or follow the car ahead). The following example a possible scenario addressed by DIR enabler (a highway overtaking which requires a lane change manoeuvre):

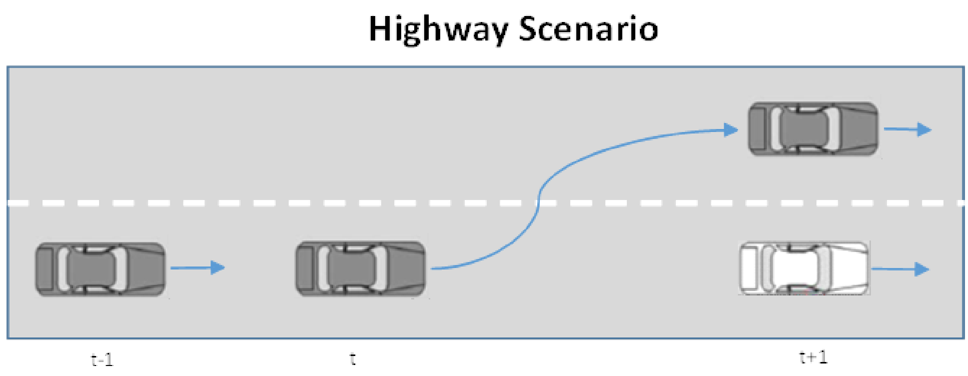


Figure 1: draft visualization of a highway scenario, which requires a decision on which manoeuvre has to be executed.

With reference to the figure above, let us suppose that a driver, travelling on a highway, approaches another (slower) car ahead: it is necessary to decide if it is better to overtake (thus before a lane-change manoeuvre must be done) or to follow the vehicle ahead (reducing the speed). Of course, this depends on many factors, such as the surrounding traffic conditions, the attitude and will of the driver, and so on. However, to make the decision, the driver will execute a plan (namely, a sequence of actions, leading her/him in front of the other car). This can be also acted directly by a system, supporting the driver or automatically performing the manoeuvre.

3.4.3 Outlook and future works

This section has described the behavioural planning for EXP4 – decision-making in unstructured environments – and the work done until now, which has been related mainly to the SOTA analysis and to the high-level considerations for the behavioural decision-making part. From this point of view, the advances in this task are above all theoretical.

Future works are the investigation and implementation of the most appropriate algorithms for behavioural planning, using the information coming from WP3, and then providing the necessary inputs for the trajectory planning task (T4.1, "Motion Planning"). This activity is planned for the first months of 2024 year.

3.5 EXP5

In the EXP5, the goal is to improve the high-speed lane merging flow by designing an efficient DM method. As stated in the section 2.4, the ego vehicle will be interpreting two roles in the same scenario. When the ego vehicle is inside the lane, the decision of changing lanes or modify the speed can be decisive since it will influence the behaviour of the merging vehicle. When merging, the ego vehicle needs to decide when is efficient to merge into the new lane.

3.5.1 Architecture

The architecture is explained in the section 2.4.1

3.5.2 Algorithmic approach

The same SoTA study of the section 2.4.2 can be applied in this section. However, the behavioural planning development in the EVENTS project lies in the development and lies in the development and adjustment of the trajectory candidate selection function. As stated, in [36] an optimization-based method was used, where merging progress, comfort and risk where evaluated. The objective is to implement a similar method with the trajectory generation resultant of the task 4.1.

3.5.3 Outlook and future works

The work done until now have been related to the SoTA analysis. Future works are the implementation of the original method, as well as the implementation of the method using the trajectories studied in the EVENTS projects and making a comparison between them in the next points.

3.6 EXP7

This work aims to develop and evaluate a novel multi-agent motion prediction module which predicts both the intention of vehicular and VRU traffic participants as well as their short - and long-range trajectories making use of the intention prediction preceded. As first described in project Deliverable D2.1 “User and System Requirements for selected Use-cases” [1], this module is part of EVENTS Experiment no. 7 (EXP7) ‘Localization/perception self-assessment for advanced ACC and other vehicles’ behaviour prediction under adverse weather or adverse road conditions’, focusing primarily in highway interaction scenarios (merges, lane changes, cut-ins) under adverse weather condition, assumed to create object-level information uncertainty.EXP7 is categorized under the third Use Case (UC3) defined in the EVENTS project, which is concerned with safe and resilient automated driving in motorways under low visibility or/and adverse weather conditions.

The ultimate objective of this work is to assist the behavioural decision making of the ego vehicle by implementing a manoeuvre and trajectory prediction module of surrounding road users based on ego-vehicle observations in its perception Field-of-View. We consider three key reasons for the uncertain future trajectory of other road users. These are a) the unknown future state of drivers/AVs including their immediate intention captured by their future longitudinal and lateral state predictions and their unknown goal destinations, modelled by probabilistic component b) their probabilistic interaction with the ego vehicle and c) the noisy sensor measurements leading to noisy object-level spatio-temporal information coming from the perception layer. Recent data-driven methods based on deep learning algorithms like LSTM have shown good performance for predicting vehicles’ short-range trajectories (1-3 secs), however prediction in longer horizon (up to 8 secs) remains an open problem and demands integration of other techniques too. More importantly, dedicated studies in simulation with adverse weather scenarios have not been expensively studied so far for the problem of agents’ motion prediction. In the following sections, a) T4.2 EVENTS object prediction module architecture is presented; b) the ongoing work on implementing a novel object intention and trajectory prediction framework is described after a short SoTA on AD motion prediction (and planning) is reviewed, and finally, c) the module’s implementation plan and its preliminary prospective evaluation plan, is outlined.

3.6.1 Architecture

A system architecture for EXP7 is designed in Deliverable D2.2 “Full Stack Architecture & Interfaces” [2], which is a subset of the project’s master architecture. In Figure 23, a small variation of the project’s master architecture is provided to better visualize the proposed module ‘s role in EVENTS WP4.

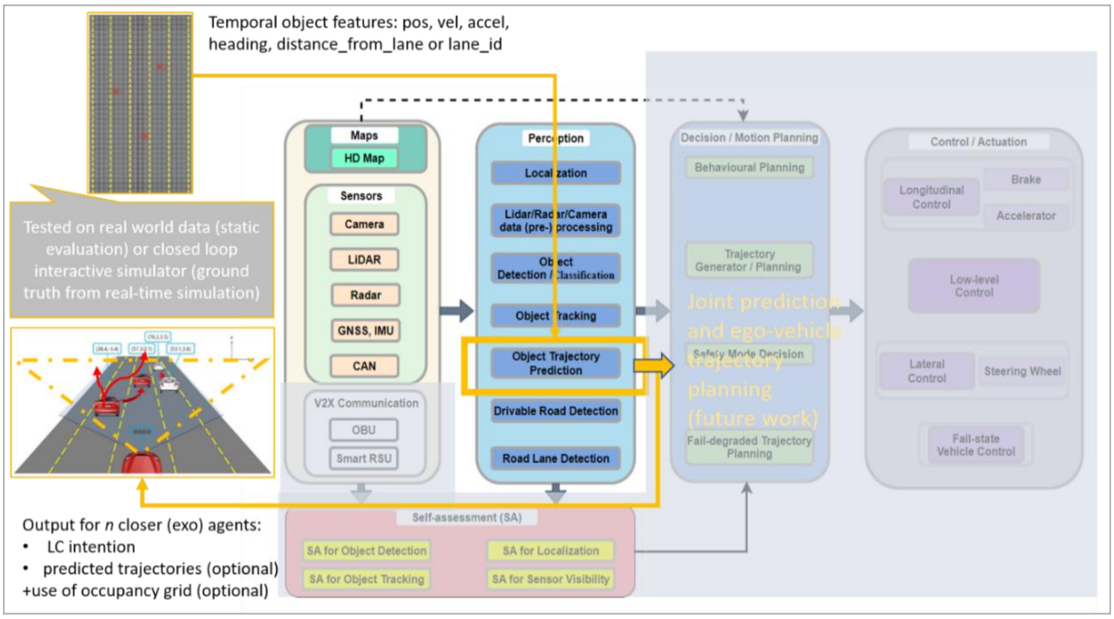


Figure 23: ICCS long-term trajectory prediction module for T4.2

As shown in Figure 23 yellow boxes' dataflow, the problem is cast as a multi-modal trajectory prediction problem for the N closest vehicle agents (exo-agents [80]) in the field-of-view of the ego-vehicle. The objective of ICCS intention and trajectory prediction module is to accurately predict exo-agents future states up to a 6 secs horizon while considering their interactions and map information, if given. The system is subdivided into two main parts: manoeuvre classification and multi-modal trajectory prediction. In our approach, we will investigate a grid-based output for predicting all road users in a scene, with an instance-based output that enables us to extract future trajectories of varied length for any road users of interest. Finally, as many recent algorithms consider the exo-agents' prediction problem jointly with the ego-vehicle trajectory planning problem, ICCS will also investigate this direction as part of wp4 work.

3.6.2 Algorithmic approach

SoTA

Vehicle intention estimation and behaviour prediction models must capture the complex, multimodal and highly uncertain traffic state by predicting the heterogeneous behavioural manoeuvres and trajectories of non-ego (exo-) drivers in different interactive driving scenarios and various environments.

The latest SoTA in multi-agent motion prediction pipelines initially form latent deep semantic representations by environment context and agent interaction effect modelling agents to form a task agnostic backbone for intention and motion prediction. Most recent works encode the vectorized HD map and surrounding vehicle information for modelling. Specifically, models such as VectorNet [75] utilize polyline vector encodings, followed by contextual feature aggregation via GNN message passing. [76], stack transformer encoders for heterogeneous data modelling, while others model the spatiotemporal context with Transformers [77] and Attention mechanisms [78]. Particular emphasis is given on learning local and global contextual representations and approaching the problem from hierarchical [79] perspective to efficiently capture fine-grained as well as coarse and long-range vehicular interaction information [80] via different deep learning (MLP, CNN, self-attention) modules. Further, emphasis is given on imposing the legal constraints on route following, merging, intersection traversal scenarios and lane changing, in a graph-based modelling approach [78]

In addition, novel works employ an agent-centric scene representation that is pose invariant [81] and can seamlessly exploit traffic symmetries [82] to improve robustness upon reference frame translation and rotation during prediction, that enable object interaction modelling in arbitrary long distances [83] . The local contextual information is captured by different heads of a DETR-inspired transformer encoder designed with Multi Head Attention mechanisms and cross attended with learned features from the encoded scene surrounding the target vehicle. Multimodal output distribution is enforced by sampling ground-truth trajectory end-points (location, speed) of the ego vehicle coupled with iterative behaviour refinement during forward rollouts via local, static environment embedding features. Other works ([82]) employ a global coordinate system, as opposed to agent-centric coordinates and encoding the entire scene symmetrically, improving memory efficiency and latency.

After feature extraction and interaction modelling, trajectory decoder models with multimodal distribution outputs are studied, using the learned deep contextual features either by conditioning on intention estimations via Bayesian networks and predicted future manoeuvre sequences [84], learning an unsupervised generative model like Gaussian Mixture Model (GMM) for trajectory regression [85] or simply conditioning on historical agent states and a centreline representation of the road segments [86].

Probabilistic conditioning using RL planners [87] with supervisory expert signals (Imitation Learning) and model-based approaches [84] with scene-compliant cost heat maps could further yield more realistic planned motion profiles for the ego vehicle. Further, a spatio-temporal Transformer model [88] with social (exo-agent) and contextual feature modelling capacities, yielding SoTA results in the Waymo Interactive Challenge bypasses heuristics via autoregressive trajectory decoding and NMS multimodal trajectory aggregation.

Finally, a previous study [89] has critically assessed the State-of-the-art in prediction evaluation, proving formally the existence of a dynamics gap between actual driving performance and dataset accuracy when evaluating predictors as part of the full AD stack. Static and Dynamic evaluation modes are compared in simulation by varying the controller dynamics of non-ego agents.

Model	Lane Change Intention	Environment	Prediction Time Window	
Motion LM [88]	Yes	Urban	8s	
PDM-Closed [86]	No	Urban	2s	
PGM [87]	Yes	Urban	8s	
MTR ++ [82]	No	Urban	8s	
HiVT [73]	No	Urban	8s	
MPF [90]	No	Urban, Highway	8s	
Combined Learning [84]	Yes	Highway	8s	
Social Pooling [91]	Yes	Highway	8s	

Table 2: Comparison of interactive prediction SoTA algorithms

Proposed prediction system

In this section, the Deep Learning based pipeline for multi-agent prediction of non-ego vehicles is presented and its inputs and outputs are formally defined. We adopt a standard prediction pipeline, similar to [92] and we enhance it by incorporating novel feature extraction modules drawn from recent literature, e.g., GNNs.

Problem statement

Assume an ego vehicle driving in highway or urban environments under fixed dynamics, predetermined by simulation software or by real-time driving scenarios (ground truth). The ego vehicle is equipped with RGB camera of frontal and back fields of view. Assuming pre-processed object data **S** $\in \boldsymbol{R}^{NxC}$**,** where *N, C* are the number of non-ego (exo) agents in current scene and the dimensionality of the sensor readings, respectively, using an exo-agent centric Cartesian Coordinate System. Also, the input data is corrupted by noise either extrinsically in simulator or intrinsically from real-world data. Further, assume existence of latent space variable z $\in \boldsymbol{R}^{GxCz}$, where *Cz* is the latent embedding space dimensionality*, G* the number of graph nodes. The latent space captures the interactions between different sensor reading modalities (agent-agent, agent-environment) in a deep feature space which learns semantically meaningful, heterogeneous input representations. The aims are to classify future vehicle intentions **I** $\in \boldsymbol{R}^{Tx3xNxK}$**,** for intentions *I* = {*LLC , RLC , LK*} denoting left-lane change, right lane change or lane keep, respectively. The output is a regression task, with multimodal, multi-agent trajectories **y** $\in \boldsymbol{R}^{\mathrm{T}xNxK}$**.** , as predicted values. *T, K* are the future horizon window and multimodal prediction count, respectively.

This is achieved by learning mappings f: $S \rightarrow Z$, g_1: $Z \rightarrow I$, g_2 : $Z \rightarrow I$, Such that: $I = g_1(Z ; \theta_1)$, $y = g_2(Z; \theta_2)$, $Z = f(S; \theta_1)$. F, g_1, g_2 are parameterized by the neural network parameters (MLP) which are optimized to maximize training data likelihood. F is a GNN, with GAT layers. The aggregation functions ϕ_{agg} for message passing are chosen empirically among (mean, sum, max). Training is coded sequentially, as an end-to-end model in this case.

Specifically, the sensory inputs required are listed below:

1. Ego Vehicle
   a. 2D target vehicle location (x, y) vector for T historical time steps
   b. 2D target vehicle speed (Vx, Vy) for T historical time steps.
   c. 2D target vehicle acceleration (Vx, Vy) for T historical time steps.
2. Non-ego traffic vehicles:
   a. 4D vehicle object annotation (vector of bounding box coordinates, time)
   b. Vehicle position, velocity, acceleration vector (3D)
   c. Vehicle orientation vector (yaw)
3. Contextual information: Road graph (Polylines from HD maps input)

Research Questions our study aims to answer include:

- **RQ1**: Which State-of-the-art predictor from the literature performs best for joint intention and trajectory prediction in Urban vs. Highway driving scenarios?
- **RQ2**: Compare model performance in static with dynamic evaluation scenarios.

RQ3: What is the model generalization and transfer learning performance across datasets collected in different environments (urban vs. highways).

System functional/algorithmic architecture

This section describes qualitatively the data flow and processing through the proposed architecture, schematized in Figure 24, for intention and trajectory prediction.

1. **Feature Extraction**: Observation and HD map (optionally) input is patched and embedded in spatio-temporal tokens for graph-based contextual feature learning and interaction modelling. We plan to experiment with LSTM, GRU for learning feature tokens .
   - State branch embeds the (pre-processed) ego vehicle sensor readings (traffic participants as objects, obstacles, traffic lights, location, etc.) using GRU encoder, inspired by [87] for time-series information processing, yielding state embedding.
   - Scene branch uses structured HD maps to extract vectorized encodings of topological, geographical and semantic information - in the area

surrounding the target agent-yielding a scene embedding. VectorNet [75] is used to fuse local heterogeneous road graph (lanes, obstructions, etc.) vector data in a graph representation which will be used in conjunction with GNN layers and multi-head cross attention during pipeline stage 2 (self-, cross-attention)

2. **Interaction modelling**: Sensor embeddings are used as values V of graph attention network *G*(V, E ; θ), whereas polylines representing road lanes and their attributes are used as edges E. Two types of edges corresponding to legal lane routes and legal lane changes are considered. The Graph specifically consists of:
    - GAT layers [93] that cross attend value (state) with scene embeddings via localized MHSA [82] to form embeddings that learn state representations in a spatially hierarchical manner. The edges connect exo-agent neighbouring scene elements.
    - As an auxiliary training task, vehicle intention prediction (change lane, stop) module is proposed to both classify intentions for each non-ego vehicle, which are input to predictor as multimodal, multi-agent manoeuvre sequences.
3. Trajectory decoding: The learned contexts between environment and agent nodes are decoded for multimodal ego-vehicle trajectory predictions, conditioned on intention manoeuvre. Similar to previous work, GMM parameters are estimated via EM algorithm or end-end (MLP) for the multimodal output distribution. The decoder is further conditioned on sampled latent variables to promote diversity (velocity, acceleration) in longitudinal output dynamics, as in [87].

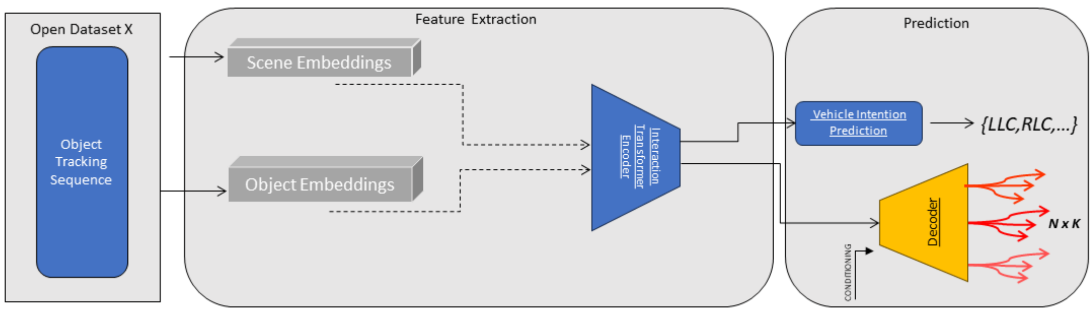


Figure 24: Logical/algorithmic architecture of the proposed intention and trajectory prediction module

Evaluation Plan

The proposed prediction models are to be evaluated in SoTA simulator environments with integrated open and closed loop testing support for prediction and later for planning also. Custom scenario generation for safety-critical (distribution tail) scenario creation will also be pursuit for re-training the proposed ML models trained on Urban database and custom highway road environments aiming to yield breakthrough performance on the use cases of the EVENTS EXP7 proposal, with respect to existing benchmarks.

The simulators investigated with both photorealistic simulation and integrated scenario generation is Scenario Net [94], which has digitized and embedded the naturalistic Urban datasets aforementioned (Table 2) therefore serving as an efficient and complete training, testing and benchmarking simulator suite for the AD stacks of EVENTS motion prediction and planning objectives. CARLA [95] simulator is also to be used for evaluation with existing scenarios created from partners of the EVENTS project. Both simulators integrate ROS for car perception, prediction, planning and control through ROS-bridge allowing testing of different behavioural strategies of different traffic participants in the interactive scenario (constant speed, reactive, non-reactive, model-based, data-driven, etc.).

Datasets and Metrics

The datasets (naturalistic or synthetic) required for the experiments of this section need to fulfil the following criteria:

- Provide long range spatiotemporal sensor coverage, to allow safe manoeuvre predictions over an 8s horizon in highways.
- Provide 3D tracked object annotations on the object-level in the area surrounding the ego-vehicle.
- Provide GT trajectories for non-ego vehicles, enabling multi-agent social modelling and interaction prediction studies.
- Provide object level annotations collected under various adverse weather conditions (fog, rain, thunderstorm, etc.)

As reported in Table 2 above, although most datasets are collected from urban environments, with less focusing on the use case of this experiment (highways), exploiting data for training deep learning models in Urban traffic use cases can distil transferable knowledge via pre-training or self-supervised learning for deployment (inference) in highway driving scenarios.

The predictors will be evaluated in open loop setup with metrics which do not penalize multimodality and hence the last row of Table 3 is of interest. Metrics adopted by Waymo motion prediction challenge can be adopted which consider multimodality by considering every generated trajectory from the predictor output distribution over an 8s. time horizon, by averaging both across steps and prediction outputs.

Metric	Explanation
MinADE	Minimum average Displacement Error
MinFDE	Minimum final displacement Error

Dynamic minADE, minFDE	As above, evaluated in dynamic scenarios.

Table 3: Popular motion prediction performance metrics

Note: Uncertainty of prediction module in safety-critical driving scenarios and harsh operational domain conditions could be self-assessed by either confidence scores generated by trajectory decoder model per decoded motion profile or directly by the learned covariance matrix of the GMM regressor.

3.6.3 Outlook and future works

Further development in the following project months is structured as listed below:

1. Implementation of PoC toy model in simulation software, using the novel nuPlan platform and development kit for studies in nuPlan, nuScenes dataset. Further studies in SUMMIT [96], CARLA [95], ScenarioNet [94] are to be conducted due to their comprehensive AD research support.

2. Python development of scenarios in simulation, followed by coding of prediction module using real-world and simulation datasets. In depth analysis deploying both static and dynamic evaluation metrics, discussed at the end of sec. 3.6.2.1 (SoTA) and following [89]. Implementation of a scoring module and metrics for primitive joint prediction and planning results.

3. Evaluate Research Questions proposed above.

4. Expand on key uncertainty reasons by introducing obstacle-aware behaviour prediction of exo-agents. Previous approaches train variational occlusion models [97] to generate occluded vehicle trajectories given visible ego-vehicle surroundings, or mask perceived occluded spatiotemporal regions in the attention matrix of GAT layers [98].

3.7 EXP8

Section 2.5 provides an in-depth overview of the experiment, while Section 2.5.1 outlines the architecture of the proposed motion planning algorithm incorporating behavioural decision-making.

Utilizing data from 3D object detection and evaluated uncertainties, the Vehicle-to-Obstacle distance is computed. Concurrently, employing enhanced slip detection through radar-based vehicle odometry, a model-based estimator assesses the motion capability to determine the feasibility and risk of the replanned trajectory. It will also influence on imposed trajectory constraints. The calculation of Time to Collision, Time to Brake, and Time to Steer guides the execution of steer and brake actions.

4. Conclusions

This Deliverable 4.1 reported on progress within tasks T4.1 and T4.2 of Work Package WP4 of the EVENTS project. The aim of this work package is to provide the behavioural and motion planning needed to facilitate the various experiments (EXP1-EXP8) specified by the EVENTS project partners. The work done in this WP has been mostly related to the SoTA research. Therefore, there are no results in this document.

Task T4.1 involved the motion planning of the vehicle, meaning a method that will provide a reference for the control to follow. Each experiment has a motion planning concept:

- EXP1: The motion planning will be performed using an MPC based method that can consider multiple objectives and dynamic obstacles. The main goal is to adapt an existing motion planner for vehicle dynamics.
- EXP2: Lane following motion planning will be tested in this task. After researching in the SoTA the trajectory generation will be chosen by making a benchmark study.
- EXP4: Two main study points are presented in this experiment. On one hand, a SoTA study has been made around unstructured roads regarding motion planning. The main contribution will be the implementation of a method of motion planning on unstructured roads. On the other hand, a methodology for HD map generation is proposed.
- EXP5: A specific SoTA study has been made around motion planning on lane merging. The main contribution will be the implementation of the trajectories studied in this experiment as trajectory candidates.
- EXP8: An MPCC for emergency evasion manoeuvre on slippery road under rain conditions is explained with positive results on simulation. Three main contributions are proposed.
    - The improvement of the tire model
    - The integration dynamic friction constrains using enhanced slip detection.
    - The integration of the perception uncertainties into the optimal problem formulation.

Task T4.2 involves the behavioural planning of the vehicle, meaning the processing of the perception system output (WP3) to choose a safe trajectory proposed by the motion planning algorithm. Several behavioural contributions have been presented in this document:

- EXP1: Both, motion planning and behavioural planning are merged in a single method. Therefore, the contribution is the same.
- EXP2: A SoTA study has been made regarding collision risk assessment. The contribution will be the implementation of a method to choose the speed profile based on the information provided by the perception system.
- EXP3: A High-level architecture has been presented. Future work will provide specifications on how the self-assessment score would impact the behaviour of the vehicle.
- EXP4: On one hand, a SoTA study has been made around unstructured roads regarding behavioural planning. Further work will stablish the method that will be implemented.
- EXP5: The behavioural planning SoTA study has been done in parallel with the motion planning SoTA study. A method for trajectory candidate choosing will be implemented.
- EXP7: A Deep Learning based pipeline for joint intention and trajectory multi-agent prediction of non-ego vehicles is presented. This method will be tested in simulated scenarios (tested as an independent step before motion planning).

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