REAL-WORLD APPLICATION OF VARIOUS
TRAJECTORY PLANNING ALGORITHMS
ON MIT RACECAR

SENIOR DESIGN PROJECT
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Project Advisor: Assoc. Prof. Dr. Tufan KUMBASAR

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YÖRÜNGE PLANLAMA ALGORİTMALARININ
MIT RACECAR ÜZERİNDE GERÇEKLENMESİ

BİTİRME TASARIM PROJESİ

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Kontrol ve Otomasyon Mühendisliği Bölümü

Tez Danışmanı: Doç. Dr. Tufan KUMBASAR

HAZİRAN, 2021
To my dearest friends and family,
PREFACE

I would like to thank my advisor Assoc. Prof. Tufan KUMBASAR for his support and guidance throughout the graduation project period. I am grateful that Artificial Intelligence and Intelligent Systems (AI2S) Laboratory opened its doors and provided a healthy study environment for this project. This research is supported by the project (118E807) of Scientific and Technological Research Council of Turkey.

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JULY, 2021

Oğuzhan KÖSE
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# Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| RACECAR      | Rapid Autonomous Complex-Environment Competing Ackermann-steering Robot |
| ROS          | Robot Operating System |
| DWA          | Dynamic Window Approach |
| TEB          | Timed-Elastic Band |
| APF          | Artificial Potential Field |
| ADAS         | Advanced Driving Assistance System |
| RRT          | Randomly Exploring Random Tree |
| RRT*         | Randomly Exploring Random Tree Star |
| PRM          | Probabilistic Roadmap |
| UGV          | Unmanned Ground Vehicle |
| GPU          | Graphical Processing Unit |
| CPU          | Central Processing Unit |
| RAM          | Random Access Memory |
| FOV          | Field of View |
| FPS          | Frame per Second |
| IMU          | Inertial Measurement Unit |
| VESC         | Vedder Electronic Speed Controller |
| BLDC         | Brushless Direct Current Motor |
| XML          | Extensible Markup Language |
| RPC          | Remote Procedure Call |
| AI2S         | Artificial Intelligence and Intelligent Systems Laboratory |
### SYMBOLS

- $\gamma$ : Steering Angle
- $L$ : Wheelbase
- $R$ : Turning Radius of the Vehicle
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REAL-WORLD APPLICATION OF VARIOUS
TRAJECTORY PLANNING ALGORITHMS
ON MIT RACECAR

SUMMARY

Autonomous vehicles are really becoming a reality as investments are made. In the last two decades, autonomous vehicles have gotten a lot of interest from academics and business because of its potential uses in military, logistics, and industry. Autonomy of the vehicles has benefits from different aspects. It will allow the driver of the vehicle to deal with different things during the journey or for the safety concerns, since the most of the accidents happen in traffic are human mistakes, autonomous vehicles can significantly reduce the number of accidents caused by human mistakes. Of course, this autonomy of vehicles will not be used directly in a short time period, but autonomous vehicle features like speed cruise speed or lane tracking systems are already in use. However, autonomy of the vehicles are come into use one-by-one. Within this project, another important feature of autonomous driving will be tried to implement on a mini car. Moving completely autonomously in a complex and dynamic environment, like traffic, is a hard problem to solve. Although, this project aims to overcome this problem for a small vehicle as a simulation of the real world. On top of a small size race vehicle, the MIT RACECAR(Rapid Autonomous Complex-Environment Competing Ackermann-steering Robot), a complex open-source platform for robotics research and teaching, includes cutting-edge sensors and processing capabilities. Commercially available mobile platforms and 1/10 scale robotic platforms have been launched, despite various constraints on advancements and research in the field, such as reliability and cost. MIT RACECAR provides a robust robotic platform for research and teaching by offering realistic vehicle dynamics with Ackermann steering that is built using fully open-source and standardized systems that use ROS(Robot Operating System). The goal of this thesis is to create a path planning algorithm for the MIT RACECAR platform that is robust to environmental variables and can function successfully in real time, as well as to offer safe vehicle travel in complex environments with obstacles. The interoperability of the Ubuntu system with ROS offers a viable platform for path planning, which is the topic of the thesis, in addition to hardware such as the ZED camera, NVIDIA Jetson TX2 developer board, and lidar on the vehicle. In order to analyze kinematic relations that govern the motion of the vehicle, a vehicle kinematic model is developed before route panning is implemented in MIT RACECAR. To avoid tracking accuracy concerns, the low-level controller structure was modeled, and the performance of the MIT RACECAR was examined with on-the-ground experiments.

In the project, the vehicle was first controlled with ROS. For this purpose, the necessary nodes were prepared to be controlled with a joystick. Afterwards, DWA(Dynamic Window Approach), TEB(Timed-Elastic Band) and APF(Artificial Potential Field) path planning algorithms were applied to MIT RACECAR, respectively. These algorithms have advantages and disadvantages against each other on different issues. For this reason, a scenario was created to compare algorithms. On a curved double lane road created according to this scenario, MIT RACECAR has to follow the lanes and when it encounters an obstacle, it has to change lanes without leaving the road and pass without hitting the obstacle. In addition, an image processing algorithm was developed to obtain the position information of the lanes needed to implement this scenario. This
algorithm detects the target point by processing the image taken from the ZED camera and gives the target point information to the path planning algorithm.

After the necessary tools were created, the algorithms were tested against the scenario. In these tests, measurements such as how many obstacles the algorithm successfully passed, how simple routes it chose, and computational costs they have. According to these results, although it was not the algorithm that successfully passed the most obstacles, APF was chosen due to its low processing load and simple working logic. It was believed that with its uncomplicated structure, APF would also provide advantages in the future stages of the project.
ÖZET

Otonom araçlar, yatırımlar yapıldıkça gerçekçe dönüştükdü. Son yirmi yılda, otonom araçlar askeri, lojistik ve endüstrideki potansiyel kullanımları nedeniyle akademisyenler ve iş dünyasından büyük ilgi gördü. Araçların otonomluğun farklı yönlerden faydaları vardır. Trafikte meydana gelen kazaların çoğu insan hatası olduğundan, otonom araçlar insan hatalarından kaynaklanan kazaların sayısını önemli ölçüde azaltabilir. Ayrıca araç sürücülerinin yolculuk sırasında farklı şeylerle uğraşmasına imkan sağlayacaktır. Tabii ki araçların bu otonomluğu kısa bir süre içerisinde doğrudan kullanılmayacak ancak sabit seyir hızı veya seat takiplerini gibi otonom araç özellikleri halihazırda yaygın olarak kullanılıyor ve araçların otonom özellikleri birer birer hayatımıza giriyor. Tabii ki araçların bu otonomluğunu kısa bir süre içerisinde doğrudan kullanılmayacak ancak sabit seyir hızı veya seat takipleri gibi otonom araç özellikleri halihazırda yaygın olarak kullanılıyor ve araçların otonom özellikleri birer birer hayatımıza giriyor. 

Bu proje kapsamında, otonom sürüşün bir diğer önemli özelliği olan bu zor probleme mini bir araba üzerinde çözüm geliştirilmeye çalışılacaktır. Bu projede gerçek dünyanın bir simülasyonu olarak küçük bir araç için bu sorunun üstesinden gelmek amaçlanmaktadır. Robotik araştırma ve öğretim için karmaşık ve dinamik bir ortamda tamamen otonom olarak hareket etmek zordur. Bu proje kapsamında, otonom sürüşün bir diğer önemli özelliği olan bu zor probleme mini bir araba üzerinde çözüm geliştirilmeye çalışılacaktır. Bu projede gerçek dünyanın bir simülasyonu olarak küçük bir araç için bu sorunun üstesinden gelmek amaçlanmaktadır. Robotik araştırma ve öğretim için karmaşık ve dinamik bir ortamda tamamen otonom olarak hareket etmek zordur. 

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Bu projede ilk olarak aracın ROS ile kontrolü sağlanabilir. Bu amaçla joystick ile kontrol edilmesi için gerekli düğümler hazırlanmıştır. Sonrasında sırasıyla DWA(Dynamic Window Approach), TEB(Timed-Elastic Band) ve APF(Artificial Potential Field) rota planlama algoritmaları MIT RACECAR’a uygulanmıştır. Bu algoritmaların birbirlerine karşı farklı konularda avantajları ve dezavantajları bulunmaktadır. Bu sebeple algoritmalar karşılaştırılacak için bir senaryo oluşturuldu. Bu senaryoya göre oluşturulkan kuvraklı çift şeritli bir yol üzerinde MIT RACECAR’ın şeritleri takip etmesi ve bir engelle karşılaştığında yoldan çıkmadan şerit değiştirerek engele çarpmadan geçmesi gerekmektedir. Bu senaryoya uygulanabilme için ihtiyaç
duyulan şeritlerin konumu bilgilerini elde etmek için görüntü işleme tabanlı bir algoritma geliştirildi. Bu algoritma ZED camera dan aldığı görüntüyü isleyerek hedef noktayı tespit edip, hedef nokta bilgisini rota planlama algoritmasına vermektedir.

Gerekli araçlar oluşturulduktan sonra, algoritmalar senaryoya göre test edildi. Bu testlerde algoritmanın kaç engeli başarıyla geçtiği, ne kadar basit rotalar seçtiği, işlem yükü gibi ölçümler yapıldı. Bu sonuçlara göre en fazla engeli başarıyla geçen algoritma olmasa rağmen işlem yükünün az olması ve basit çalışma mantığından dolayı APF seçildi. Kompleks olamayan yapısıyla APF'nin projenin ileriki aşamalarında da avantaj sağlayacağını inanılmaktadır.
1. INTRODUCTION

Autonomous vehicles are a rapidly expanding market and research field. In recent years, the automotive industry has increased its projects and importance in this area in order to reduce the number of deaths caused by crashes [11]. Furthermore, according to [12], the autonomous vehicle market is expected to grow 36.9% between 2017 and 2027 and reach $126.8 billion dollar market value. And the fact that it is such a big economy enables it to renew itself as something. In this direction, studies are carried out for smartening and autonomy in the design of automobiles. According to a World Health Organization research, road traffic collisions are the seventh leading cause of mortality across all age categories, accounting for about 1.35 million deaths in 2016, with cyclists, motorcyclists, and pedestrians contributing for more than half of the deaths [13]. Considering the complex traffic situations and the increase in traffic accidents due to carelessness, misbehavior, fatigue or distraction, the improvements seen in different levels of autonomous vehicles are motivated to reduce injuries and deaths caused by complex traffic scenarios and errors. Injuries and deaths caused by traffic accidents can be reduced with more accurate Advanced Driver Assistance System (ADAS) applications.

In light of all of this knowledge, in order to be able to prevent crashes or pass through an obstacle, path planning algorithms are being developed for decades. Path planning algorithms are basically used to enable autonomous vehicles to move in environments with obstacles. Also, as mobile robots have recently started to work in dynamic environments where people are also present, path planning algorithms have gained more importance in order for autonomous vehicles to work safely. To achieve autonomous driving skills, different path planning algorithms use different approaches. While algorithms like RRT (Rapidly-Exploring Random Tree), RRT* (Rapidly-exploring random tree (star)) and PRM (Probabilistic Roadmap) use probabilistic methods for path planning, algorithms like APF use geometric approaches.
When it comes to real-world applications, such as autonomous vehicle deployment, testing the boundaries of safety and performance on real cars is expensive, inaccessible, and dangerous. Commercially available mobile systems such as Jackal UGV (Unmanned Ground Vehicle) [14] and TurtleBot2 [15] have been developed to resolve these concerns. Several small-scale robotic platforms have been built in recent years to further research, particularly in the area of autonomous driving. Many of these platforms are built on a small-scale racecar with a mechanical framework to support the electronic components, generally 1/10 size of an actual vehicle. In 2014, Mike Boulet, Owen Guldner, Michael Lin, and Sertac Karaman developed RACECAR (Rapid Autonomous Complex-Environment Competing Ackermann steering Robot) that was the first mobile robot with a strong graphics processing unit (GPU) [16]. By offering realistic car dynamics with Ackermann steering and drive trains, the RACECAR platform provides a robust robotic platform for research and education. It is built on completely open-source and standardized systems that use ROS and its related libraries.

1.1 Purpose of The Thesis

This project mainly focuses on implementing and testing different path planning algorithms on MIT RACECAR platform. These algorithms are expected to avoid obstacles while following the road on a high curvature road. It is expected to determine the path planning algorithm that implements this scenario most successfully and to create a starting point for the solution of complex problems such as overtaking and escape maneuver using this algorithm in the period after the thesis. A lane finding algorithm based on image processing had to be developed at the same time in order to implement the scenario. Within this project, necessary tools will be developed and, route planning algorithms will be evaluated by creating a scenario environment.
1.2 Literature Review

Since path planning is a subject that has been studied for a long time, many algorithms related to path planning have been developed. DWA is one of the most popular algorithms. Fox proposed DWA algorithm in 1997 but, it is still frequently used. Also, algorithms that rely on geometric relations like APF are very successful with a low computational cost [17]. Also, algorithms based on optimization of dynamic parameters like TEB are proposed by Rösmann and it is shown that it can navigate complex environments [18]. Several vision-based lane detection algorithms have been presented in the literature to reliably detect lanes. These approaches may be divided into two types: feature-based and model-based. Detecting the evident properties of lanes that distinguishes them from the rest of the objects on the lane image is the basis of the feature-based technique. The task of feature detection would be split into two parts: edge detection and line detection. To identify lane edges and model lane borders, edge-based techniques have been developed. The accuracy and computing needs of more sophisticated implementations of these models rise, while the resilience to noise decreases. For feature extraction, the Canny edge detection method is presented, which offers an exact match to lane lines and is adaptable to a complex road environment [19]. Improvements to Canny edge detection can successfully deal with numerous noises in the road environment, according to [20]. Furthermore, defining the targeted region of the picture where lane borders are located, called to as region of interest (ROI), enhances performance efficiency [21]. To ease the identification procedure, the region of interest would be split into left and right sub-regions based on the width of the lane.
2. Platform Overview

RACECAR is a full stack robotics system that provides high computing power with reliable mechanical structure. RACECAR platform serves as a strong robotic platform for research and education by providing realistic vehicle dynamics with Ackermann steering, and drive trains. It is designed based on fully open-source and standardized systems that take advantage of ROS and its associated libraries [22]. MIT RACECAR has sensors that can be listed as:

- StereoLabs ZED Stereo Camera
- RPLidar A2 Lidar
- Sparkfun 9DoF Razor IMU

Because of its numerous sensors and well documented software, MIT RACECAR was chosen to be used in this project as the robot that trajectory generation algorithms will be tested on.
2.1 Hardware

2.1.1 Chasis
Chassis of MIT Racecar platform is Slash 4×4 Platinum Truck model from Traxxas. These chassis is giving providing enough performance parameters and has enough space for installation of other equipments. The chassis is able to drive 40 mph with its default Velineon 3500 Brushless Motor, but VESC software the maximum speed is limited by 5 mph for safety concerns. Power required by BLDC is provided by a 2S 4200 mah LiPo battery [23].

2.1.2 NVIDIA Jetson TX2
NVIDIA Jetson TX2 is high power graphical processing unit which is widely used in robotics applications. It has enough processing power for trajectory planning and other tasks. Jetson TX2 has an ARM CortexA57 CPU(Central Process Unit) and 256 CUDA enabled GPU with an 8 GB RAM(Random Access Memory) [1].

![Figure 2.2 : NVIDIA Jetson TX2](image)

2.1.3 StereoLabs ZED Stereo Camera
StereoLabs ZED Stereo Camera is one of the enviromental awareness sensors MIT Racecar. ZED camera comes with dual 4 MP Camera which that provides 110° FOV(Field of View). ZED camera provides real-time pointcloud data in addition to getting 1080p HD video at 30 FPS or WVGA at 100 FPS(Frame Per Second) thanks to its SDK(Software Development Kit) [2].
2.1.4 RPLidar A2 Lidar

RPLidar A2 Lidar is a low-cost 2d lidar that developed by SLAMTEC will give us the obstacle distance information which is necessary for trajectory generation. It can measure distances with a 360 degree field of view with maximum 16 meters range [3].

2.1.5 Sparkfun 9DoF Razor IMU

Sparkfun 9DoF Razor IMU is reprogrammable IMU (Inertial Measurement Unit) with an MPU-9250 9DoF (9 Degrees of Freedom) sensor. Sparkfun IMU is a easy-to-use IMU with its various connection types like UART, I2C and USB. In MIT RACECAR platform it is fully integrated by a USB connection but in this project it is not actively used [24].

2.1.6 VESC Electronic Speed Controller

BLDC (Brushless DC Motor) and steering servo of the MIT Racecar is controlled by Vedder Electronic Speed Controller (VESC). Unlike conventional ESCs, VESC also provides useful data over USB connection like current and voltage data for each motor phase and wheel odometer data. VESC is capable of controlling speed and
steering angle of MIT Racecar successfully. These low level controllers of VESC allow researchers to be more focused on developing solutions to higher level problems.

2.2 Software

The MIT RACECAR software relies on JetPack and ROS as two main components. JetPack is a special software for NVIDIA Jetson computers that specializes Ubuntu for them. Along with specialized OS for Jetson it also provides libraries, APIs, samples and developer tools for AI applications and GPU computing [25].

As the other main component of The MIT RACECAR software, RACECAR ROS package provides robotic capabilities on ROS as subpackages and it consists of sub-packages like; `ackermann_cmd_mux`, `joy_node rplidar_ros`, `sparkfun-9dof-razor-imu`, `zed_ros_wrapper`. These packages are required for collecting sensor data from vehicle, applying commanded control signals, making necessary transformations between different frames. As an addition to these packages, for data collection and logging `rosbag` package is used. The rosbag package allows us to save the sensor data as time-series and then play it back in real time. `Rosbag` package also allows us to measure performance of developed algorithm. Also, for visualization purposes, another ROS package `rqt` is used.

2.2.1 Robot Operating System (ROS)

ROS is an open-source framework that mainly handles communication between nodes and creates a baseline for researchers. Since it also has useful packages like transformation calculations etc., it is very helpful for beginners in robotics programming and accelerate prototyping processes for researchers.

![ROS Topics Communication System](image)

*Figure 2.5: ROS Topics Communication System*
| NODE NAME     | PACKAGE        | DESCRIPTION                                                                                                                                 |
|--------------|----------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| ackermann_cmd| ackermann_cmd   | Ackermann velocity command inputs are multiplexed in this node. It controls incoming ackermann command topics but, based on priority, allows one topic command at a time. |
| _mux         | _mux           |                                                                                                                                             |
| joy_node     | joy            | This node is used for generic joystick to ROS. It publishes joy message that includes joystick all possible states of buttons and axes.          |
| rplidarNode  | rplidar_ros    | Driver for RPLIDAR sensor that converts messages that come from lidar sensor to laser scan messages and publishes to a topic.                  |
| zed_camera   | zed-ros-wrapper| Driver for ZED camera that outputs pointcloud, camera left and right images and pose information of robot.                                  |
| _node        |                 |                                                                                                                                             |
| rosbag_node  | rosbag         | It is a tool for recording the messages published on topics to bag files which are specially formatted files that stores timestamped ROS messages. | It also used for replaying the recorded topics. |
| rqt_node     | rqt            | This node is used for visualization purpose. It provides tools to easily plot data in real-time, displays rostopic messages etc.            |

Table 2.1: The ROS nodes of MIT RACECAR software package

Communication architecture of ROS is communication between nodes with a publish-subscribe messaging model. This communication is only possible with a **master** which serves as an XML-RPC based server. **Master** makes the communication between nodes with an address which is named **topic**. **Topics** are special messaging addresses with a specific data type and name.

The ROS nodes of MIT RACECAR can be seen in Table 2.1.
2.3 Vehicle Kinematic Model

Ackermann steered vehicles like MIT RACECAR are commonly expressed as bicycle kinematic model. Bicycle kinematic model for Ackermann steered vehicles assumes that front wheels and rear wheels are combined amongst themselves and end up with a two-wheel bicycle [4]. In addition to this, bicycle kinematic model also assumes that the vehicle only moves on XY plane and thanks to these assumptions, bicycle kinematic model is a simple geometric relationship between the steering angle and the curvature that the rear axle of the vehicle will follow.

\[
\tan(\gamma) = \frac{L}{R}
\]  \hspace{1cm} (2.1)

The geometric relationship can be written as equation 2.1 where \( \gamma \) is steering angle, \( L \) is the wheelbase and \( R \) is the turning radius of the vehicle. It should be noted that this geometric relationship gives acceptable results for only low speed and moderate steering angles.

\[\text{Figure 2.6 : Simple Bicycle Model [4]}\]
3. PATH PLANNING

Path planning algorithms are used to enable mobile robots to perform their most basic tasks, which are their ability to move. These algorithms mainly consist of two parts which is path planning and trajectory planning. While path planning is responsible for the higher level motion of the robot, trajectory planning algorithms calculates the required actuator behavior for following via-points generated by path planning [26]. This project focuses on trajectory planning algorithms. In ROS methodology, path planning algorithms corresponds to global planner and trajectory planner corresponds to local planner.

Figure 3.1: An example view of local and global planners [5].
In this project, the performance of different trajectory planning algorithms like DWA, TEB and APF, will be compared by their performance. In the realization phase of the project, the algorithms will be tested on the Racecar Platform in a curvy road. The algorithms are implemented in the ROS environment. Thanks to the useful features of ROS, implementation and testing of the algorithms could be done easily.

3.1 Main Elements of Path Planning

Path planning processes may become complex processes. In order to make path planning more tidy and less complex, some auxiliary ROS packages will be used. Before diving into path planning algorithms, these auxiliary packages will be examined.

3.1.1 Global Planner

Global planners are responsible for creating a collision free path for the robot. Global planners generate this path around the obstacles from a geometric approach, and they don’t take into account vehicles dynamics. Unlike local planners, generally they plan for a larger map. A*, Dijkstra’s Algorithm, RRT, RRT*, and PRM can be counted as examples of global planning algorithms. The output of Global planners is a roadmap or waypoints to the target point. These roadmap provides local planner the points to follow.

In this project, base_global_planner package from ROS navigation stack will be used as global planner. This package provides a good baseline that can be configured to use different algorithms for global planning. In this project, since global planning is not one of the main tasks of this project, the package is configured for the Dijkstra’s algorithm for calculating the shortest path that has the lowest cost without including robot kinematic parameters. Dijkstra’s algorithm is mainly chosen for its simplicity and being computationally cheap. Global planners are basic algorithms for choosing the path that has minimum costs. Though, their performance heavily depends on configuration of global costmap. Since there is no mapping in this project, we are using our global planner with respect to the base_link frame.
3.1.2 Local Planner

Local planner is the planner that calculates the short term plan and executes the plan. Unlike global planner, local planner includes robot kinematic parameters and calculates the plan according to these parameters. This extra calculation comes with a computational cost. In order to decrease the computational cost of local planners, boundaries of the local planner generally being selected small and local planner aims the furthest point that is on the global plan that is inside of local planner boundaries, not the real target point.

Global planners produce waypoints or roadmaps as output and local planners get the output of global planners as inputs and calculates the required control signal to follow these waypoints. This control signal is generally a ROS message type named "/geometrymsgs/Twist". The ROS message contains the commanded linear and angular velocity data, and another node takes this message and controls the vehicle with respect to these commanded velocities.

![Local Planner trajectory generation](image)

**Figure 3.2**: Local Planner trajectory generation [6].

3.1.3 Global and Local Costmaps

Costmaps are basically maps that stores the costs of every point on the map that is calculated based on sensor measurements or provided by a known map. 2D and 3D costmaps can be constructed, but for ground vehicles like the MIT RACECAR 2D costmaps are more suitable since the movement in z-axis can be neglected.
Mainly, the costs of cells in costmaps are calculated based on whether there is an obstacle on that cell. In addition to this, another source of cost is the distance of the cell to an obstacle. This "distance" is named inflation in ROS Navigation stack. The inflation is calculated by parameters called inflation_radius and cost_scaling_factor. These parameters are required for deciding whether the cell will be determined as near an obstacle or not, and decay rate of inflation cost. The effect of inflation parameters on the cost of a cell can be seen in Figure 3.3.

![Figure 3.3: The effect of inflation parameters on cell cost](image)

Also, another important parameters of costmaps are cost_factor and neutral_cost. These parameters determine the smoothness and the curvature of the calculated path. The effects of these parameters can be seen in Figure 3.4 and Figure 3.5.
And lastly, it should be noted that, as the names suggest, global costmaps are for global planners and local costmaps are for local planners. Although, there is no difference between global costmaps and local costmaps in fact, their parameter configurations are differs. The map sizes and sensors are main elements that can be difference between them.
3.2 Trajectory Planning Methods

In this project, 3 different trajectory planning algorithms is considered and applied on MIT RACECAR platform. These algorithms are; Dynamic Window Approach(DWA), Time Elastic Band(TEB) and Artificial Potential Field(APF).

3.2.1 Dynamic Window Approach

DWA is a proven concept that is used for a long time in robotics. The method was first proposed in 1999 [27]. And it is still a popular method for mobile robots. DWA provides a controller between global path and the robot. It calculates the cost function for different control inputs and searches for the maximum scored trajectory to follow. Thanks to its simplicity and easy implementation, DWA is a good choice as the first algorithm for trajectory planning. Basic working principle of DWA can be expressed as below.

1. Take dx, dy and dtheta samples from control space
2. Predict next states from current states based on sampled dx, dy and dtheta.
3. Score each trajectory from predictions with distance to obstacles, distance to the goal, distance to the global path, and speed and remove the trajectories that collide with obstacles.
4. Choose the trajectory with the highest score and send the trajectory to the robot.
5. Repeat until goal is reached.

In order to be able to use DWA effectively, DWA needs to be configured properly. DWA has parameters that will configure robot configuration, goal tolerance, forward simulation, trajectory scoring and global plan. One of the important parameters of the DWA is sim time parameter. Sim time is essentially the time length that will DWA plan for, and this parameter heavily affects computation time of the trajectory. In tests, it is seen that when sim time is set to low values like 2.0 seconds or less, the performance of DWA is not sufficient for passing complex pass ways because it can not see what
will happen after the sim time. This result in a suboptimal trajectory. Also, it should be noted that, since all trajectories generated by DWA is simple arcs, setting the sim time to high value like 5 seconds will result in long curves that are not very flexible. Thus, in order to achieve good performance with DWA, setting sim time to an optimum value is a must.

Figure 3.6: The Effect of Simulation Time on Generated Trajectory (sim_factor=1.5, sim_time=4.0) [8]

Aside from sim time, there are a few other factors to consider. Samples of velocity vx sample and vy sample are two parameters that determine how many translational velocity samples should be taken in the x and y directions, respectively. The number of rotational velocities samples is controlled by vth sample. The number of samples you want to take is determined by your computer's processing power. Because turning is generally more complicated than moving straight ahead, it is preferred to set vth samples to be higher than translational velocity samples in most cases. Since, our vehicle is non-holonomic there is no need for velocity samples in y direction. Simulation granularity is the step size between points on a trajectory that is referred to as sim granularity. It essentially means how often the points on this trajectory should be examined. A lower value indicates a higher frequency, which necessitates more processing power.

Lastly, as an addition to all of these parameters, DWA can also plan both for holonomic and non-holonomic robots, but it does not support Ackermann drive robots as MIT RACECAR. Still, DWA was implemented on MIT RACECAR and got acceptable results.
3.2.2 Time Elastic Band

Time Elastic Band (TEB) planner was proposed by Rösmann as an improved version of elastic band algorithm [9]. The classic elastic band algorithm is based on optimizing a global path for the shortest path length. However, TEB optimizes the path by the time-optimal objective function. Also, while elastic band does take into account of dynamic constraints, TEB considers kino-dynamic constraints in the trajectory planning. Additionally, TEB planner also supports non-holonomic car-like robots.

TEB planner is essentially a solution to a sparse scalarized multi-objective optimization problem. The multi-objective problem includes constraints like maximum velocity, maximum acceleration, minimum turning radius etc. Since this optimization problem does not always have only one solution, TEB can get stuck in locally optimum points. Thus, sometimes the robot can not pass an obstacle even if there is a possible trajectory which the robot can follow. In order to solve this local minimum problem, an improved version of TEB was proposed [18]. With this improved version, TEB optimizes a globally optimal trajectory parallel to the multi-objective optimization problem that it already solves. The algorithm switches to this new globally optimum solution when necessary, and this way the local minimum problem of TEB is solved.

Due to being numerous kino-dynamic constraints for a car-like robot, TEB has numerous weights for each constraint and effects of weights on the generated trajectory depends on other weights. For this reason, optimizing TEB planner parameters requires good understanding of the concept, attention and controlled experiments. In this project, in order to simplify this process, initial values of the TEB planner was optimized in simulation environment and final configuration fine-tuned in real time tests. The results showed that while MIT RACECAR can avoid obstacles smoothly with TEB planner, the planner still requires more tuning for getting better results while driving narrow areas.
Figure 3.7: Flowchart of TEB Algorithm [9]
3.3 Artificial Potential Field Method

Artificial Potential Field (APF) Method is a basic approach for trajectory planning that is widely used by both industrial and academical applications. APF basically creates artificial attractive vectors that diverts vehicle to the goal position and repulsive vectors from obstacles that diverts vehicle from obstacles. Basically, addition of these attractive and repulsive vectors results in a target direction and speed for the vehicle.

\[ U(q) = U_{\text{attractive}}(q) + U_{\text{repulsive}}(q) \]  

(3.1)

And additionally, magnitudes of these vectors are defined by user. By tuning these magnitudes, the user can tune how close the robot will navigate through obstacles. With the help of this simple calculation, APF calculates how much it should divert from current heading.

As an addition to determining target orientation of the vehicle, speed of the vehicle can be calculated with the help of APF method by the density of obstacles. Simply, the density of obstacles determines the targeted velocity for the vehicle.

\[ V = V_{\text{max}} - K_{\text{gain}} \cdot n_{\text{obstacles}} \]  

(3.2)

**Figure 3.8**: Basic trajectory generation of APF Method

APF method has a very basic approach for trajectory planning. And this approach provides a non-complex solution to the problem with less computational costs. The
main reason for choosing this method is this direct approach, but it has some problems that we will discuss in the next chapter.

3.3.1 Problems of APF Method

The main problem with the APF method is the local minimum problem. Similar to the previous version of TEB algorithm, APF can get stuck in local minimum points. As it can be seen in figure below, when repulsive forces from obstacles are equal in both directions, it calculates the resultant vector as the vehicle moves towards to the obstacle. This can result in a collision for the vehicle. Another problem of the APF method is Goal Non-reachable with Obstacles Nearby (GNRON) problem. In such cases that the goal point is near an obstacle, the repulsive force from the obstacle can prevent the robot from reaching the goal point by resulting in a local minimum that is close to the goal point.

These two problems are primary problems of APF method and various solutions are proposed like Evolutionary APF [28], Fuzzy APF [29] as modified APF algorithms.

![Figure 3.9: Goal points with GNRON and local minimum problem][1]

While implementing APF to the MIT RACECAR, these problems were solved by implementing a local minimum detection method. This method, simply checks the calculated repulsive and attractive forces and if it determines that the robot is stuck in a local minimum point, it adds a vector that will divert the vehicle from going towards to the obstacle.
4. Testing and Results

Real life experimentation of trajectory planning algorithms on MIT RACECAR requires additional work. Until this part, MIT RACECAR platform is inspected by its hardware and software. Also, numerous helper package of ROS is expressed and how trajectory planning algorithms can be applied. For the real time testing of different trajectory planning algorithms, there should be a measurement for determining how well the algorithm works. For that purpose, an environment was set up in Artificial Intelligence and Intelligent Systems(AI2S) laboratory. As the scenery, a double lane curvy road with obstacles in different locations was chosen. MIT RACECAR was expected to stay in lane and when it encounters to an obstacle, to pass the obstacle by changing the lane.

As a result of the chosen scenery, it is needed to detect lanes on the road. For achieving this, ZED Camera was used for image processing. Image processing in this project is achieved by OpenCV library. An image processing algorithm that detects lanes and returns goal points was designed with Python. Goal points are generated from detected lanes with respect to the look ahead distance that is determined by velocity of the vehicle dynamically.

Another aspect of the project is obstacle detection. Obstacle detection is done with the help of RPLidar A2 2D lidar. RPLidar provides users a ROS package that handles communication between computer and lidar and publishes obstacle information as a ROS topic. Lastly, all of these outputs are given to the path planning algorithm as target points and obstacles.

4.1 Test Environment

In order to create the required environment, a double lane curvy road was draw on the floor of AI2S Laboratory by electrical tapes. While making the road for MIT RACECAR, constraints like width of the vehicle, minimum turning radius of the vehicle are considered. Also, it is tried to avoid environmental effects like flare on
the floor because of the lights. Since, the reference is being obtained from image processing, the flare is changing the quality of the reference signal in a bad manner and causes the vehicle to go out of the lane.

Also, the turning radius is an important constraint in such small environments, especially when obstacle avoidance is required. Thus, the curvature of the road was tried to be kept small enough to turn but also, big enough to see the limits of the algorithm.

Double lane structure of the road was chosen for lane changing when encountered by an obstacle. This structure also provides a good use case like lane changing and overtaking problems as future works. Besides, the middle lane of the road was chosen red in order to provide easier recognition of the lane. Since red color is easy to recognize with color filters like HSV, this provides a good starting point for the lane detection and leaves more time to focus on trajectory planning algorithms. The most painful part of the generated scenario for this study was that the changeable light conditions in the environment had a serious effect on the lane recognition algorithm’s performance.

![Testing environment image](image)

**Figure 4.1**: Testing environment
4.2 Lane Detection Algorithm

Lane detection algorithm, which is a crucial part of the scenery that is chosen for the project, will be explained in this section. Lane detection algorithm consists of OpenCV functions that will not be explained since it is out of the scope of the project. The algorithm is designed to have two main parts for its being modular and easy to understand.

![Figure 4.2: Main structure of the lane detection algorithm](image)

The first part of the algorithm, the pre-processing part, is responsible for extracting lane information from camera input by eliminating everything except lanes itself from the image. The first idea for the algorithm was based on the idea to extract black lanes and red lane individually. For this purpose, a complex image processing algorithm that can be seen in Figure 4.3 was proposed. However, the computational cost of this proposed method was not affordable for Jetson TX2. As a result of this problem, feedback loop of the system is updated only on 5-8 times average in one second and this situation was resulting in a hard control problem and slow response system.
In order to overcome these problems, a new, more plain algorithm that can be seen in Figure 4.5 was proposed. The idea of the new algorithm is that it is not needed to find all the lanes individually, it is only needed to find red lane which is easier to find respectively. As a result, the new proposed method is less accurate but more effective and faster, and this loss of accuracy is a neglectable amount.
The pre-processing part of the algorithm uses mainly HSV masking, morphological operations and filtering contours based on sizes and area. The flow of the algorithm with an example input image can be inspected in Figure 4.5.

![Example output of pre-processing image with stages](image)

**Figure 4.5**: Example output of pre-processing image with stages

The second part of the algorithm takes the binary image that is the output of the pre-processing part as input. This part of the algorithm firstly takes the perspective transformation of the lane image to the Bird-Eye view. After taking transformation, the contour information of the image is extracted and applied some filtering again. After all of these processes, a basic second degree polynomial is fit for the lane. This is required because in some cases, only a small part of the lane is visible and the coordinates of the target point at the look ahead distance is required for path planning. Additionally, some coordinate transformations is applied to the target point and the point is passed as output of the lane detection algorithm. The flow of the entire algorithm can be seen in Figure 4.6 and an example output of the lane detection algorithm is also can be seen in Figure 4.7.
Figure 4.6: The flow of the entire lane detection algorithm
Figure 4.7: An example output of the lane detection algorithm
4.3 Testing and Results

In this chapter, an overall qualitative assessment of the trajectory planning algorithms is given. This assessment relies on how successfully the vehicle followed the lanes, how many obstacles the vehicle pass through without collision and some special comments on the algorithm behavior. Since there is no global position data source in AI2S laboratory environment, an overall numeric error can not be calculated.

While testing the algorithms, it is tried to keep the environment same for all the algorithms. Nevertheless, some environmental circumstances like lighting condition can be changed. During the testing a Rviz is used which can be seen in Figure 4.8 for visualizing the vehicle condition from the vehicle’s perspective, global plan and local plan that is manipulated by trajectory algorithm.

![Figure 4.8](image)

**Figure 4.8** : An example Rviz view with global plan (red) and local plan (purple)

In addition, how the trajectory planning manipulates the target points which are determined by lane detection can be seen in Figure 4.9. At the top side of the figure, how the vehicle sees the environment can be seen and below the image from camera and lane detection algorithm can be seen. While the red arrow is the output of the lane detection algorithm, the purple arrows indicates the planned trajectory that will avoid the obstacle without leaving the road.
Figure 4.9: An example view that trajectory planning is running (red arrow is the output of the lane detection, the purple arrows are the planned trajectory)
The final assessment about the trajectory planning algorithms can be inspected in Table 4.1. But as a matter of fact, it should be said that this assessment is only according to the chosen scenery, it is not about which trajectory planning algorithm is better than the others. Besides, determining which algorithm is superior to others depends on the application scenery. As a conclusion, artificial potential field algorithm has better results according to the project requests and it is chosen to continue to the project with APF algorithm from now on. Since it provides reasonable performance with low cost, when considered possible future development of the project, the APF method is chosen.

| Trajectory Planning Algorithm       | Obstacles Avoided | Comments                                                                                                                                                                                                 |
|-----------------------------------|-------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Dynamic Window Approach           | 5 out of 7        | DWA planner is easy to implement and tune. Its performance was acceptable and stable. Also, while avoiding obstacles, it could stay in the course, but sometimes, its effort was not enough to avoid obstacles. Also, it gets stuck in complex situations like narrow pass ways |
| Time-Elastic Band Planner         | 7 out of 7        | TEB planner is very successful to model the vehicle, and it is suitable for complex environments. But, it is very hard to tune effectively and sometimes having so many parameters to tune is turning into a disadvantage instead of an advantage. Also, since it heavily relies on an optimization problem, computational cost gets very high, especially in complex environments. |
| Artificial Potential Field        | 5 out of 7        | APF is the easiest to implement and tune by far. Thanks to its basic logic based on simple math, it provides an acceptable result with low cost. And also, in line with the application scenery that is selected for this project, it is not too much deviates the vehicle from the road. |

Table 4.1: The assessment of the experiments of the trajectory generation algorithms
5. Conclusion and Future Works

Path planning algorithms are gaining more and more importance as autonomous vehicles become more widespread and important nowadays. There are many types of path planning applications used as the navigation unit of autonomous vehicles or for security purposes in semi-autonomous vehicles. In this project, which aims to implement and test a few of the path planning applications in real-time, a testing environment was first established and an image processing-based lane tracking algorithm was developed for this environment as reference signal to the vehicle. After the test environment was created, DWA, TEB and APF methods were implemented and tested separately. Since problems such as overtaking will be studied in the later parts of the project, it is of great importance to choose an algorithm that is predictable and low in cost. For this reason, it was deemed appropriate to continue the next stages of the project with APF. However, this does not mean that APF is better than others. However, all route planning applications have advantages and disadvantages over each other.

In addition, in the next stages of the project, it is aimed to establish an end-to-end neural network structure and to carry out an end-to-end control with this structure. It is aimed to give sensor data such as camera and lidar as input to neural network and to obtain control signals such as vehicle speed and steering angle.
REFERENCES

[1] NVIDIA, NVIDIA JETSON TX2, https://www.nvidia.com/tr-tr/autonomous-machines/embedded-systems/jetson-tx2/.

[2] StereoLabs, StereoLabs ZED Stereo Camera, https://www.stereolabs.com/zed/.

[3] Slamtec, RPLidar A2 Lidar, https://www.slamtec.com/en/Lidar/A2.

[4] Snider, J.M. et al. (2009). Automatic steering methods for autonomous automobile path tracking, Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RITR-09-08.

[5] Le, A.V., Prabakaran, V., Sivanantham, V. and Mohan, R.E. (2018). Modified a-star algorithm for efficient coverage path planning in tetris inspired self-reconfigurable robot with integrated laser sensor, Sensors, 18(8), 2585.

[6] Open Robotics Foundation, DWA Local Planner, http://wiki.ros.org/dwa_local_planner.

[7] Open Robotics Foundation, Costmap 2d, http://wiki.ros.org/costmap_2d.

[8] Zheng, K. (2017). Ros navigation tuning guide, arXiv preprint arXiv:1706.09068.

[9] Rösmann, C., Feiten, W., Wösch, T., Hoffmann, F. and Bertram, T. (2012). Trajectory modification considering dynamic constraints of autonomous robots, ROBOTIK 2012; 7th German Conference on Robotics, VDE, pp.1–6.

[10] Triharminto, H., Wahyunggoro, O., Adji, T., Cahyadi, A. and Ardiyanto, I. (2016). A novel of repulsive function on artificial potential field for robot path planning, International Journal of Electrical and Computer Engineering, 6(6), 3262.

[11] Clements, L.M. and Kockelman, K.M. (2017). Economic Effects of Automated Vehicles, Transportation Research Record, 2606(1), 106–114, https://doi.org/10.3141/2606-14, https://doi.org/10.3141/2606-14.

[12] Clements, L.M. and Kockelman, K.M. (2017). Economic effects of automated vehicles, Transportation Research Record, 2606(1), 106–114.

[13] Organization, W.H. et al. (2018). Global status report on road safety 2018: Summary, Technical Report, World Health Organization.
[14] **Clearpath Robotics Inc.** Jackal Small Unmanned Ground Vehicle, [https://clearpathrobotics.com/jackal-small-unmanned-ground-vehicle/](https://clearpathrobotics.com/jackal-small-unmanned-ground-vehicle/).

[15] **Open Robotics Foundation.** TurtleBot2, [https://www.turtlebot.com/turtlebot2/](https://www.turtlebot.com/turtlebot2/).

[16] Karaman, S., Anders, A., Boulet, M., Connor, J., Gregson, K., Guerra, W., Guldner, O., Mohamoud, M., Plancher, B., Shin, R. and Vivilecchia, J. (2017). Project-based, collaborative, algorithmic robotics for high school students: Programming self-driving race cars at MIT, *2017 IEEE Integrated STEM Education Conference (ISEC)*, pp.195–203.

[17] Vadakkepat, P., Tan, K.C. and Ming-Liang, W. (2000). Evolutionary artificial potential fields and their application in real time robot path planning, *Proceedings of the 2000 Congress on Evolutionary Computation. CEC00 (Cat. No.00TH8512)*, volume 1, pp.256–263 vol.1.

[18] Rösmann, C., Hoffmann, F. and Bertram, T. (2017). Integrated online trajectory planning and optimization in distinctive topologies, *Robotics and Autonomous Systems*, 88, 142–153.

[19] Wang, J.G., Lin, C.J. and Chen, S.M. (2010). Applying fuzzy method to vision-based lane detection and departure warning system, *Expert Systems with Applications*, 37(1), 113–126, [https://www.sciencedirect.com/science/article/pii/S0957417409004400](https://www.sciencedirect.com/science/article/pii/S0957417409004400).

[20] Srivastava, S., Lumb, M. and Singal, R. (2014). Improved Lane Detection Using Hybrid Median Filter and Modified Hough Transform.

[21] Chen, C.Y., Chen, C.H. and Dai, Z.X. (2012). An evolutionary computation approach for lane detection and tracking, *Advanced Science Letters*, 9(1), 342–347.

[22] Karaman, S., Anders, A., Boulet, M., Connor, J., Gregson, K., Guerra, W., Guldner, O., Mohamoud, M., Plancher, B., Shin, R. et al. (2017). Project-based, collaborative, algorithmic robotics for high school students: Programming self-driving race cars at MIT, *2017 IEEE integrated STEM education conference (ISEC)*, IEEE, pp.195–203.

[23] Traxxas, Traxxas Slash 4x4 Rally Car, [https://traxxas.com/products/%20models/electric/74076rally](https://traxxas.com/products/%20models/electric/74076rally).

[24] Sparkfun, 9DoF Razor IMU, [https://www.sparkfun.com/products/14001](https://www.sparkfun.com/products/14001).

[25] NVIDIA, JetPack, [https://docs.nvidia.com/jetson/jetpack/index.html](https://docs.nvidia.com/jetson/jetpack/index.html).

[26] Gasparetto, A., Boscariol, P., Lanzutti, A. and Vidoni, R., (2015). Path Planning and Trajectory Planning Algorithms: A General Overview, Springer International Publishing, Cham, pp.3–27, [https://doi.org/10.1007/978-3-319-14705-5_1](https://doi.org/10.1007/978-3-319-14705-5_1).
[27] Brock, O. and Khatib, O. (1999). High-speed navigation using the global dynamic window approach, Proceedings 1999 ieee international conference on robotics and automation (Cat. No. 99CH36288C), volume 1, IEEE, pp.341–346.

[28] Qixin, C., Yanwen, H. and Jingliang, Z. (2006). An evolutionary artificial potential field algorithm for dynamic path planning of mobile robot, 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, pp.3331–3336.

[29] Stoian, V., Ivanescu, M., Stoian, E. and Pana, C. (2006). Using artificial potential field methods and fuzzy logic for mobile robot control, 2006 12th international power electronics and motion control conference, IEEE, pp.385–389.
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