A solution to ethical and legal problem with the decision-making model of autonomous vehicles

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***Abstract* - With the development of autonomous vehicles technology, the ability to avoid appropriate obstacles to ensure safety and improve the effectiveness on transportation has been increased. However, not all collisions can be avoided and autonomous vehicles play as an identification of making ethical and legal decisions in emergency situations. In this article, the problem will be presented regarding the ethical and legal issues included in the decision-making model in an emergency situation, with indicators related to the operating environment considered to be indicators of cooperation in the car navigation behavior and the model's input variable to be built.**

Keywords—Autonomous vehicle, fuzzy logic, neural network, path planning, motion planning, intelligent transportation systems.

I. INTRODUCTION

In an intelligent autonomous system, autonomous vehicles will perform the operation in a thoughtful and accurate manner, including perceptions of the surrounding environment, motion planning, operational decisions...[4]. In these issues, the process of handling and decision-making in operations to be able to handle in complex operating environments requires appropriate mathematical models [7].

An important challenge for the problem of decision-making support is the limitation on identification models and obstacle detection, but most of the obstacles are due to encounter blind spots, light reflections, weather conditions and sensor error [2]. Therefore, some collisions will inevitably occur in situations.

Few studies focus on the issue of decision-making support in vehicles in these emergency situations. The design of a drive assistance system in an emergency situation also faces difficult situations of ethical and legal problems. In encounter such problems, it is difficult to get consensus in making decisions when facing situations that need to be sacrificed.

In general, the problem of making decisions about car navigation behavior has been studied with many different methods such as using neural networks [9], decision-tree models [12], support vector regression [13], fuzzy set theory [1], expert system and Petri network.

The combination of the final state of fuzzy logic and the self-learning ability of neural networks have created fuzzy neural networks that has the ability to deduce uncertain knowledge and the ability to self-study have retained necessary advantages. Therefore in this paper, we use a combination model between fuzzy system and artificial neural network (FNN) to establish and make decisions to navigate the movement of vehicles.

On the other hand, the parameters in FNN have clear physical meaning and can be acknowledged according to human experience so the convergence rate of the problem is significantly improved. Besides with simple computation ability, it handle well with large number of training samples and at the same time with adaptive learning ability, FNN continuously fixes the parameters through self-study.

For driving behavior decision, both moral and legal factors must be considered and cannot be ignored. In addition, this problem must be solved in a specific situation so that we can assess whether the decision of vehicle navigation behavior is suitable to ethical and legal rules or not. Therefore in this paper, we limit the consideration and resolution of problems only in the case of motion planning at the location of traffic signals.

The next section of the article will present the emergency situation taking place at the traffic signal, then the driving decision-making models will be established in this situation to ensure the legality and morality. Next, we introduce the experiment for the decision-making model and conduct the evaluation by analyzing empirical data. Finally is the conclusion with some suggestions for further research.

II. ANALYSIS ON EMERGENCY SITUATION REGARDING MORAL AND LEGAL FACTORS

In this article, the emergency situation that we provide to solve the problem is the pedestrian road crossing behaviors at traffic signal lights, the objects crossing the road may be pedestrians, vehicles without engines. These objects are called as as abnormal targets and the behavior causing emergency situations is described as follows: when the traffic signal light changes from Red to Green, vehicles in traffic are allowed to move pass the red lights. However the abnormal situation is that instead of stopping at the zebra crossing in accordance with the regulations, the abnormal targets continue to move and cross the road. With this behavior, there is a possibility of a collision. As illustrated in Figure 1, the autonomous vehicle is the middle one. The bus moving to the left has limited visibility without detecting an unusual target crossing the road. This time is about to occur emergency and danger situation.

To address the situations caused by unusual goals, in this article, we make decisions on vehicle handling behavior based on the driver's ethical issues. The ethics mentioned here are the principles, norms and orientations of social values that are recognized. The ethical values are considered to help the autonomous vehicle achieve safety factors when they operate in defense, actively avoid accidents, be ready to respond to dangerous situations and comply with road traffic laws. For autonomous vehicles treating as a human during operation, a module is required to analyze the standards of internal values and external behaviors of the driver [8]. This is considered as moral values and they are converted into indicators for the input values in machine learning model.

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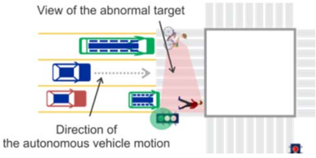

Figure 1. Emergency and danger situation in traffic

Based on the analysis and statistics with hundreds of questionnaires, interviews and combined with specific contexts of emergency situations, moral indicators of making decision on vehicle handling behavior, we can classify into the following issues [8]: Abnormal target types, Number of abnormal targets, Special states of the abnormal targets, Level of protection priority.

In fact, when analyzing and examining the above-mentioned indicators, the size and complexity of the problem of decision-making on car navigation behavior will increase significantly. At the same time, due to differences in the perception of each individual person, there will be disputes in the selection of specific indicators. Therefore, in this paper, we choose the first two indicators, the type and number of the abnormal targets as a basis for studying according to the principle of selecting moral factors as follows: distinguish pedestrians, vehicles without engines, regardless of age and gender and regardless of brand or value of the vehicle.

For legal issues, there is currently no legislation on autonomous vehicles operation in traffic in Vietnam, so in this study we base on the current legal documents for the legal analysis of traffic accident responsibilities. Specifically, once there is a collision at a traffic intersection with a signal light is determined whose responsibility for traffic accidents with the following cases:

1. In an emergency situation, if the signal light turns green and allows the vehicle to move but the abnormal target has crossed the center line and is on the lane for pedestrians, the autonomous vehicle must be obliged to give way and avoid collisions.

2. If the green lights are already during a period of time and the abnormal object does not cross the middle of the zebra crossing, then the responsibility is determined according to specific situations.

The judgment of responsibility when colliding with an abnormal target while moving across the stop signal line and changing lanes is determined as follows: if the decision to change lanes is given in risk conditions, it is determined as emergency risks. If the decision made that can ensure the total damage due to change of direction and the possibility of collision is smaller than not changing lanes, the decision to change the lane will be allowed and the party causing the dangerous situation must bear full responsibility.

III. BUILDING MATHEMATICS MODEL FOR CONTROL DECISION-MAKING PROBLEM

Based on the information obtained from the surrounding environment, after analyzing logical reasoning, the central control system makes decisions for controlling operation for autonomous vehicles. In particular, the control decision-making module is the mathematical model of the decision-making system. It plays an important role in avoiding collisions and avoiding obstacles when moving. It makes decision on using information of the situation, information of the surrounding environment system through sensors to detect emergency situations as reported in this article. Then, the decision-making system will classify and predict the behavior of the targets in situations according to a specific classification (Figure 2).

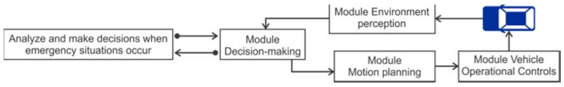

Figure 2. Vehicle control system

Module vehicle operational controls is said to be capable of self-study, so that it can be completed during self-study. Therefore, the entire operation of this module is separated into two separate parts, part 1 is a theoretical model, which consider the impact factors of decision making in emergency situations with behaviors of abnormal targets [14]. Factors including vehicles, roads, environmental factors, as well as ethical and legal issues are considered input variables of the module vehicle operational controls, and the output variables of this module is to determine the vehicle's movement direction. The second part is the data collecting system, which is done by surveys, interviews and virtual driving simulation with emergency situations such as the problem given with the purpose of providing training data to the module.

However, when analyzing moral and legal factors, some unclear concepts still exists to build input indicators to describe control decisions. In this study, for the module makes fuzzy information processing decisions and self-study, we will establish a decision-making control module based on Fuzzy Neural Network (FNN) and conduct an evaluation, compared with Backpropagated Neural network (BNN) to prove the effectiveness of the proposed solution.

By combining the deductive ability of fuzzy logic and self-learning ability of artificial neural networks to form fuzzy neural network (FNN), it has created a powerful tool capable of solving the problem uncertain and nonlinear math. Since the results of fuzzy rules are a nonlinear equation, in the process of handling multivariate systems, the number of fuzzy rules can be effectively reduced. At the same time, in combination with an easier self-adaptive method, this solution is widely used in the field of intelligent control and decision making.

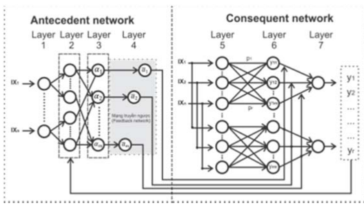

Figure 3. Neural - Fuzzy network structure (FNN)

The basic principle of FNN is to represent the degree belonging to $u_f(u)$ of each u element to a fuzzy subset f with specific numerical values. The specific rules are able to describe many fuzzy concepts quantitatively as follows:

Assuming $x = [x_1, x_2, \dots, x_n]^T$ denotes 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 jth 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.

III.1 The Antecedent Network of FNN

According to research [5], the Antecedent network in this solution is divided into 4 sub-layer as follows:

Layer 1 (Input layer): Containing the input nodes. These values are transmitted directly to layer 1. The number of nodes is determined by the number of inputs and is used to transmit each input variable.

Layer 2 (Fuzzification layer): Each node in this layer is associated with a member function of each direct input variable from layer 1. The output value of each layer in this level is the fuzzy value of the node import. In this study, Gauss's function is computed as follows:

$$y = e^{-\frac{(x-c)^2}{\sigma^2}} \quad (1)$$

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 layer corresponds to a rule. This layer is used to compute the intensity of the weighted activation α_j of all fuzzy rules. The consecutive multiplication operator is computing as follows:

$$\alpha_j = u_{A_1^j}(x_1) * u_{A_1^j}(x_1) * \ldots * u_{A_n^j}(x_n) \quad (2)$$

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

Layer 4 (normalized layer): is the standardized layer, used to compute 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 compute the ratio as follows:

$$\bar{\alpha}_j = \frac{\alpha_j}{\sum_{i=1}^m \alpha_i} \quad (3)$$

III.2 The Consequent Network of FNN

The Consequent network in this paper is divided into 3 layers, including parallel subnets with the same network structure. Each subnet creates an output variable.

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

Layer 6 (Function layer): used to compute the consequence parameters of the rules. Setting the input weight average for unadjusted rules as follows:

$$y_{ij} = p_{j0}^i + p_{j1}^i x_1 + \ldots + p_{jn}^i x_n \quad (4)$$

Layer 7 (Combined layer): is a layer combining rules. In this layer, 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, computed as follows:

$$y_i = \sum_{j=1}^m \bar{\alpha}_j y_{ij} \quad (5)$$

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.

The 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 is in the Antecedent network.

Assumming a given with the error cost function as follows:

$$E = 1/2 \sum_{i=1}^r (t_i + y_i)^2 \quad (6)$$

Where t_i is the desired output, y_i is the reality output. Therefore, the learning algorithm of parameter p_{ji}^l is:

$$\frac{\partial E}{\partial p_{ji}^l} = -(t_1 - y_1)\bar{\alpha}_j x_i \quad (7)$$

$$p_{ji}^l(k+1) = p_{ji}^l(k) + \beta(t_1 - y_1)\bar{\alpha}_j x_i \quad (8)$$

The structure of the FNN network can be simplified by adjusting the parameter p_{ji}^l. The simplified structure is also a multi-layer feed forward network. Therefore, we shifted the back propagation network (BPN) algorithm back to the algorithm to adjust the parameters performed as follows:

$$c_{ij}(k+1) = c_{ij}(k) - \beta \frac{\partial E}{\partial c_{ij}} \quad (9)$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - \beta \frac{\partial E}{\partial \sigma_{ij}} \quad (10)$$

IV. SETTING THE PARAMETERS FOR MODULE CONTROL DECISION-MAKING

Base on the study [10] with the classification of factors affecting decision making, along with the moral and legal factors presented. We only gave out 16 impact indicators to design a questionnaire, an emergency interview that was posed for the problem of crossing road at a traffic light of abnormal target.

Table 1. Regulating impact indicators

No	Index	Interpretation content
1	V_A	velocity of autonomous vehicle
2	B_A	braking capability of autonomous vehicles
3	D_A	distance between the vehicle and obstacles
4	T_A	type of the right-lane autonomous vehicle
5	V_B	velocity of the right-lane
6	L_A	road line shape
7	W_A	lane width
8	RM_A	lane pattern
9	TR_A	duration of signal light
10	WE_A	weather conditions and visibility of the autonomous vehicle
11	AT_A	type of abnormal targets
12	AN_A	number of abnormal targets
13	AS_A	state of abnormal targets
14	AV_A	velocity of abnormal targets
15	θ_A	angle before collision
16	DA_A	damaged area

For input variables, if the number of inputs is small, the too simple model will not be able to accurately reflect the rules that determine the control process. Or if the number of input variables is too many and the interaction relationship is other influencing factors will increase the complexity of decision-making model and training time. In this study, the principal component analysis (PCA) was used to convert many correlation indicators into less linear correlations [6].

In order to evaluate the given indicators, we conducted a survey to evaluate the effectiveness with 16 indicators. The number of samples handed out 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 2.

Table 2. Indicators set of decision module

No	Index	Interpretation content
1	V_A	velocity of autonomous vehicle
2	D_A	distance between the vehicle and obstacles
3	V_B	velocity of the right-lane
4	RM_A	lane pattern
5	TR_A	duration of signal light
6	AT_A	type of abnormal targets
7	AN_A	number of abnormal targets
8	AS_A	state of abnormal targets

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 and the number of abnormal targets relate to moral issues. The other indicators relate to legal issues for operating vehicles on the road. However, for road markings indicators, due to the situation given in this problem taking place at the stop line of the signal light, the road mark is the line regulated not to encroach on the other lane when moving, so this indicator is removed because it is not necessary. Finally, the input variables of the module remain only 7 indicators which will be specified constraints as in Table 3.

Table 3. Input variable set of decision-making module

Var	index	Constraints according to regulations
IX_1	V_A	If $V_A \in [0,50km/h] \rightarrow \forall IX_1$ Conversely, remove IX_1
IX_2	D_A	Computing from the center of each object in situations, regardless of the height of the vehicles.
IX_3	V_B	If $V_B \in [0,50km/h] \rightarrow \forall IX_3$, Conversely, remove IX_3
IX_4	TR_A	If $TR_A \in [0,30s] \rightarrow IX_4 = 1$ Conversely, then $IX_4 = 2$
IX_5	AT_A	If AT_A as passengers, then IX_5=1 If AT_A as motorless vehilces, then IX_5=2 Conversely, then IX_5=3
IX_6	AN_A	If the target number is AN_A=1 then IX_6=1. Conversely, IX_6=2
IX_7	AS_A	If the object state properly comply with traffic law IX_7=1, Conversely, then IX_7=2

For the output value of the decision model (OD). The emergency situation set out in this problem is that a autonomous vehicle is located in the middle lane and an abnormal target operates in front of the head of the vehicles at the lane for people and rudimentary vehicles crossing the road. In this case, decision making for the direction of movement of the vehicle is divided into 3 situations seen in Table 4.

Table 4. Output value of control decision model

Control decision	Index	Threshold	Output Threshold range
braking and going straight	OD_1	0.5	[0,1]
braking and turning left	OD_2	1.5	(1,2)
braking and turning right	OD_3	2.5	[2,3]

The value of OD_1 leads to the decision of braking and going straight, which means that the autonomous vehicle will move along the current lane while braking. With this decision the abnormal target will be injured, while the person on the vehicle and other vehicles on adjacent roads will be safe. The OD_2 values only decide to brake and turn left. This decision will make the vehicle turn left while braking. At this time the vehicle to the left lane of the autonomous vehicle will be at risk at the driving position but the autonomous vehicle goes the right lane and abnormal targets will be safe. The OD_3 value only decide to brake and turn right. With this decision, the car on the right lane will be in danger, but the autonomous vehicle and the abnormal target will be safe (this decision model is described as in Figure 4).

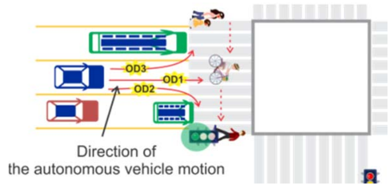

Figure 4. The feasible decisions of the movement navigation

V. EXPERIMENTS AND CONCLUSION

V.1 Experiment

After the process of building model with 7 input variables and 1 output variable, the next step will be the simulation to provide training samples and verify the elements of the module decision-making for vehicle operation control as the proposed initial objective.

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 that the traffic light signal has just turned green to allow vehicles to move and ban objects across the road. In case 2, the green signal light is on for a period of over 30 seconds. In both cases of signal lights, the abnormal targets selected for evaluation are pedestrians and rudimentary vehicles when crossing the road. The position of the abnormal targets is the zebra crossing for pedestrian and is divided into two positions: having crossed the middle road or not having crossed the middle road, the state of the abnormal target is considered to be standing still or moving.

Based on such number of experimental scenarios, the number of input variables IX_4, IX_5, IX_6 and IX_7 are used as the basis for the division of experimental contexts. After processing the data, the data of input variables IX_1, IX_2 and IX_3 relating to the velocity of the objects can be used to compute the decisions making.

In the experimental process, we chose 50 of the 500 participants to answer the questionnaire. They have more than 5-year experience in driving in the urban environment By taking the number of abnormal targets as a basis for statistics, with 3 types of decisions as presented (OD_1, OD_2, OD_3), deciding to brake and go straight takes up to 60%, deciding to brake and turn right accounts for 36%, only 4% decided to brake and turn left.

With the data obtained through surveys and interviews to simulate, we evaluated and compared the decision-making model using back propagation neural network (BPNN). With integrated system, clear algorithmic process with data identification and simulation function, backpropagation neural network is one of the popular learning algorithms with good ability to solve nonlinear problems [3,13]. The assessment of the relationship between the factors affecting the decision and decision making of the model as in the study [13], specifically computing and comparing the mean absolute error (MAE) value and root mean square error (RMSE). MAE can better reflect the actual situation of predictive error values, and its computing formula is as follows:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|f_i - y_i| \quad (11)$$

RMSE is used to measure the deviation between observed value and actual value, RMSE is computed as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}|f_i - y_i|^2} \quad (12)$$

Where f_i is the predictive value, y_i is the actual value and m is the number of samples.

Computing results are shown in Table 5.

Table 5. Comparison of FNN and BPNN

	FNN		BPNN	
	OD1	**OD3**	**OD1**	**OD3**
MAE	7.25%	10.8%	11.5%	15.5%
RMSE	0.004	0.008	0.009	0.15
Maximum absolute error	19.5%	17.5%	32.5%	29.5%

V.2 Conclusion

This article has proposed a decision-making module (DDM) to make control decisions for autonomous vehicle in emergency situations. The problem presented in this article is an emergency occurred at the location with traffic signal lights with the behavior of crossing the road when the green signal lights allow the vehicles to move. Ethical and legal factors have been considered quantitatively when developing the module, and applying PCA to identify the 7 main influencing factors as input variable. The driving control decision is developed to complete tasks in motion planning. Braking and going straight, braking and turning left, braking and turning right are counted as the output variable for the module. Therefore, module vehicle operational controls is established based on neural networks fuzzy (FNN). Combining the empirical questionnaire, we can analyze the causes of the above data as follows:

- Most of the interviewees and survey respondents said that breaking and turning left would have more serious consequences because when turning left the autonomous vehicle would hit directly into the abnormal target and at the same time it would collide the driving position of the vehicle on the left lane. This will cause greater damage when the left vehicle loses control from the driver.

- If the abnormal targets are pedestrians as well as a rudimentary vehicle and there is no discrimination in the number, then braking and going straight, braking and turning right will be the decisions to minimize the damage.

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 article integrates moral and legal elements into the driving control decision-making module, there are still many limitations when the goal to achieve is autonomous vehicles will not minimize accurately human behavior. And in reality, problems arise when there is interaction between people and autonomous vehicles.

Safety is always a top priority and therefore the first thing for manufacturers is to standard the criteria for autonomous vehicles. Unfortunately, autonomous vehicles are still not properly equipped the human instincts. That the autonomous vehicles make immediate decisions on when to reduce velocity, change direction or increase velocity, etc. is a big and never-ending challenge for manufacturers. The setting up a dynamic and real-time vehicle control decision module is necessary for the future research.

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