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QUACH HAI THO

RESEARCH DEVELOP SOME SOLUTIONS SUPPORTING THE CONTROL OF AUTONOMOUS VEHICLES

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Supervisors: 1. Assoc. Prof. PhD Huynh Cong Phap

2. PhD Pham Anh Phuong

Reviewer 1:

Reviewer 2:

Reviewer 3:

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INTRODUCTION

1. OVERVIEW

The revolution in science and technology taking place every day is comprehensively and profoundly changing people's lives and production processes. In particular, the field of automotive technology with autonomous vehicles cars is an area that is being developed by researchers. Autonomous vehicles use a variety of techniques and devices to detect the surrounding environment, from which the control system will analyze the information received from the surrounding environment to adjust the appropriate and very useful direction of traveling in planning a path to a desired destination.

Some issues are raised: How should autonomous vehicles be designed to be able to move to the destination in a complex environment with obstacles, traffic regulations, arising cases in the process of participating in traffic ... and can perform responses in all cases to reduce traffic accidents.

2. URGENTITY OF THE DISSERTATION

Although there are many methodological problems with autonomous vehicle research, the challenge faced and the task that is of interest to researchers in the field of autonomous vehicles is to create an optimal motion trajectory. The trajectory will include certain criteria such as creating a smooth and slippery movement, creating comfort and achieving good energy efficiency. At the same time, it must meet the limitations arising during the operation of the vehicle such as regulations on road traffic laws, external environmental factors and diverse and complex situations that we often encounter in traffic conditions. Although there have been many studies directed to this topic, these are still open research issues, topical and attracting the attention of the research community. In Vietnam, autonomous technology is classified as high technology and encouraged by the Government, creating a mechanism for development, but the results achieved are still limited.

With the analysis of the actual situation, along with the desire to contribute to the development in the field of autonomous vehicle technology, I have researched and implemented this dissertation. Through the topic conducted within the framework of the doctoral dissertation majoring in information systems, it will solve some outstanding issues in order to improve the safety, ensure the legality and ethics in the operation of autonomous vehicles. Specifically, the dissertation researches and develops some control support solutions by building control decision support modules in autonomous vehicles. The topic of the dissertation has scientific and practical significance. Its approach is to solve under the optimal control of mathematics and soft computing – tools that are suitable for the research context and existing conditions.

3. OBJECTIVES OF THE DISSERTATION

The overall goal of the dissertation, in order to support safe vehicle control, is to study a solution to effectively operate autonomous vehicles through intelligent control, find the optimal route in which legal factors and ethics are taken into account. The research results of the dissertation can serve as a premise to develop some modules on autonomous vehicles to improve performance and improve safety features during the operation of autonomous vehicles.

The specific goal of the dissertation is to research and develop some solutions to support safe control as well as ensure legal and ethical factors, with modules built as motion planning module, control decision support module, motion control support module, motion tracking control module and contingency motion planning module.

The proposed solutions for research and development are as follows:

- Proposing a motion planning solution using a sampling technique-based approach to generate the optimal trajectory from the set of trajectory candidates. The goal of this solution is to not only improve computational efficiency, but also deal with uncertainty in environmental data.

- Proposing solutions to ensure legal and ethical factors for the operation of autonomous vehicles by establishing motion trajectories and control decision-making models. Based on ethical and legal factors, 02 modules will be built, including a module for setting motion trajectories with a set of constraints of road traffic laws and a control decision support module with elements of driver ethics to control the operation of autonomous vehicles.

- Proposing a solution to support safe control for autonomous vehicles, including a motion control support module, a motion tracking control module and a contingency motion planning module.

The objectives listed above also describe the scope and research object of the dissertation. The research method implemented in the dissertation is a theoretical research method combined with experiment, simulation and evaluation to evaluate the effectiveness of the proposed solution.

4. CONTRIBUTION OF THE DOCTORAL DISSERTATION

The first contribution of the dissertation is to propose a motion planning method using a sampling technique-based approach with the aim of improving computational efficiency and handling uncertainty in environmental data. This technique is simple, effective with information obtained from sensor signals and navigation systems.

The second contribution of the dissertation is to build a module to solve the problem of decision support for autonomous vehicles with a set of constraints that are regulations on road traffic laws and drivers' ethics. This control support module includes a solution for setting motion trajectory and control decision-making model.

The third contribution of the dissertation is to improve the safety features for autonomous vehicles by building a set of modules to support decision making for safe control including the following modules: the first module is control motion tracking, the second module is for motion control support, and the last one is a contingency motion planning module.

5. STRUCTURE OF THE DOCTORAL DISSERTATION

The content of the dissertation includes the introduction, the content consisting of 4 chapters and the conclusion, as follows:

Chapter 1. Overview of autonomous vehicle control

In this chapter, in order to have a basis for building a control support solution in the operation of autonomous vehicles, in addition to an overview of autonomous vehicles with the process of building, developing and determining the level of hierarchy according to autonomous vehicle operation, I will present the problems that exist and then provide solutions to build support modules. These are the objectives to be achieved of the dissertation.

And to solve the problems proposed by the dissertation, this chapter will present the preparatory knowledge as a theoretical basis to solve the proposed problem, including: building mathematical models, methods of solving problems to be studied and the related research results.

The content of this chapter is in the author's articles 3, 4 and 9

Chapter 2. Proposed solutions finding the optimal path for autonomous vehicles

This chapter will present an overview of techniques for setting up paths for autonomous vehicles. Analyze and evaluate the advantages and disadvantages of each technique to serve as a basis for building an optimal path-finding module for autonomous vehicles using sample-based techniques. This motion planning module solves the problem of generating optimal trajectories, achieving computational efficiency and dealing with uncertainty in environmental data.

The content of this chapter is in the author's articles 9 and 11.

Chapter 3. Proposed solutions to legal and ethical issues of autonomous vehicles

This chapter will address legal and ethical issues in the operation of autonomous vehicles with a system of 02 modules, including:

- Motion planning module with constraints set of road traffic laws to solve legal problems when participating in traffic of autonomous vehicles.

Control decision support module with a set of constraints is built from the driver's behavioral characteristics. This module will solve the problem of driver ethics applied to the modular system of autonomous vehicles.

The content of this chapter is in the author's articles 5 and 7.

Chapter 4. Proposed solutions to support safe control of autonomous vehicles.

Based on existing problems with solutions, set goals, along with theoretical basis and mathematical tools presented in chapter 1, this chapter will build a set of modules to improve efficiency and support safe control of autonomous vehicles, with a system of 03 modules, including:

- Motion tracking control module will solve the problem of navigation control with the desire that the vehicle's movement is accurate and stable.
- Motion control support module solves diverse and complex situations commonly encountered in traffic environment conditions.
- The contingency motion planning module solves situations that ensure vehicle safety when participating in high-speed traffic.

The content of this chapter is summarized based on the research results of the author's articles 1, 2, 6, 8 and 10.

The last part are some conclusions of the dissertation.

CHAPTER 1
OVERVIEW OF CONTROL OF AUTONOMOUS VEHICLES

This chapter will present an overview of autonomous vehicles, the process of building, developing and determining the level of hierarchy according to the operation of autonomous vehicles. To solve the problems posed by the dissertation, this chapter will present the preparatory knowledge as a theoretical basis, including: building mathematical models, methods to solve the problems that will be studied and the related research results.

1.1 Overview of autonomous vehicles

1.2 Existing problems and solutions for the processing module system in autonomous vehicles

1.2.1 Existing problems

Motion planning or route setting is an important component of determining vehicle movement. It will provide the autonomous vehicle with a route to the desired points to be safe and avoid collisions, the motion planning process will perform calculations including: determining the path, the dynamics of the vehicle. vehicle, its maneuverability in the face of obstacles, rules and traffic systems. Setting the path is not only about moving to the final destination, but the difference in setting the route of an autonomous vehicle is that the execution of the motion plan depends on the network of traffic rules and the rules of the road. situations that may arise in the public transport environment.

Analyze the problems that exist in the system of processing modules and then study to come up with solutions. That is also the goal that needs to be done in this dissertation. Specifically, it is necessary to develop the following modules: Optimal pathfinding module for autonomous vehicles, a module that addresses the legal and ethical issues of autonomous vehicles, and safety control support module for autonomous vehicles.

1.2.2 Ways to solve the remaining problems

To solve the remaining problems, this dissertation will give specific solutions for each module as follows:

- Solution for Module 1: Build a motion planning module using a sampling technique-based approach.
- Solution for Module 2: Building an autonomous vehicle legal and ethical problem-solving module, consisting of component modules: The module for setting motion trajectories solves the legal problem autonomous vehicle management and the driver decision support module addresses the ethics of autonomous vehicles.
- Solution for Module 3: Building a safe control support module for autonomous vehicles, including component modules: Motion control support module, tracking control module motion and the contingency motion planning module.

1.3 Knowledge of preparation

1.3.1 Lane representation and vehicle dynamic model building

1.3.2 Monte Carlo Simulation and Particle filter

1.3.2.1 Monte Carlo Simulation

1.3.2.2 Particle filter

1.3.3 Overview of Model Predictive Control

1.3.3.1 Model prediction control and objective function construction

1.3.3.2 Motion planning based on predictive control model

1.4 Conclusion of chapter 1

Chapter 1 presents an overview of the literature on research issues for autonomous vehicle systems, including the formation and development of autonomous vehicle systems, processing module systems, some difficulties as well as a thorough examination of a series of recent studies in this area. These issues are used as the basis for building modules to improve the operation process in planning the motion of autonomous vehicles in this dissertation.

The content presented in this chapter shows that many problems still exist in the study of motion planning of autonomous vehicles. However, because the research scope of the dissertation focuses mainly on the process of improving the operational efficiency of control support modules, the module enhancing safety features in the transition planning process for autonomous vehicles, so the dissertation will focus on proposing methods to solve important problems as set goals, specifically as follows:

- Develop a plan for motion planning using a sampling technique-based approach. This technique is simple, effective with information obtained from sensor signals and navigation systems. The solution for building this motion planning module is presented in chapter 2.
- Building a module to solve the problem of supporting decision-making for autonomous vehicles based on the aspects of road traffic laws and drivers' ethics. This proposed solution is presented in chapter 3.
- Build a module to improve safety features for autonomous vehicles, by building a set of control support modules including the first module to control motion tracking, the second module to support motion control assistant and the last module is the contingency motion planning module. The specific content of this solution to build 03 modules will be presented in Chapter 4.

CHAPTER 2
PROPOSED SOLUTIONS FOR FINDING THE OPTIMAL PATH FOR AUTONOMOUS VEHICLE

This chapter will present the solution to find the optimal path for autonomous vehicles by building a motion planning module based on sampling technique to solve the problem of creating an optimal trajectory, achieving computational efficiency and handling uncertainty in environmental data.

2.1 Overview of techniques for setting up paths for autonomous vehicles

Motion planning in autonomous vehicles has been a topic of research for decades. Most studies divide the problem into two directions including global plan and local plan. Motion planning techniques can be divided into four groups: graph search, sampling based, interpolation curves and optimization methods.

2.1.1 Motion planning based on search graph

2.1.2 Motion planning based on sampling

2.1.3 Motion planning using interpolation curves

2.1.4 Motion planning by optimal method

2.1.5 Comparing the pros and cons of motion planning techniques

The synthesis and analysis of motion planning techniques of autonomous vehicles from two perspectives:

1. Evaluation and classification of various technical factors in the process of building a motion plan, including: Graph search, pattern-based, interpolation and optimization methods.

2. Reviewing the results of research groups around the world that have implemented the motion planning technique on autonomous vehicles from simulation to reality.

From the things mentioned above, it can be seen that, the research team uses two main algorithms: interpolation and search in the graph.

2.2 Building a motion planning module based on sampling technique

2.2.1 Statement of problems

To find the optimal path for the self-propelled vehicle of this dissertation, I propose a solution to build a motion planning module by sampling technique based on the structure of the Particle filter. This motion planning module has the set goal of not only improving computational efficiency, but also dealing with uncertainty in the proposed vehicle system and environment data.

2.2.2 Motion planning solution

The motion planning solution is implemented based on sampling technique, so the trajectory candidates are managed iteratively to generate the trajectory. The element filtering process is applied to manage the candidates effectively. In this motion planning process, four main steps are used: candidate time update, environmental data update, trajectory selection, and motion target resample. In these 4 steps, trajectory candidate time update and environmental data update are designed to account for the uncertainty of positioning data and environmental data during motion planning. In addition, the moving target re-sampling step is intended to improve computational performance by managing the moving targets of trajectory candidates.

Specifically, the steps are as follows:

a. Initialization

Initialize the motion target (s_0^i, n_0^i) and the weight q_0^i of the trajectory candidates is set according to the value of $\mathcal{N}$ of the trajectory candidates which is important impact on computational performance in sample-based planning; Therefore, the consideration to come up with some $\mathcal{N}$ of suitable trajectory candidates is a problem that computational solutions in motion planning must take into account.

Given the $\mathcal{N}$ value of the trajectory candidates, the initial moving targets (s_0^i, n_0^i) are uniformly chosen along the vehicle's straight axis, and the q_0^i weights of each trajectory are initialized as the following: $q_0^i = 1/\mathcal{N}$

b. Update trajectory candidate time

Do the same as updating the time in the Particle filter operation. However, the timing updates of the trajectory candidates made with the system model designed for vehicle motion are:

$$\begin{bmatrix} X_k^- \\ Y_k^- \end{bmatrix}_e = \begin{bmatrix} X_{k-1}^+ \\ Y_{k-1}^+ \end{bmatrix}_e + \Delta T\, v_{k-1}^+ \begin{bmatrix} \cos(\theta_{k-1}^+) \\ \sin(\theta_{k-1}^+) \end{bmatrix} \tag{2.1}$$

Where: $[X \;\; Y]_e^T$ is the vehicle position defined in Cartesian coordinate system, ΔT is the system update interval, v is the speed and θ is the steering angle.

Trajectory candidates are sets that include updated path and motion information to connect from vehicle position to each moving target; because the path information including position (X, Y), angle θ and curvature κ of the trajectory candidate is a representation of the vehicle's motion along the road.

The end result to be obtained are trajectory candidates which can include an updated set of trajectory nodes and non-stationary motion information.

c. Update environmental data

In order to increase the weights for each candidate trajectory located in the lane, the geometry of the path with the adaptability p_r is defined as follows:

$$p_r\left(z_k | \mathcal{X}_{i,k}^{j-}, m\right) = \begin{cases} exp\left(-\dfrac{\left|n_k^{j-} - n^{tar}\right|^2}{2\sigma_t^2}\right) & , \quad if \;\; \left|n_k^{j-} - n^{tar}\right| < 0.5W_{lane} \\ g_{o_\beta} exp\left(-\dfrac{\left|n_k^{j-} - n^{o_\beta}\right|^2}{2\sigma_{o_\beta}^2}\right), & if \;\; \left|n_k^{j-} - n^{o_\beta}\right| < 0.5W_{lane} \\ 0 & , \quad if \;\; \left|n_k^{j-}\right| > n^{bou} \end{cases} \tag{2.8}$$

where n^j is the lateral position of the jth trajectory node; n^{tar} is the lateral position of the destination lane; n^{o_β} is the lateral position of the other β^{th} lane; n^{bou} is the lateral position of the line boundary, σ_{o_t} is the target probability distribution; σ_{o_β} is the probability distribution of the other β^{th} lane.

In this study, it is assumed that the environmental data system feeds the processing system a static obstacle map and a dynamic obstacle list from the data of the sensors.

d. Trajectory selection

Trajectory selection is done based on updated weights of trajectory candidates, the final trajectory T_k^+ at time step k is chosen in the trajectory selection step. To choose the optimal trajectory, we find the maximum value of the inductive evaluation method:

$$T_k^+ = \underset{T_k^+}{\operatorname{argmax}}\left[\hat{q}_k^i\left(T_k^{i-}\right)\right] \tag{2.13}$$

where argmax is the function to find the candidate trajectory T_k^+ of the domain $\hat{q}_k^i$ at which the value is maximal.

e. Resampling a moving target

This moving target re-sampling step is performed if the condition $N_{eff} = \frac{1}{\sum_{i=1}^{N}\left(q_k^i\right)^2} < \mu N$ [71]; where N_{eff} is the effective number of candidates, representing the concentration of the weights; μ is the threshold rate and is a factor designed to be used for determining the frequency of a resampling operation.

If resampling is specified, then two types of moving targets are reconstructed: fixed moving targets and random moving targets. To test the safety of all lanes, a fixed-motion target is created in the center of each lane, and very few moving targets are reconstructed as a fixed-motion target; which most moving targets are reconstructed by applying low variance sampling technique based on the weights of trajectory candidates, this technique has low computational complexity and good spatial coverage of the sample space.

2.2.3 Experimental assessment

The solution built in this module is based on random sampling technique, so the same experimental cases can still have different results. In order to ensure objectivity and reliability when evaluating, the experimental simulation in Matlab environment is conducted many times in the same scenario. The simulation scenario is conducted on straight and curved roads with small corners, as follows:

Scenario 1: This scenario is conducted on a straight road (Figure 2.17).

Scenario 2: This scenario is conducted on the curve segment (Figure 2.18).

To evaluate the motion planning solution performance based on the Particle filter design, the motion planning process is performed based on this random sampling technique. This dissertation has applied the Monte Carlo simulation method with a test scenario that is repeated many times and performed simultaneously with the motion planning method using the RRT tree technique. The same test scenario is applied to both methods.

The quantitative evaluation of the solution will analyze the computation time and failure rate with the simulation scenario as the performance evaluation process. Each scenario tested 50 times for the Monte Carlo simulation. If the chosen trajectory causes a collision during the simulation, then this test case is marked as a failure case. The results are presented in Table 2.2.

As shown in Table 2.2, the execution time of the proposed solution is larger than that of using an RRT tree for the same number of candidates because this method needs to update the trajectory planning time and resample the local motion. However, the safety performance of this solution is higher, and this solution has a lower failure rate despite the small number of candidates because this solution repeats the process of changing the moving target using weights.

2.3 Conclusion of chapter 2

In this chapter, the theoretical basis presented is the path setting techniques that have been studied in the past time, thereby propose a solution to build a motion planning module based on the structure-based sampling technique of the Particle filter. This motion planning module has the set goal of not only improving computational efficiency, but also dealing with uncertainty in the proposed vehicle system and environment data.

As a result of the evaluation of safety conditions, the proposed solution has been effective and this motion planning method has created an optimal trajectory that allows an autonomous vehicle to drive along the road and avoid safe obstacles. To improve computational efficiency and consider the probability of uncertainty of environmental data and general trajectory positioning; then the performance of this proposed solution also depends on the probabilistic model of the system to generate adaptive fields. Therefore, probabilistic analysis and the method of representing the driving situation need to be more integrated for the application to the actual vehicle.

CHAPTER 3
PROPOSED SOLUTIONS TO LEGAL AND ETHICAL ISSUES IN AUTONOMOUS VEHICLE OPERATIONS

Based on the existing problem with solutions, objectives, along with the theoretical basis and mathematical tools presented in Chapter 1. This chapter will build a set of modules to solve legal problems and ethics in autonomous vehicle operations. This set of modules includes:

- The control decision support module to solve the ethical problem of the driver is applied to the module system of the autonomous vehicle, the constraint set is built from the behavior characteristics of the driver car.

- The module sets the motion trajectory with the set of constraints being the road traffic laws to solve the legal problem when participating in traffic of autonomous vehicles.

3.1 Building a control decision support module

3.1.1 Statement of problems

To solve the problem posed in the process of setting up this module, this problem must be solved in each specific situation, so that we can evaluate whether the decision to navigate behavior is consistent with ethical and legal rules.

Based on analysis and statistics with hundreds of survey questionnaires, interviews and combined with specific contexts of emergency situations, ethical indicators of decision-making about driving behavior can be classified into the following problems [53]: Abnormal target type; Abnormal number of targets; Abnormal target's special status; Protection priority.

In this problem, only the first two indexes are selected, namely the type and quantity of the anomalous target as the basis for research according to the principle of selecting ethical factors as follows: distinguishing pedestrians and vehicles, non-motorized vehicles, regardless of age, gender and vehicle's property value.

3.1.2 Building a mathematical model for the control decision support module

In order for the decision support module to process fuzzy information and have self-learning ability, this module will be built based on fuzzy neural network (FNN). The fuzzy neural network structure is divided into two subnets, including the Antecedent network layer and the consequential network layer (Figure 3.2). In each of these network layers will be divided into subnet layers.

The basic principle of FNN is to represent the degree of belonging $u_f(u)$ of each u element to a fuzzy subset f with specific numerical values, in order to be able to describe many fuzzy concepts quantitatively, then with specific rules as follows: Assuming $x = [x_1, x_2, \dots, x_n]^T$ as an input vector, each component x_i, is a fuzzy linguistic variable, then

$$R_f: If\ x_1\ is\ A_1^j, x_2\ is\ A_2^j, \dots, x_n\ is\ A_n^j\ Then\ y_j = p_{j0} + p_{j1}x_1 + \dots + p_{jn}x_n$$

Where R_j is the j^{th} fuzzy rule, A_i^j is the j^{th} linguistic value of the input variable x_i, y_i is the output value according to fuzzy rule p_{ji} is the fuzzy system parameter.

3.1.1.1 The Antecedent Network of FNN

the Antecedent network in this solution is divided into 4 sub-classes as follows:

Layer 1: Input layer

Layer 2: Fuzzification layer. In this study, Gauss's function is calculated as follows:

$$y = e^{-\frac{(x-c)^2}{\sigma^2}} \tag{3.1}$$

Where the parameters c and σ are central points of the function and the corresponding width of the Gauss function.

Layer 3: Rule layer, each node in this class corresponds to a rule, and this class is used to calculate the intensity of the weighted activation α_j of all fuzzy rules. The consecutive multiplication operator is calculated as follows:

$$\alpha_j = u_{A_1^j}(x_1) * u_{A_1^j}(x_1) * \ldots * u_{A_n^j}(x_n) \tag{3.2}$$

Where $u_{A_i^j}(x_i)$ is the corresponding membership function.

Layer 4: Normalized layer, which is the standardized layer, used to calculate the normalized activation intensity of the corresponding rules, the value of $\bar{\alpha}_j$ will receive the output value of the previous layer and then calculate the ratio as follows:

$$\bar{\alpha}_j = \frac{\alpha_j}{\sum_{i=1}^{m} \alpha_i} \tag{3.3}$$

3.1.1.2 The Consequent Network of FNN

The Consequent network in this dissertation is divided into 3 layers, including parallel subnets with the same network structure, each creating an output variable.

Layer 5: Input layer, to compensate the constant in the fuzzy rule, the 0th node of the input layer has the value $x_0 = 1$.

Layer 6: Function layer. Used to calculate the consequence parameters of the rules. Set the weight average input for unadjusted rules as follows:

$$y_{ij} = p_{j0}^{i} + p_{j1}^{i} x_1 + \ldots + p_{jn}^{i} x_n \tag{3.4}$$

Layer 7: Combined layer, is a rules combination, in this class, there is only 1 button that summarizes the output from the previous layer. The output value at this node is the sum of the values exported from the previous layer, calculated as follows:

$$y_i = \sum_{j=1}^{m} \bar{\alpha}_j y_{ij} \tag{3.5}$$

Where y_i $(i = 1 \ldots r)$ is the total weight of each rule. The output value of the antecedent network is used as the connection weight of layer 7.

Setting the learning parameters of the FNN network is mainly the weight of connection p_{ji}^{l} of the network effect and the central value C_{ij}, the width σ_{ij} in the membership function of each node in layer 2 in the Antecedent network.

3.1.3 Setting the parameters of module

In this dissertation, only gave out 16 impact indicators to design a survey questionnaire, an emergency interview that was posed for the problem of the street crossing at a traffic light with abnormal target. In this dissertation, the principal component analysis (PCA) was used to convert many correlation indicators into less linear correlations.

In order to evaluate the indicators, we conducted a survey to evaluate the effectiveness with 16 indicators, the number of samples generated was 500 samples, the number of effective questions of the indicators accounted for 95%. Through the analysis and processing of questionnaire data, the input variables of the model are defined as table 3.2.

The index set of decision-making modules shows that factors with a large correlation coefficient have an important impact on decision-making. Indicators of abnormal target types, the number of abnormal targets is related to moral issues, the remaining indicators relate to legal issues for vehicle operation on the road. However, for road markings, due to the situation given in this problem taking place at the stop line of the signal light, the road mark is the line with the regulation not encroaching on the other lane when moving, so this index is removed because it is not necessary. Finally, the variables input of the module only have 7 indicators.

For the output value of the decision model (OD). The emergency situation set out in this problem is that an autonomous vehicle is located in the middle lane and an abnormal target operates in front of the vehicles at the rudimentary lane for people and vehicles crossing the road. In this case, decision making for the direction of movement of the vehicle is divided into 3 situations: braking and going straight, braking and turning left, braking and turning right.

3.1.4 Experimental assessment

In order to ensure objectivity and reliability of the evaluating, we conduct the simulation with 6 different scenarios, in which the simulation scenario with case 1 is the traffic light signal in the green state to allow vehicles to move and ban objects across the street, and case 2 is a green signal light that has been lit for a period of over 30 seconds. In both cases of signal lights, the abnormal target selected for evaluation is pedestrians and rudimentary vehicles when crossing the street, the location of the abnormal target is the area of the runway in the lane for the pedestrian is divided into two positions: having crossed the center line or has not crossed the center line, the state of the abnormal target is considered to be standing still or moving.

With the data obtained through surveys and interviews to simulate, we evaluated and compared the decision-making model using back propagation neural network (BPNN). The assessment of the relationship between the factors affecting the decision and decision making of the model as in the study [51], specifically calculates and compares the mean absolute error values (MAE) and standard deviation (RMSE).

Ethical and legal factors have been considered quantitatively when developing the module, and applying PCA to identify the 7 main influencing factors that turn input and driver control decisions are developed to complete tasks in motion planning braking and go straight, braking and turn left, braking and turn must be counted as the output variable for the module. Therefore, a driver control decision module is established based on neural networks fuzzy (FNN). Experiments show that FNN's outputs are less accurate and erroneous than BPNN with moral and legal factors in the decision-making process.

Although this solution integrates moral and legal elements into the driver decision-making module, many limitations when the goal to achieve self-driving will not exactly reduce the child's behavior and in fact, reality problems arise when there is interaction between people and autonomous vehicles.

3.2 Building a motion trajectory establish module

3.2.1 Statement of problems

The main idea when building a motion trajectory solution is to use a model predictive control (MPC) method, in which the set of constraints is constructed as logical propositions, including constraints on legal and ethical issues of traffic behavior. Based on the provisions of Vietnam traffic law, we perform logical clauses to introduce the constraint set in traffic.

3.2.2 Building a model predictive control

With the idea of using the model predictive control and the first part of the proposed vehicle model with the state vector ω, control vector u as the basis for the research problem as follows:

$$\omega = \left[s_x, v_x, s_y, v_y\right]^T \text{ and } u = \left[a_x, a_y\right]^T$$

where s_x, s_y represent vertical and horizontal position, v_x, v_y are velocity and a_x, a_y are vehicle acceleration along the x, y axes of the vehicle in inertial frame.

Then the dynamic model of the vehicle is represented with zero matrices of proper dimension, as follows:

$$\dot{\omega}(t) = \begin{bmatrix} A & 0 \\ 0 & A \end{bmatrix} \omega + \begin{bmatrix} B & 0 \\ 0 & B \end{bmatrix} u \quad \text{where} \quad A = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \; B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \qquad (3.15)$$

In this problem, we make the assumption that the control vector u is a constant function at each time step τ. Therefore, the dynamical model of the vehicle is represented approximately with initial values including state vector $\omega(k)$ and control vector $u(k)$ in time interval $[k\tau, (k+1)\tau]$ as follows:

$$\omega(k+1) = \begin{bmatrix} A^d & 0 \\ 0 & A^d \end{bmatrix} \omega(k) + \begin{bmatrix} B^d & 0 \\ 0 & B^d \end{bmatrix} u(k) \quad (3.16)$$

where $A^d = \begin{bmatrix} 1 & \tau \\ 0 & 1 \end{bmatrix}$, $B^d = \begin{bmatrix} \frac{1}{2}\tau^2 \\ \tau \end{bmatrix}$

In order to achieve computational efficiency with the limitations of the vehicle's dynamic system as well as the provisions about motion direction when overtaking obstacles on the road, it is necessary to consider the constraints on the state $\omega(.)$, the input control signal $u(.)$ and the motion direction of the vehicle $\theta(.)$ must meet the following conditions so that when the motion trajectory is built.

In addition, in this problem we incorporate a set of constraints that are the provisions of the road traffic law. These provisions are considered as logical clauses and will perform the conversion into a set of linear inequalities with integer variables.

3.2.3 Objective function

To determine the objective function for this solution, we will introduce a new value vector variable $\delta(k) = \{0,1\}^m$ and δ_r, where $\delta(k)$ is a collection of all the binary variable results from the rebuilding the provisions of law on road traffic into linear inequalities and δ_r is the reference trajectory for the binary variables where we can make options on some binary states.

Thus, at time $t = 0$, the optimal problem of the model predictive control with the objective function can be written as follows:

$$\min_{u,\delta} J(\omega, u, \delta) = \sum_{k=0}^{K} \left(\|\omega(k) - \omega_r(k)\|_Q^2 + \|\delta(k) - \delta_r(k)\|_R^2 + \|u(k)\|_S^2 + \|\Delta u(k)\|_W^2 \right) \quad (3.35)$$

Conditions satisfied:

$$\omega(k+1) = \begin{bmatrix} A^d & 0 \\ 0 & A^d \end{bmatrix} \omega(k) + \begin{bmatrix} B^d & 0 \\ 0 & B^d \end{bmatrix} u(k) \text{ with } k = [0, \dots, K-1] \quad (3.36)$$

$$\omega(k) \in [\omega_{min}, \omega_{max}] \text{ with } k = [0, \dots, K] \quad (3.37)$$

$$\omega_{min} = \left[0, 0, s_{min_y}, v_{min_y}\right]^T \quad (3.38)$$

$$\omega_{max} = \left[\infty, v_{max_x}, s_{max_y}, v_{max_y}\right]^T \quad (3.39)$$

$$u(k) \in [u_{min}, u_{max}] \text{ with } k = [0, \dots, K] \quad (3.40)$$

$$u_{min} = \left[a_{min_x}, a_{min_y}\right]^T \quad (3.41)$$

$$u_{max} = \left[a_{max_x}, a_{max_y}\right]^T \quad (3.42)$$

$$\theta \in [\theta_{min}, \theta_{max}] \text{ with } \theta = arctan\,(v_y/v_x) \quad (3.43)$$

$$v_y(k) \in [v_x(k)\tan(\theta_{min}), v_x(k)\tan(\theta_{max})] \text{ with } k = [0, \dots, K] \quad (3.44)$$

$$\Delta u(k) = u(k) - u(k-1) \text{ with } k = [0, \dots, K] \quad (3.45)$$

$$C \begin{bmatrix} \omega \\ \omega_r \\ \delta \end{bmatrix} \leq D \quad (3.46)$$

where the matrices C, D, Q, R, S and W are positive weight matrices of proper dimension, the final constraint (3.46) is the set of all provisions of road traffic law into linear inequality is represented in matrices.

From the idea raised for this problem and in order to evaluate the effectiveness of the solution for the specific operating environment of the vehicle, the cost function is designed to optimize operational control with the initial condition that the vehicle velocity is constant and the horizontal deviation will change over time during the travel distance. Therefore, the expression $\|\delta(k)-\delta_r(k)\|_R^2$ in the optimal problem (3.35) will not be considered, so the cost function built in this study is given as follows:

$$J=\sum_{k=0}^{K}\Big(q_1(v_x(k)-v_r)^2+q_2(y(k)-y_r(k))^2+q_3\big(v_y(k)\big)^2+q_4(a_x(k))^2 \\ +q_5\big(a_y(k)\big)^2+r_1(a_x(k)-a_x(k-1))^2+r_2\big(a_y(k)-a_y(k-1)\big)^2\Big) \tag{3.47}$$

3.2.4 Experimental assessment

In order to ensure the reliability, objectivity and effectiveness of the solution, we have conducted simulations with different scenarios such as assessments on the roads with speed limit signs, determining the motion trajectory of the vehicle when there is an obstacle or a motion trajectory of the vehicle when overtaking in the same direction.

Scenario 1: In this scenario, the autonomous vehicle will move into a road with limited speed (Fig 3.5). During the simulation process, with the parameters shown, the construction of constraints according to Rule 7 (R7) is carried out.

The simulation results show that the movement speed of the vehicle from position T4 to position T10 according to the vehicle's planning of movement decreases below the speed of $\boldsymbol{v_r} \leq 40km/h$, so the motion controller has been effectively applied.

Scenario 2: In this scenario, the autonomous vehicle will move in the same lane with other vehicles and the autonomous vehicle will perform the right overtaking for the vehicle ahead (Fig 3.6). At the time of T3, the vehicle in front of the vehicle moved at a constant speed, in this situation, the vehicle would either self-drive or reduce the speed of $v_r \leq 30km/h$ or perform an overtaking operation or an accident will occur. During the simulation, we choose to overtake and to ensure that overtaking does not violate road traffic rules, autonomous vehicle must perform overtaking in accordance with Rule 2 (R2).

Scenario 3: In this scenario, the autonomous vehicle will move through an intersection, no traffic lights, no priority roads and no priority vehicles.

The simulation results show that the speed of the autonomous vehicle decreases when preparing to enter the intersection area and then returns to the original speed, while moving through the intersection after all other vehicles. For a comparative basis, we tried to change the position of the autonomous vehicle at the new positions (45.45). Observing the process, we realized that the autonomous vehicle moved through the intersection behind vehicle 1 and 2, but in front of vehicle 3 and the speed of vehicle 3 decreases when entering the intersection to make way for the autonomous vehicles to pass.

3.3 Conclusion of chapter 3

This chapter presents the theoretical basis with basic theories to build a motion planning solution with the constraints of current road traffic laws and presents a case for building a support module. Ethical decision-making support for drivers in emergency situations.

In the decision support module, ethical and legal considerations were quantitatively taken into account when developing the module and applying principal component analysis (PCA) to determine the main influencing factors as input variables and control decision making developed to accomplish the task in motion planning include: Brake and go straight, Brake and turn Left, Brake and turn Right are counted as variables output for this module. This navigational decision-making process is implemented using a hybrid model of fuzzy system and artificial neural network. This is also the founding element of the control decision-making module.

In the motion planning module with constraints are the road traffic laws. The main feature of this solution is to create the optimal trajectory with the model-based predictive control approach and the constraint set built from the road traffic laws. This approach is suitable for complex environmental conditions as these constraints can arise from different aspects of motion planning subject to traffic rules.

CHAPTER 4
PROPOSED SOLUTIONS SUPPORTING SAFETY CONTROL OF AUTONOMOUS VEHICLE

This chapter will present a solution to propose a control support tool, with the aim of creating safe movements for autonomous vehicles, meeting traffic conditions with diverse situations and in complex environments.

Building autonomous vehicle safety control support module with the following 3 modules:

- Motion control support module to solve the problem of creating a safe motion trajectory for autonomous vehicles, when encountering diverse and complex situations in traffic environment conditions.
- Motion tracking control module will solve the problem of navigation control with the desire that the vehicle's movement is accurate and stable.
- Contingency motion planning module to deal with situations that ensure vehicle safety when participating in high-speed traffic, the remaining processing time is too short to perform emergency braking to avoid the obstacles.

4.1 Rationale for building modules

In order to have a basis for building control support modules to improve safety features for autonomous vehicles as the original problem posed in this dissertation, we need to build linear models in autonomous vehicle structure as follows.

Building linear models: The most common linear method is to assume a small angle (when $\delta < 5^0$and $\cos(\delta) \approx 1$), the nonlinear dynamic model of the vehicle can be rewritten as follows:

$$\dot{\beta} \approx \frac{F_{yf} + F_{yr}}{mU_x} - r \tag{4.1}$$

$$\dot{r} \approx \frac{aF_{yf} - bF_{yr}}{I_{zz}} \tag{4.2}$$

However, in the case where the vehicle moves in a large curvature, the steering angle can be very large and thus assuming the small steering angle is invalid, the model is represented by (4.1) and (4.2) will not simulate the vehicle's response to the operating conditions of the vehicle.

Consider the following assumptions:

Assumption 1: Suppose increasing the steering angle is fixed at all steps on each predictive horizon and independent of the control sequence $u(.)$ ie:

$$\triangle\, \delta_a(k+i) = \Delta\delta_{N_P} \text{ with } i = 0, \dots, N_{P-1} \tag{4.3}$$

Where: $\triangle\, \delta_a(k+i)$ is the steering angle increase at step $i+1$ and $\Delta\delta_{N_P}$ is the corresponding fixed increase and will be determined later.

Assume 2: Assuming the vehicle will move to the desired destination at the step N_P of the predictive horizon, and then operate on the trajectory without deviation. Therefore, the operation of the vehicle at step N_P is assumed to be steady.

According to the above assumptions, the assumption of increasing the steering angle can be computed as follows:

$$\Delta\delta_a(k+i) = \frac{\delta(k)-\delta_a(k+N_P-1)}{N_P} \text{ with } i = 0, \dots, N_P - 1 \tag{4.10}$$

Thus, it can be seen that when the velocity of the vehicle changes, the driving angle increase is determined as follows:

$$\Delta\delta_{N_P} = \begin{cases} \Delta\delta_a & if \ |\Delta\delta_a| \le \Delta\delta_{max} \\ sign(\Delta\delta).\Delta\delta_{max} \end{cases} \tag{4.11}$$

and the assumed steering angle at each predicted horizon is:

$$\delta_a(k+i) = \delta(k) + i.\Delta\delta_{N_P} \tag{4.12}$$

with $i = 0, \dots, N_P - 1$

Combining (4.12) with (1.1) and (1.2) will have a new linear version for the nonlinear vehicle model as follows:

$$\dot{\beta}(k+i) = \frac{F_{yf}(k+i)\cos\big(\delta_a(k+i)\big) + F_{yr}(k+i)}{mU_x} - r(k+i) \tag{4.13}$$

$$\dot{r}(k+i) = \frac{aF_{yf}\,(\mathrm{k+i}).\cos\big(\delta_a(k+i)\big) - bF_{yr}(k+i)}{I_{zz}} \tag{4.14}$$

with $i = 0, \dots, N_P - 1$

Thus, the linear equations resulting for the motion equation are described as follows:

$$\dot{\beta}(k+i) = \frac{F_{yf}(k+i)\cos\big(\delta_a(k+i)\big) + \left[\bar{F}_r - \bar{C}_r(\beta(k+i) - \frac{b.r(k+i)}{U_x} - \bar{\alpha}_r\right]}{mU_x} - r(k+i) \tag{4.17}$$

$$\dot{r}(k+i) = \frac{aF_{yf}\,(\mathrm{k+i}).\cos\big(\delta_a(k+i)\big) - b\left[\bar{F}_r - \bar{C}_r(\beta(k+i) - \frac{b.r(k+i)}{U_x} - \bar{\alpha}_r\right]}{I_{zz}} \tag{4.18}$$

with $i = 0, \dots, N_P - 1$

In the motion model, creating small angle approximations for β and $\Delta\psi$ is as follows:

$$\Delta\dot{\psi}(k+i) = r(k+i) - U_x\kappa(k+i) \tag{4.19}$$

$$\dot{e}(k+i) = U_x(\beta(k+i) + \Delta\psi(k+i)) \tag{4.20}$$

$$\dot{s}(k+i) = U_x \tag{4.21}$$

with $i = 0, \dots, N_P - 1$

Since the assumption of velocity does not change on the predictive horizon, the longitudinal distance along the trajectory can take an axiom as follows:

$$s(k+i) = s(k) + \sum_{j=0}^{i} U_x \text{ with } i = 0, \dots, N_P \tag{4.22}$$

4.2 Building a motion tracking control module

4.2.1 Statement of problems

The Motion Tracking Control Module is built with the goal of controlling navigation with the expectation that the movement of the autonomous vehicle will be precise and stable. It also plays an important role in the task of controlling the movement of the vehicle, especially when the vehicle is operating at high speed. Specifically, the method designing this module is to incorporate time-varying uncertainties to moving obstacle predictions into the optimization problem, also providing constraints for boundary limits and moving obstacles while maintaining the vehicle's motion plan for a limited period of time.

4.2.2 Building a solution

The problem for this module is to use the initial course deviation for motion direction $\Delta\psi$ as a control reference state that does not increase the vehicle's capacity to the maximum level. The deviation $\Delta\varphi$ is the angle between the vehicle velocity vector and the direction of motion, indicating the true deviation of the vehicle's direction of motion and also the direction of the lateral deviation, when the side slip β is small and $\Delta\psi$ is close to the value of $\Delta\varphi$, the

$\Delta\psi$ - based controller can keep track deviation within a small range. However, when the difference between $\Delta\psi$ and $\Delta\varphi$ is large, especially close to the processing limit which the rear slip angle is high and the difference rate is high, the side slip value β is high. The controller based on $\Delta\psi$ will not minimize the tracking deviation, which is especially important when the vehicle moves through corners with a physical limit of wheel friction, in which the slope β of the vehicle can reach 5^0 and cannot be ignored at this level.

By using the zero-order hold a discretization method, we can take the discrete vehicle model from equation (4.17) - (4.22), as follows:

$$\mathrm{x(k+1) = A_c x(k) + B_{F_{yf}} F_{yf}(k)} + B_\kappa(k) + d_{\bar{\alpha}_r} \tag{4.24}$$

Where: $x = [\beta \quad r \quad \Delta\psi \quad e]^T$ is the state vector, and

$$A_c = \begin{bmatrix} \frac{-2\bar{C}_r}{mU_x} & \frac{2\bar{C}_r b}{m{U_x}^2} - 1 & 0 & 0 \\ \frac{2\bar{C}_r b}{I_{zz}} & -\frac{2\bar{C}_r b^2}{I_{zz}} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ U_x & 0 & U_x & 0 \end{bmatrix},\ B_{F_{yf}} = \begin{bmatrix} \frac{2\cos(\delta+i)}{mU_x} \\ \frac{2a\cos(\delta+i)}{I_{zz}} \\ 0 \\ 0 \end{bmatrix},\ B_\kappa = \begin{bmatrix} 0 \\ 0 \\ -U_x \\ 0 \end{bmatrix},\ d_{\bar{\alpha}_r} = \begin{bmatrix} \frac{2(\bar{F}_r + \bar{C}_r\bar{\alpha}_r)}{mU_x} \\ -\frac{2b(\bar{F}_r + \bar{C}_r\bar{\alpha}_r)}{I_{zz}} \\ 0 \\ 0 \end{bmatrix}$$

In the model building process, the design of safety constraints is determined by the limit of two important indicators of vehicle stability. According to the assumptions for the problem moving into a corner at steady state and the given wheel model, the limits of β and r reflect the wheel's maximum ability.

Thus, the optimal problem for model predictive control can be rewritten as follows:

$$\begin{aligned} \min_{\Delta F_{yf},\varepsilon_v} J_{N_P} &= \textstyle\sum_{i=1}^{N_P} \left(\eta(k+i)\right)^T Q\eta(k+i) + \sum_{i=1}^{N_C} R\left(\Delta F_{yf}(k+i)\right)^2 + W\varepsilon_v \\ &= \textstyle\sum_{i=1}^{N_P} \xi(k+i)^T C^T Q C \xi(k+i) + \sum_{i=1}^{N_C} R\left(\Delta F_{yf}(k+i)\right)^2 + W\varepsilon_v \end{aligned} \tag{4.32}$$

Satisfy the conditions:

$$H_v\xi(k+i) \le G_v + \varepsilon_v \ \text{ with } \forall i$$
$$\left|\Delta F_{yf}(k+i)\right| \le \Delta F_{yf,max} \quad with \quad i = 0, \dots, N_c - 1$$
$$\Delta F_{yf}(k+i) = 0 \quad \text{with} \quad i = N_C, N_C + 1, \dots, N_P - 1$$
$$\left|F_{yf}(k+i)\right| \le F_{yf,max} \quad \text{with} \quad i = 0, \dots, N_c - 1$$

Where $\Delta F_f = \left[\Delta F_f(k), \Delta F_f(k+1), \dots, \Delta F_f(k+N_C-1)\right]^T$ is a sequence of future input increases and $Q, R\ and\ W$ are weighted matrix with appropriate dimensions. $\Delta F_{f,max}$ and $F_{f,max}$ are the ability to change velocity and maximum lateral force.

Since $|H_v\xi(k)| \le G_v$ based on steady state assumptions, the vehicle status can exceed the limit and still return to the limit range after a short period of operation. To ensure that the optimal problem is always feasible, it is necessary to use the non-negative compensation variable ε_v, at this time the solution vector of the optimal problem in (4.32) is expanded as follows:

$$\Delta U^* = \left[\Delta {F^*}_{yf}, {\varepsilon^*}_v\right]^T \tag{4.33}$$

Whether or not the optimal input of the front lateral force is achieved depends on the first element of the following optimal solution sequence:

$$F^*{}_{yf} = F_{yf}(k-1) + \Delta F^*{}_{yf}(k) \tag{4.34}$$

In addition, the steering angle δ will be applied to the vehicle, by mapping $F^*{}_f(k)$ into the equation $\delta = \beta + \frac{ar}{U_x} - f_{wheel}^{-1}(F_{yf})$

4.2.3 Experimental assessment

To test and evaluate the proposed solution, we conduct experimental simulations of processes in Matlap environment. In order to ensure objectivity and reliability when evaluating, we conduct the simulation with 2 scenarios on 2 different path models (Figures

4.2a and 4.2b) designed with different curvature, road structure divided into 3 segments, in which the middle point of each segment is determined for comparison evaluation.

The simulation process is carried out with 3 motion controllers by different predictive models, including: linear controller, initial controller and proposed controller. In which the linear controller uses the steering angle as the control input, and uses the linear vehicle and wheel models. The original controller uses the vehicle dynamic model and the nonlinear wheel as shown. Another difference is that the controller used as a reference uses the initial deviation $\Delta\psi$ and the lateral deviation e as the reference state, the longitudinal controller and vehicle stability limit are used for all cases.

The simulation results show the absolute lateral deviation $|\bar{e}|$, standard deviation $\sigma(|e|)$ and the maximum value of the absolute lateral deviation $\max(|e|)$ of the linear controller are much higher than the other two controllers. In addition, the simulation results show that the steering angle of the linear controller continues to increase until it reaches the maximum level, as well as the lateral deviation continues to increase. The cause of this phenomenon is due to the linear model cannot predict the lateral force when the wheel reaches the non-linear region. On the other hand, controllers with the proposed dynamic model can maintain the lateral deviations in a small range. This shows that the proposed linear method in part 2 can keep nonlinear characteristics of the vehicles even in high velocity conditions.

The performance part of the original controller and the proposed controller are quite close. However, the value $||\bar{e}|$ and $\sigma(|e|)$ of the proposed controller is lower, but the max value $(|e|)$ is nearly the same. Thus, at a certain time, the front lateral force needed to reduce the minimum deviation that has overcome the friction force can be used and there will be no other problems when the motion controller can do to take the vehicle operation back to the desired motion trajectory with large lateral acceleration.

Finally, using the linear controller comparison method, the simulation results demonstrate that the proposed MPC controller with linear model can maintain a small deviation within small range, even under large lateral acceleration conditions. The analytical results show that the motion controller with direct deviation minimizes the average of the absolute lateral deviation from the controller with the head deviation, which proves that the proposed path-tracking controller can ensure accurate tracking and steady-state of vehicles under high-velocity that can be applied to motion problems for autonomous vehicle.

4.3 Building a Motion Control Support Module

4.3.1 Statement of problems

In order to meet safety standards when participating in traffic in a complex environment, control tools are an issue that needs attention to create safe movements for autonomous vehicles. We offer a motion control assistance solution to create a safe motion trajectory for the vehicle. The design of this control support system has two main goals: the first is minimal intervention - that is, applying autonomous control when necessary, the second is to ensure safety - meaning the vehicle's collision-free state is clearly enforced through optimal constraints.

4.3.2 Building a solution

This problem is built on two basic principles: the first is minimal intervention, the second is to ensure safety, meaning the probability of a collision involving the surrounding environment and other traffic objects must be below certain thresholds. And this problem is done in discrete time intervals $k \triangleq t_k$, with $t_k = t_0 + \sum_{i=1}^{k} \Delta t_i$ (t_0 is the current time, Δt_i is the i time step of the plan).

At each given state, each object will occupy one space $\mathcal{B}^i\left(z_k^i, \sigma_k^i, p_\epsilon\right) \subset \mathbb{R}^2$ having probability greater than p_ϵ (p_ϵ is the acceptable probability of collision that may happen), the model of the object and this occupied space are shown in Figure 4.4.

In this study, with the set of states $z_{0:m} = [z_0, \dots, z_m] \in \mathbb{Z}^{m+1}$ and input set $u_{0:m-1} = [u_0, \dots, u_{m-1}] \in \mathcal{U}^m$, we will build a general discrete time constraint optimization at m time steps with a time limit $\tau = \sum_{k=1}^{m} \Delta t_k$.

Thus, the goal of the solution is to calculate the optimal input values $u^*_{0:m-1}$ for autonomous vehicle with minimizing cost function $\hat{J}_h(u_{0:m-1}, u_0^h) + \hat{J}_t(z_{0:m}, u_{0:m-1})$.

This optimum problem follows a set of constraints: the first is to use the vehicle transition model, the second is the non-collision constraint with static obstacles and the third is the probability that no collision will occur p_ϵ with other traffic participants.

And the optimal trajectory of the vehicle is given as follows:

$$u^*_{0:m-1} = \underset{u_{0:m-1}}{\arg\min} \hat{J}_h(u_{0:m-1}, u_0^h) + \hat{J}_t(z_{0:m}, u_{0:m-1}) \quad (4.37)$$

where: $z_{k+1} = f(z_k, u_k)$; $\mathcal{B}(z_k) \cap \mathcal{O} = \emptyset$;

$\mathcal{B}(z_k) \cap \bigcup_{i\in\{1,\dots,n\}} \mathcal{B}^i(z_k^i, \sigma_k^i, p_\epsilon) = \emptyset$; $\forall k \in \{0, \dots, m\}$

$z_{0:m}^i$, $\delta_{0:m}^i$ with $i = 1, \dots, m$: are parameters for all other traffic objects, z_0 is the initial state of vehicle.

During the motion planning process, if the actual path deviates from the reference path, the delay error from the first approximation point in time progression to the next point and the position error referenced to the horizontal roads θ_k along the tangential path t_k are defined as follows:

$$e^{\sim l}(\boldsymbol{z}_k, \theta_k) = \frac{\boldsymbol{t}_k^T}{\|\boldsymbol{t}_k\|} \begin{bmatrix} x_k - x^P(\theta_k) \\ y_k - y^P(\theta_k) \end{bmatrix} = -cos\emptyset^P(\theta_k)\big(x_k - x^P(\theta_k)\big) - sin\emptyset^P(\theta_k)\big(y_k - y^P(\theta_k)\big) \quad (4.42)$$

When projected on the standard path between the actual position and the predicted position, we will determine the contouring error by the deviation of these two positions, as follows:

$$e^{\sim c}(z_k, \theta_k) = \frac{n_k^T}{\|n_k\|} \begin{bmatrix} x_k - x^P(\theta_k) \\ y_k - y^P(\theta_k) \end{bmatrix} = \sin\emptyset^P(\theta_k)\big(x_k - x^P(\theta_k)\big) - cos\emptyset^P(\theta_k)\big(y_k - y^P(\theta_k)\big) \quad (4.43)$$

and the contouring error is a standard for establishing good motion planning when the vehicle is in motion not deviated from a given reference path. Therefore, the cost function of predictive state control is built based on the balance between the contouring error factors $e^{\sim c}(z_k, \theta_k)$, delay error $e^{\sim l}(z_k, \theta_k)$ and the process of building approximate path v_k to achieve the best combination, as follows:

$$J_{av}(z_k, \theta_k) = e_k^T Q e_k - v_k \quad (4.44)$$

with path error vector formed from delay error and contouring error as follows:

$$e_k = \begin{bmatrix} e^{\sim l}(z_k, \theta_k) \\ e^{\sim c}(z_k, \theta_k) \end{bmatrix} \quad (4.45)$$

Because the relationship between the path and the direction of the vehicle is relative, we need to establish a constraint between the direction of the path $\emptyset^P(\theta_k)$ and the movemen direction of the vehicle $\emptyset_k$, as follows:

$$\|\emptyset_k - \emptyset^P(\theta_k)\| \leq \Delta\emptyset_{max} \quad (4.47)$$

In the general case, we propose a model for generating indeterminate positions of vehicles with uncertainty $\sigma_k = [\sigma_k^a, \sigma_k^b]^T$ at the time k and $\sigma = [\sigma^a, \sigma^b]^T$ is the uncertainty incurred. Therefore, the value of the variance is determined to approximate to adjust the direction of the vehicle motion aligning the main axis of the surrounding ellipse. The generation of indeterminate positions in the horizontal direction of the vehicle is limited by a maximum value to consider the maximum rationality of the maximum flow of vehicles currently in the current lanes.

As our goal of the solution in this research is to minimize the intervention of the driving, that is, the control system only intervenes with the steering operation when really necessary with the minimum intervention time:

$$J_h(z_k, u_k, u_0^h) = \begin{bmatrix} u_k^a - a_0^h \\ \delta - \delta_0^h \end{bmatrix}^T K \begin{bmatrix} u_k^a - a_0^h \\ \delta - \delta_0^h \end{bmatrix} \quad (4.52)$$

where $u_0^h = [\delta_0^h, a_0^h]^T$ is the inconsistent value of system state, δ^h is the steering angle value and a^h is the acceleration value at the time t_k.

Finally, the solution proposed is the optimization problem. It is done by the minimum factor combining linear between the cost of intervention into the system and trajectory cost, as follows:

$$J_{av}(z_k, u_k, \theta_k, u_0^h) = \beta\omega(t_k)J_h(z_k, u_k, u_0^h) + \big(1 - \omega(t_k)\big)J_t(z_k, u_k, \theta_k) \quad (4.54)$$

in which, the weight β and exponential decay function $\omega(t_k) = exp(-\alpha t_k)$ are used to enhance the input value for the system.

We have chosen the solution to make the weight β reach a high value, so that when moving forward in the predictive model, the system will be able to respond well to inputs but still depend on J_t. By doing so, the solution presented in this study can plan a full implementation without having to predict the planned motion trajectory. Therefore, the nonlinear optimization problem with constraints on state, dynamics, paths and obstacles is constructed as follows:

$$u_{0:m-1}^* = \arg\min_{u_{0:m-1}} \sum_{k=1}^{m} J_{av}\,(z_k, u_k, \theta_k, u_0^h)\Delta t_k \quad (4.55)$$

where: $z_{k+1} = f(z_k, u_k)$; $\theta_{k+1} = \theta_k + v_k\Delta t_k$; $z_k \in [z_{min}, z_{max}]$; $u_k \in [u_{min}, u_{max}]$; $\|\dot{\emptyset}_k\| < \dot{\emptyset}_{max}$; $\|\emptyset_k - \emptyset^P(\theta_k)\| < \Delta\emptyset_{max}$; $d(z_k, \theta_k) \in [b_l(\theta_k) + \omega_{max}\,, b_r(\theta_k) - \omega_{max}]$; $c_k^{obs,i}(z_k) > 1$, $i = \{1, \dots, n\}$; $\forall k \in \{0, \dots, m\}$

4.3.3 Experimental assessment

To test and evaluate the proposed solution, we have conducted empirical simulation of processes in the Matlap environment. At the same time, in order to ensure the objectivity and reliability when evaluating, we have conducted simulations with different scenarios and autonomous vehicles controlled moving with steering angle δ_0^h and desired acceleration a_0^h. Input variables will be handled using model predictive control to ensure generating safe movement, the reference path and the left boundary b_l, right boundary b_r are designed and determined accordingly with the road system.

***Scenario 1*:** In this scenario, the autonomous vehicle will move into a corner, with the input values for the control system will be able to make the vehicle's direction of travel out of the limit of traffic lanes.

***Scenario 2*:** In this scenario, the autonomous vehicle will implement the movement plan from the slip road and turn left to enter the main traffic lane, the initial positions and the speed of other traffic participants are initialized randomly.

During the experiment, we can see that the uncertainty in the predictive of other vehicles is very important because the future states of the predictive model can deviate from the desired predictive point. In the case of omitting uncertainty, the motion planning process needs to provide more precise and specific constraints to ensure the vehicle safety.

4.4 Building a contingency motion planning module

4.4.1 Statement of problems

The contingency motion planning is built to meet safety in all traffic situations. For this problem, the motion trajectories of other traffic participants need to be known in advance, thereby building the optimal path based on the assessment of the mobility of other traffic participants in a certain period of time. Each moving trajectory will calculate adaptive emergency maneuvers. This problem faces difficult challenges to solve such as: The presence of moving obstacles, the combined effect of internal dynamics and vehicle structure, planning cycle and inappropriate response time.

To solve the problem for the contingency motion planning module, the dissertation will implement a model-based predictive control solution approach combined with models of vehicle kinematics for modular construction.

4.4.2 Building a solution

A solution for the establishment of a contingency plan for the safety of the autonomous vehicle by building an optimal path based on the assessment of the mobility of other vehicles in a certain period of time, then with each motion trajectory will compute the adaptation emergency operations.

The first part of the predictive model is proposed as follows:

$$\dot{S}_x = v\cos\theta \tag{4.56}$$

$$\dot{S}_{\mathrm{y}} = v\sin\theta \tag{4.57}$$

$$\dot{\theta} = \frac{\vartheta}{l\left[1+\left[\frac{v}{v_{ch}}\right]^2\right]}\delta \tag{4.58}$$

$$\dot{\delta} = u_1 \tag{4.59}$$

$$\dot{v} = u_2 \tag{4.60}$$

Where: the notation $\dot{x}$ represents the first derivative of x; S_x, S_y and v are the reference position of the vehicle and the corresponding velocity; θ indicates the movement direction of the vehicle; δ is the steering angle of the wheel; velocity and time derivative of the vehicle velocity act as inputs u_1 and u_2 of the system.

This model has the following advantages: There is no singularity at $\mathrm{v} = 0$ and it allows the brake to stop completely, and the dynamic system is not rigid, so the simulation time step of the decoder has quite large size, so the optimal speed of the model increases.

In order to compute the drawbacks of the traction wheel, the driving system of the vehicle as well as the regulating direction when overcoming obstacle, some constraints need to be set when building the trajectory. The constraints set on state and input must meet the following conditions: $v \in [0, v_{max}]$, $u_2 \in [a_{min}, a_{max}]$, $\mathrm{u}_1 \in [\dot{\delta}_{\min}, \dot{\delta}_{\max}]$, $\delta \in [\delta_{\min}, \delta_{\max}]$, $\mathrm{d_r} \in [\mathrm{d_{r,min}}, \mathrm{d_{r,max}}]$ and $(\mathrm{S_y}, \mathrm{S_y}) \in \mathrm{lanes}$

However, instead of solving the optimal convergence problem on the left or right side of the obstacle, in this case it is necessary to introduce the constraints and regulations that are the constraints in front of the vehicle. Therefore, it is necessary to introduce additional variables $\xi_m(r), m \in 1 \ldots M$ used to denote the vector from the center of the obstacles to the location of the vehicle. Also, the predictive time $r \in T_{hor}$ needs dertemining.

$$t_{d_{min,m}} \coloneqq \underset{t}{\operatorname{argmin}}\, d_m(r) \tag{4.72}$$

At this point, the distance from the obstacle m to the vehicle of the smallest value $d_m(r)$ with $n(r)$ is the normal vector to the motion trajectory $\left[S_x(r), S_y(r)\right]^T$.

Thus, developing the formula for overcoming an obstacle using the dot product is as follows: The left (or right) obstacle movement depends on the value of $t_{d_{min,m}}$ if $\xi_m^T(r) > 0$ will override left or $\xi_m^T(r) < 0$ will override right. The construction of these constraints will provide effective and accurate obstacle avoidance operations, even if the vehicle must be stopped by obstacles ahead.

In order to achieve optimal trajectory, it is necessary to treat the cost function with a minimum value and at the same time the constraints need to be separated. For handling emergency situations of autonomous vehicles, the idea is to reduce the vehicle's speed of movement to a minimum.

Thus, the cost function J will be formulated by combining two components: the cost of motion and the cost associated with the obstacle as follows:

$$J(x, u_1) = J_{mov}(x, u_1) + J_{objs}(x) \tag{4.75}$$

Motion costs are calculated as follows:

$$J_{mov}(x, u_1) = \int_t^{t+T_{hor}} \left\{ u_1^2 + \sum_{i \in \{v,a,j,\theta,k\}} k_i \Delta_i^2(x, u_1) \right\} dr \tag{4.76}$$

The main idea to build a contingency motion planning consists of three stages:

Stage 1: Calculating the possibility of operating of surrounding objects to build the initial trajectory.

Stage 2: In order to ensure safety when moving in the initial motion trajectory, all possible trajectories of the vehicles ahead must be considered [54]. Therefore, for a certain period of time with any trajectories of vehicles ahead, the operating system of the autonomous vehicle can perform an emergency operation to stop the vehicle safely and the solving system turns to stage 3.

Stage 3: Implementing the evaluation the standards to assure its safety (distance to the vehicle ahead, the space generated by set of trajectories of the vehicle ahead), then the solving system will provide assessment if contingency trajectory should be performed or not for safety or continue to operate in the initial optimal trajectory (Fig. 4.11).

To calculate the most likely trajectory, comparing the current path and the center position of the lane should be performed to provide the most likely trajectory prediction for at each time point t_i in period of time T_{h1}. In addition, at each time t_i a polygon region generated by the trajectories representing each vehicle ahead will be calculated and these predictions are used as constraints in generating motion trajectories for autonomous vehicles.

In the interval T_{h1}, after the possible trajectories of the vehicles ahead are determined, the selection for generating the optimal trajectory will be performed and this trajectory generated with the main aim is to avoid collisions through reducing vehicle's speed and avoiding vehicle shake, jerk in order to create a smooth trajectory. Therefore, the cost function (4.75) is changed to control the deviation from the reference trajectory (the central location of each lane) and to avoid the predictions of the vehicle(s) ahead.

Thus, each vehicle ahead $OBJS_i$ $i \in \{1 \ldots n\}$ will have a space region prediction representing at each time i and constraints related to the distance between the generated trajectory and the predicted objects have to be considered to avoid collisions with vehicles ahead. The minimum distance d_i between the rectangle r_i surrounding the vehicle and the predictive area of the vehicle(s) ahead $OBJS_i$ is calculated at time i (Fig. 4.12) as follows:

$$d_i = \min_i distance\ (r_i, OBJS_i) \tag{4.84}$$

and the minimum distance d_i will be compared with a parameter λ to determine if there is a collision with the vehicle $OBJS_i$ or not, the minimum value of the cost function will minimize the variation of the speed and steering mode as follows:

$$J_1 = \int_t^{t+T_{h1}} [\gamma_1 u_1^2 + \gamma_2 u_2^2 + \gamma_3(\theta - \theta_r)^2 + \gamma_4 \delta^2 + \gamma_5 d_r^2]\, dr \tag{4.85}$$

Where: satisfies the conditions (4.55) - (4.60), (4.65) - (4.70) and θ_r is the direction of the reference trajectory; dr is the distance to the reference trajectory; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ are weighted parameters.

Thus, the cost function is built to produce the optimal trajectory described in (4.85) with the difference that velocity v decreases to a minimum over time T_{h1}:

$$J_2 = \int_{t}^{t+T_{h1}} [\gamma_1 u_1^2 + \gamma_2 u_2^2 + \gamma_3(\theta - \theta_r)^2 + \gamma_4 \delta^2 + \gamma_5 v^2]\, dr \qquad (4.86)$$

Where: satisfies the conditions (4.55) - (4.60), (4.65) - (4.70), $(S_y, S_y) \in lanes \backslash OBJS_i$ and θ_r are the direction of the reference trajectory; dr is the distance to the reference trajectory; $\gamma_{1,}\gamma_2, \gamma_3, \gamma_4, \gamma_5$ are weighted parameters.

4.4.2 Experimental assessment

In order to ensure objectivity and reliability of the evaluation, we conducted simulations with three different scenarios in which the first simulation scenario found motion planning without considering operations to generate contingency trajectories The others apply this operation with different parameters for a comparative assessment.

Scenario 1. When motion planning for autonomous vehicle, only the predicted trajectories of the vehicles ahead are calculated.

Scenario 2. With the same scenario as scenario 1, in this scenario, the motion plan of the autonomous vehicle is supplemented with actions to create contingency trajectory and predict motion ability of the vehicles ahead at every step of the time.

Scenario 3. In this scenario, two vehicles joining the traffic in front of the autonomous vehicle will be considered.

Since autonomous vehicles can move a significant distance in a short period of time (a fraction of a second), the time taken to perform calculations and suggested optimal solution cannot be ignored. Therefore, in the implementation process, the expected delay time according to prediction as in [1] and the stability of the predictive model should be applied, this nonlinear optimization problem can be realized sequentially [1] by the conventional Runge-Kutta method (RK2) with a step size of 0.02s.

4.5 Conclusion of chapter 4

This chapter builds a set of modules to support safe control of autonomous vehicles with 03 modules including: motion tracking module, motion control support and contingency motion planning for autonomous vehicles.

The main feature of the motion tracking module is that this solution is realized using a predictive control model, which is based on a linear model that allows for precise and desired motion direction tracking at high speed with controlled control. large lateral acceleration event.

The feature of the motion control support module is to shorten the motion planning cycle in order to minimize deviations from the forecast input, while ensuring safety according to the motion plan.

The last module is used for planning backup movements for the safety of autonomous vehicles, the optimum specification of this module is achieved by considering the likely trajectories of the vehicles upstream. before. The element of safety is achieved by maintaining a system to calculate every possible trajectory of the vehicles ahead in a given period of time.

CONCLUSION

The goal of the dissertation is to research and provide some supporting modules in the overall system of common modules in the operation control system for the purpose of enhancing operational performance and improving safety features for self-driving cars. The research results of the dissertation have some new results as follows:

1. Propose motion planning solution in motion planning module by sample-based approach to generate optimal trajectory from set of trajectory candidates. The goal is not only to improve computational efficiency, but also to deal with uncertainty in environmental data.

This improved solution is implemented based on sampling technique with recursive operation process and based on element filtering method, so the final trajectory of the candidates is selected by probability optimization schemes. Element filtering is applied in motion planning for efficient candidate management. This process uses four main steps: candidate time update, environmental data update, trajectory selection, and moving target re-sampling. In these four steps, trajectory candidate time update and environmental data update are designed to account for the uncertainty of positioning data and environmental data during motion planning. In addition, the moving target re-sampling step aims to improve computational performance by managing the moving targets of trajectory candidates.

2. Develop a mathematical model and methodology to provide a solution to set up 02 modules of motion trajectories and control decision-making models with elements that ensure ethical and legal aspects, in which the motion trajectory is established with a set of constraints that are regulations on road traffic laws.

The decision support module is a mathematical model of a decision-making system. It plays an important role in avoiding collisions and avoiding obstacles in motion. This module is said to be self-taught so it can be perfected during self-study. Therefore, the entire operation process of this module is separated into 2 separate parts, including: part 1 is a theoretical model that considers the influencing factors of decision making in emergency situation. Impact factors include vehicles participating in traffic, road systems, environmental factors, as well as legal and ethical issues. These factors are considered as input variables of the module and the output variables of this module determine the direction of vehicle movement. The second part is the data collection system made by survey, interview with emergency situations like the problem given for the purpose of providing training data for the module. In order for the decision support module to process fuzzy information and have self-learning ability, this dissertation has built a control decision-making module based on fuzzy neural network (FNN). The research results on the construction of this module are verified by computer simulation programming and evaluated and compared with back-propagation neural networks (BNN) to demonstrate the effectiveness of the proposed solution.

The module for setting motion trajectories is built based on the predictive model control (MPC) method, in which the set of constraints includes the legal and ethical constraints of the behavior of traffic participants. The information is constructed as logical propositions and performs the conversion to a set of linear inequalities with integer variables. In this dissertation, in order to solve the given problem and to evaluate the effectiveness of the solution for the specific operating environment of the vehicle, the cost function is built so that the operational control efficiency is maximized. The advantage is that the initial condition is that the speed of the vehicle is constant and the horizontal deviation of the vehicle will change with time during the travel distance.

Experimental simulation results with many different traffic scenarios for the module set the motion trajectory in order to determine the set goal of the solution, which is to create the optimal trajectory with the model-based predictive control approach and the constraint set built from the road traffic laws.

3. Develop methodology to design predictive controller for nonlinear system and propose new solutions in optimization strategy of predictive control of nonlinear system, namely building 03 support modules controller, consisting of the first module which is the motion control support module, the second module which is the motion tracking control module, and the last module which is the contingency motion planning module.

The construction of the motion control support module has two main goals: the first is minimal interference, which means that the motion control support system only applies autonomous control when necessary; the second is safety assurance, i.e., the collision-free state of the vehicle is explicitly enforced through optimal constraints.

Specifically for this motion tracking control module design solution is to incorporate time-varying uncertainties to moving obstacle predictions into the optimization problem, while also providing constraints for boundary limits and moving obstacles while maintaining the vehicle's motion plan for a limited period of time.

Finally, the contingency motion planning module aims to ensure the safety of the autonomous vehicle by building an optimal path based on the mobility assessments of other road users in the vehicle in a certain period of time, after which for each trajectories adaptive emergency maneuvers are calculated.

Experimental results are based on simulations conducted independently on each module, with different scenarios. The simulation process is conducted with motion controllers using different predictive models, with comparison and evaluation methods to check the effectiveness of the proposed solution.

In the future, in order to increase the reliability of this solution, the settings that have been tested by simulation will be transferred to the real environment with the experimental vehicle fully equipped with sensors, and when the actual experiment will add some factors to analyze the stability of the system so that the traffic behavior of the objects is predicted more accurately. Widespread deployment of this driver assistance solution to semi-autonomous or fully autonomous vehicles in vehicle control systems will be able to reduce a large number of damages as well as create a safe movement plan for the future.