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RESEARCH ARTICLE

An Ethical Behavioral Decision Algorithm Awaring of VRUs for Autonomous Vehicle Trajectory Planning

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ABSTRACT The advancement in autonomous vehicle technology's independence and ethical considerations have led to the development of the field of machine ethics. The issue of ensuring the safety of autonomous vehicles for usage in real-world traffic is currently a topic of extensive discussion among society, industry, and the scientific community. Enabling autonomous vehicles to make ethical behavioral decisions is constantly emphasized. This work provides an ethical behavioral decision algorithm awaring of VRUs for autonomous vehicle trajectory planning to allocate risk during autonomous vehicle driving in a sensible manner. The principles include maximum acceptable risk, vulnerability risk adjustment, risk minimization, distance, and maximin. The methods led to a 90.6% decrease in average risk and a 95.18% decrease in cumulative harm in typical scenarios, with notable reductions in the highest roadway risk values. The simulation demonstrates that modifying the weight parameters can significantly impact the autonomous vehicle's driving characteristics. This work considers this ethical behavioral decision algorithm crucial for the widespread acceptance of autonomous vehicles.

INDEX TERMS Ethical behavioral decision algorithm, trajectory planning, autonomous vehicles, road risk.

I. INTRODUCTION

Recent technological advancements have brought autonomous vehicles (AVs) from theoretical concepts to practical applications in daily life. AVs can greatly influence transportation stress, safety, and efficiency [1]. However, various moral and ethical considerations must also be considered [2]. Some individuals contemplate a dilemma [3]. For instance, deciding how to allocate harm or risk among several individuals with opposing interests. Others consider common concerns that occur throughout normal driving. There is a significant ethical concern regarding the values that should be incorporated into the decision-making algorithm of AVs [4]. AVs must determine how to allocate risk among traffic participants in common traffic scenarios. This decision holds normative significance. Occasionally, unique dilemmas may require individuals to make the most significant ethical decisions [5]. Risk has become a significant worry in the realm of autonomous driving [6].

The following questions drive this research and highlight the significance of adhering to ethics in AV trajectory planning:

1. An AV is driving on a city road when a massive truck approaches in relative motion, and a person is cycling not far ahead of the AV. How can the AV ensure the cyclist's safety while also realizing its own? The algorithm must autonomously make logical decisions.
2. Pedestrians and cyclists are considered the most vulnerable road users (VRUs), accounting for 26% of road traffic fatalities. Research has illustrated that

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traffic injuries on the road are the primary cause of death among children aged 5-14 [7]. This raises a question that has to be focused on: what should be done to minimize road injuries in VRUs?

3. Various age groups exhibit varying degrees of vulnerability, and how to allocate risk appropriately to safeguard individuals with heightened vulnerability?

4. The equilibrium between safety and traffic efficiency must be evaluated. Increasing the safety distance reduces risk. However, if risk reduction is excessive, it can result in worse traffic conditions.

Some methods should be implemented to allow AVs to monitor risk during travel and make trajectory-planning decisions based on that risk. This work adopts an ethical behavioral decision algorithm awaring of VRUs to allocate risk efficiently and minimize risks for road users. This work quantifies risk and utilizes time-varying risk to address road-related issues more efficiently and promptly in real-time.

For pedestrian age recognition, there is an efficient multi-task model for pedestrian detection, tracking, and attribute recognition, which targets the understanding of pedestrians by AVs. The remaining 14 tasks in its second phase use high-resolution imagery. The JAAD dataset is used in the fourth training for joint training in multiple tasks and is capable of accurately and quickly recognizing attributes such as the age of pedestrians [8].

The innovations and contributions of this study are outlined below:

- Compared to other algorithms, the algorithm in this work shows significant reductions in average risk, cumulative harm, and highest risk on the road.
- This is the first time, as far as we know, that this work is grading populations according to their vulnerability. Age was used as the grading standard. This aligns more closely with the mainstream societal idea of safeguarding vulnerable populations. The third question presented in the previous paragraphs is solved here.
- This work allocates a higher cost factor to VRUs, which improves the safety of VRUs. The maximin principle in the method proposes to focus only on the highest harm without considering probability, which reduces the road harm of VRUs even more. The second question presented in the previous paragraphs is solved here.
- This work sets a reasonable maximum acceptable risk value. A value that is too small will prevent the AV from activating or keep it too far away from obstacles, while a value that is too large will compromise the AV's safety. By adjusting the weighting parameters of the four principles, it is possible to control the AV from engaging in risky costly behaviors. The first and fourth question presented in the previous paragraphs is solved here.

Subsequently, the article is organized as outlined below. Section II provides a summary of the relevant research. Section III will provide a detailed explanation of the methods. The results are evaluated in Section IV. A summary is finally created.

II. RELATED WORK

Risk and safety concerns in the AV industry have always existed. The methods or standards for managing risk are becoming more important. Extensive research and discussion have been carried out in connected realms. The following provides a summary of research on standards, laws, and regulations concerning AVs, as well as various trajectory planning methods associated with risk.

A. SAFETY STANDARDS AND LAWS IN THE REALMS OF AUTONOMOUS DRIVING

Risk-based security for AVs is currently addressed by standards such as ISO 26262 and ISO/PAS 21448 [9]. ISO/PAS 21448, also known as Safety of the Intended Functionality (SOTIF). The standard is published to identify risks resulting from insufficient functionality corresponding to software and hardware performance limitations [10]. ISO 26262 is a functional safety standard for automotive electronics. The standard outlines a risk classification system (Automotive Safety Integration Level, ASIL). The harm and risk assessment process focuses on identifying the harms that may result from the failure behavior of electrical/electronic (E/E) safety-related systems and mitigating those harms by identifying safety objectives [11]. ASIL is identified by considering controllability, severity, and probability of exposure. It determines the security procedures that need to be implemented to ensure that only an acceptable level of residual risk is maintained. ISO 26262 suggests that security does not mean the complete absence of risk but that some inherent risks will exist [12]. However, consequence-based risks are not considered on a system-wide basis. Therefore, the standard cannot be linked to trajectory planning for AVs.

The German Act on Autonomous Driving is the first national framework for Level 4 self-driving cars and has received a lot of attention from policymakers, AI ethicists, and autonomous driving law experts. The three guiding principles of the key regulations for autonomous driving are established by the German Autonomous Driving Act. The general setting of ethical requirements for autonomous driving is also detailed. In general, the goal of the system should be to reduce the number of road fatalities and, more importantly, to prioritize human life over other factors, such as potential harm to property [13].

B. TRAJECTORY PLANNING METHODS CONSIDERING RISK

A sampling-based trajectory planning method is proposed by focusing on the risk of sensor occlusion. This method allows the vehicle to deal with occluded areas based on phantom pedestrian estimates. A measure is introduced to calculate the worst-case harm in a collision with a crossing pedestrian, and it demonstrates how driving behavior can be modified to meet a specific harm threshold [14]. An integrated trajectory planning method based on stochastic model predictive control (SMPC) is used for both transverse and

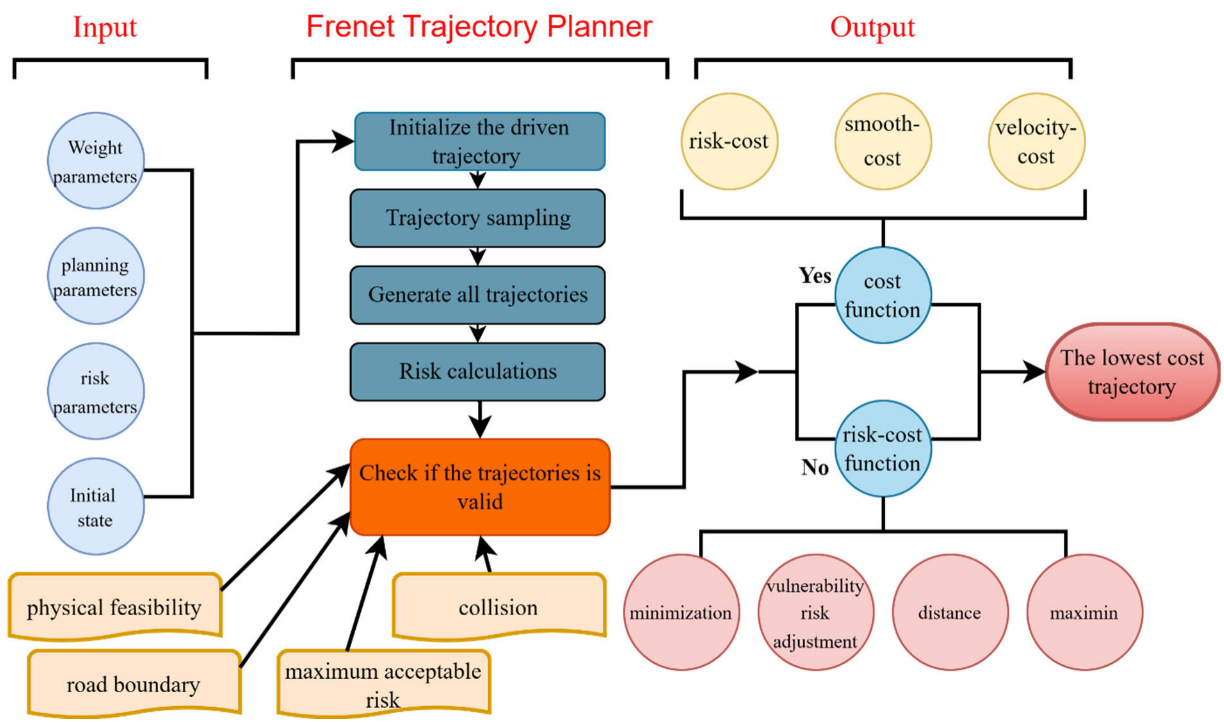

FIGURE 1. Schematic diagram of the ethical behavioral decision algorithm awaring of VRUs. The process of trajectory sampling to the selection of the lowest cost trajectory is repeated with a cycle of 0.1 s.

longitudinal directions. Based on the analysis of the causes of deadlock situations, a quantitative risk method is proposed for occlusion-aware trajectory planning to develop a nonconservative, deadlock-free driving strategy [15].

Risk-based trajectory planning for AVs acknowledges the presence of inherent risks on the road. The goal is to quantify and minimize the risk to the road. Since risk evaluation during development cannot fully predict the various hazards during real-time autonomous driving operations, more and more attention is being paid to run-time risks [16].

To take into consideration the real-time risk in trajectory planning, various methods add criticality metrics, for instance, time-to-react or time-to-collision parameters [17].

A study developed a data-driven model to observe driving behavior through video inferences. Risks that could lead to collisions were identified through driver behavior analysis [18].

A study proposes a dual Transformer-based prediction model for predicting the lane-changing intentions of target vehicles, which provides a design reference for risk warning algorithms [19]. A study proposes a risk-oriented architecture. The system includes perception, intent recognition, and planning subsystems for deducing uncertainty and limiting collision risk [20]. Also, the severity of the predicted collision can be integrated to extend the risk measures [21].

C. EXISTING ISSUES

The risk-considering trajectory planning methods mentioned aim to minimize the ego risk of AVs. However, other road traffic participants are ignored. Research indicates that the preferences of AV users might conflict with those of other individuals using the road [22]. Rationalizing the distribution of risk among road users is crucial. Furthermore, there are no algorithms available to classify the vulnerability of individuals on the road, such as pedestrians and cyclists.

III. METHODS

The algorithm consists of four steps in general, as shown in Figure 1: (1) Trajectory sampling and risk calculation in the Frenet coordinate system, (2) conducting a physical feasibility evaluation, (3) determining whether the trajectory is a valid trajectory by doing collision, road boundary, and maximum acceptable risk checks, (4) if yes, the lowest cost trajectory is selected using the cost function calculation; if no, the lowest cost trajectory is selected using only the risk-cost function.

This work calculates the expected value by multiplying the probability of an event occurring by a measure of the consequences induced by the event. In autonomous driving, risk(R) is defined as the product of the probability of a collision (P) and the estimated harm (H) of that collision.

$$R = PH \tag{1}$$

The probability of a potential collision is caused by various uncertainties in autonomous driving. These uncertainties involve environmental sensing, such as predicting the trajectories of other road users. In simulation scenarios, IDs are added to each road user, and the AV can achieve recognition and detection of each road user within the detection range

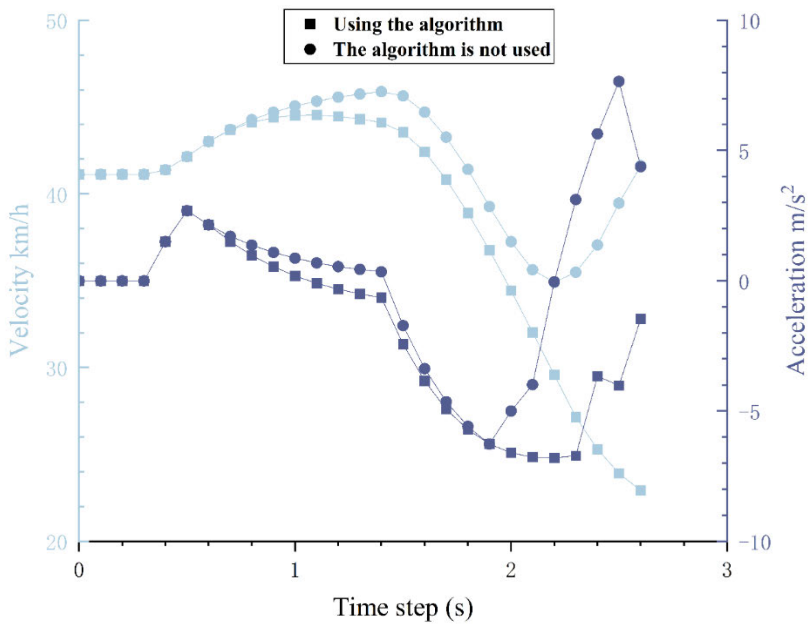

FIGURE 2. Comparison of the velocity and acceleration of AVs with the algorithm versus without the algorithm in the scenario involving a pedestrian.

specified by the program. This work extends the prediction by adding information about the direction, speed, and shape of the predicted road users. This work calculates the collision probability using the cumulative distribution function of the multivariate Gaussian distribution.

This work uses a neural network model based on long and short-term memory [23]. The model is trained on trajectories from the CommonRoad scenario [24]. The model outputs probability-based trajectory predictions and calculates a self-collision probability for each road user [25]. However, due to the uncertainty of the prediction, the estimation of the harm caused raises moral and ethical concerns. The harm model in this work is designed to quantify the harm caused into the interval 0-1, with 0 indicating no harm to humans and 1 indicating maximum harm (i.e., death). Applying the harm model, this work calculates the risk of AVs over time using Equation 1, which results in a time-varying risk for each trajectory sampled, with the maximum value being the trajectory's risk. This is due to the uncertainty of the projections. When the relationship is uncertain, it may be the only reasonable option. This work uses the maximum acceptable risk idea here to set a risk threshold [25]. Through physical feasibility, collision, and road boundary checks, a set of trajectories is considered valid if the risk to any road user from these trajectories is below the maximum acceptable risk. This work goes from Equation 2 to obtain the set of valid trajectories I_V, I being the trajectories in the above set. In the equation, $R(i)$ refers to the risk value of the i th trajectory and $R_{\max}$ refers to the maximum acceptable risk.

$$I_V = \{i \in I \mid R(i) \leq R_{\max}\} \tag{2}$$

An essential aspect of trajectory planning for AVs is to rationally address various influencing factors. Upon choosing a valid trajectory, this work will now introduce the concept of the cost function. The cost function needs to consider three variables: safety, smoothness, and velocity. Therefore, the calculation of the trajectory t total cost function J_{total} is a combination of these three:

$$J_{\text{total}}(t \mid l_v = \text{valid}) = J_{\text{risk}}(t) + J_{\text{smooth}}(t) + J_{\text{velocity}}(t) \tag{3}$$

However, when valid trajectories are inaccessible, this work cannot calculate the cost function based on equation 3. The AI4People-Automotive committee recommends that safety be the primary goal [26]. At this point, this work has to prioritize the safety of the self-driving vehicle over smoothness and velocity, focusing solely on safety. This work changes the cost function formula and focuses only on the risk cost function J_{risk}:

$$J_{\text{total}}(t \mid I_v \neq \text{valid}) = J_{\text{risk}} \tag{4}$$

This work mathematically represents the cost of the trajectory and use a weighting method to determine the weights. The cost function consists of the Risk Minimization Principle J_B, the Vulnerability Risk Adjustment Principle J_V, the Distance Principle J_D, and the Maximin Principle J_M. The weighting factor φ determines the degree allocated to each principle.

$$J_{\text{risk}}(t) = \varphi_B J_B(t) + \varphi_A J_V(t) + \varphi_D J_D(t) + \varphi_M J_M(t) \tag{5}$$

The cost of the risk minimization principle is defined by Equation 6. S_R is a set of risks for all road users [22].

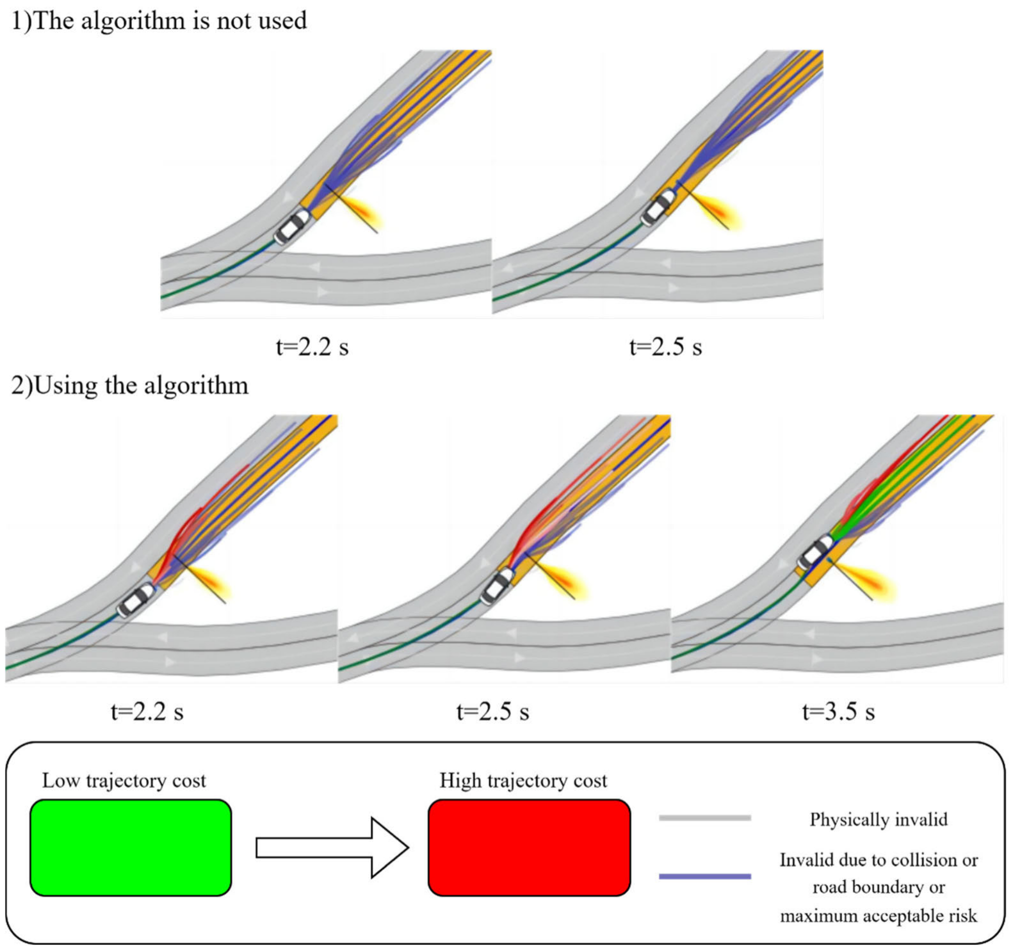

FIGURE 3. AVs identify the pedestrian to trigger automated behavioral reactions as a qualitative case. Failure to implement the algorithm will result in the AV being unable to decelerate, leading to a collision. The AV using the algorithm will make a trajectory plan to pass safely after considering the velocity cost and risk cost.

$R_i\,(t)$ refers to the risk value of the trajectory t for each object on the road.

$$J_{\mathrm{B}}(t) = \frac{\sum_{i=1}^{|S_R|} R_i(t)}{|S_R|} \tag{6}$$

The vulnerability risk adjustment principle is more in line with the will of the people and the prevailing ethical values of society by allocating different risks to people with different levels of vulnerability. This work calculates the average risk for all road users and then allocates this risk among various groups of individuals using an adjustment factor. This increases the risk cost in trajectory planning, hence transferring the risk to the road users who are protected. Here a high-risk cost factor K_{V} of 1.8 is allocated to those under 18 years of age. A low-risk cost factor of 1.2 is allocated to those between 18 and under 60 years of age (the figure of 60 is derived from PRC Law On Protection of the Rights and Interests of the Elderly). A medium-risk cost factor of 1.5 is allocated to those 60 years of age and over. The above cases are given by equations (7)-(9):

$$\begin{Bmatrix} K_{\mathrm{V}}(\text{age} < 18) = 1.8 \\ K_{\mathrm{V}}(18 \leq \text{age} < 60) = 1.2 \\ K_{\mathrm{V}}(\text{age} \geq 60) = 1.4 \end{Bmatrix} \tag{7}$$

$$J_{\mathrm{E}}\,(t) = \frac{\sum_{i=1}^{|\mathrm{S}_R|} \sum_{j=i}^{|\mathrm{S}_R|} \left|R_i\,(t) - R_j\,(t)\right|}{|\mathrm{S}_R|} \tag{8}$$

$$J_{\mathrm{V}} = J_{\mathrm{E}} K_{\mathrm{V}} \tag{9}$$

The distance principle, as described in Equations 10 and 11, claims that the risk cost increases as the distance between AVs and potential collision objects decreases during trajectory execution. The Euclidean distance is used here.

$$J_{\mathrm{D}}(t) = (D_{\text{AV-otheruesr}})^{-1} \tag{10}$$

$$D\,(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{11}$$

The maximin principle (Equation 12) focuses on the highest harm without considering probability, thus enabling a

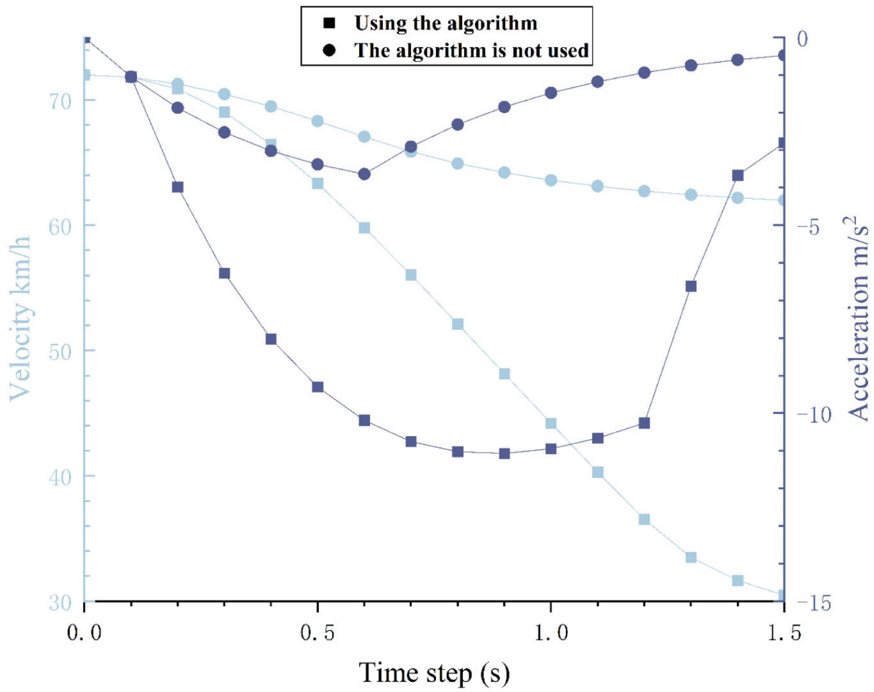

FIGURE 4. Comparison of the velocity and acceleration of AVs with the algorithm versus without the algorithm in the scenario involving a bicycle.

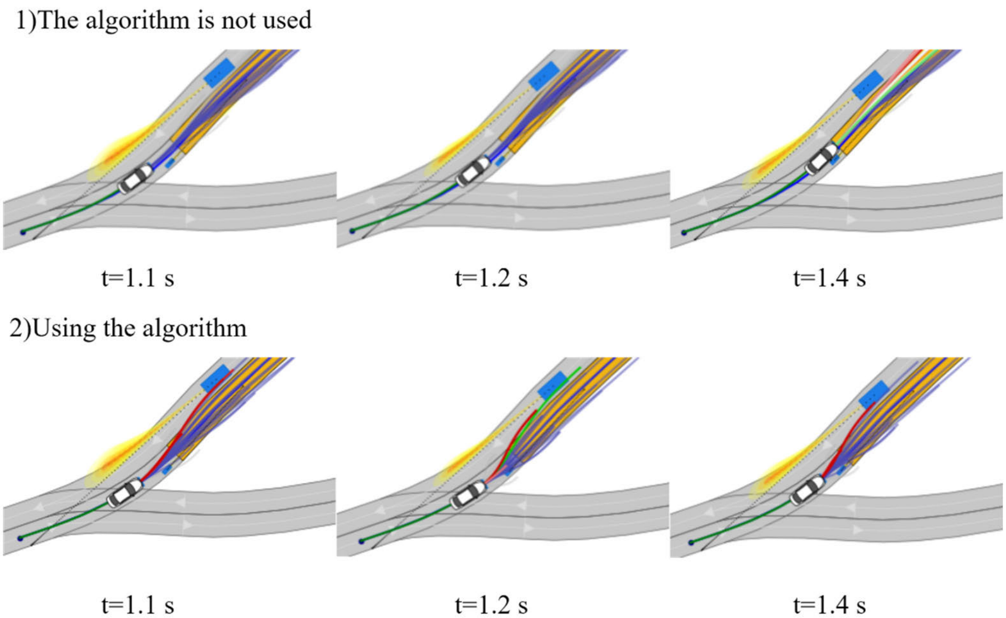

FIGURE 5. AVs identify the bicycle to trigger automated behavioral reactions as a qualitative case. Failure to implement the algorithm will result in the AV engaging in overtaking behavior, leading to a collision. The AV using the algorithm will make a significant deceleration to abandon the overtaking after considering the risk.

decoupled evaluation of risk. Since the low probability of an event occurring is ignored, this work introduces a factor δ. S_H refers to a set of harms for all road users [25]. $H_i(t)$ refers to the harm value of the trajectory t for each object on the road.

$$J_{\mathrm{M}}(t) = \left[\max_{H_i(t)}(\mathrm{S}_H)\right]^{\delta} \tag{12}$$

IV. RESULTS

This work proposes an ethical behavioral decision algorithm awaring of VRUs for rationally allocating risk to guide trajectory planning for AVs. Next, this work quantitatively analyzes and evaluates the risk generated by the method. This work conducts both a qualitative analysis and uses the

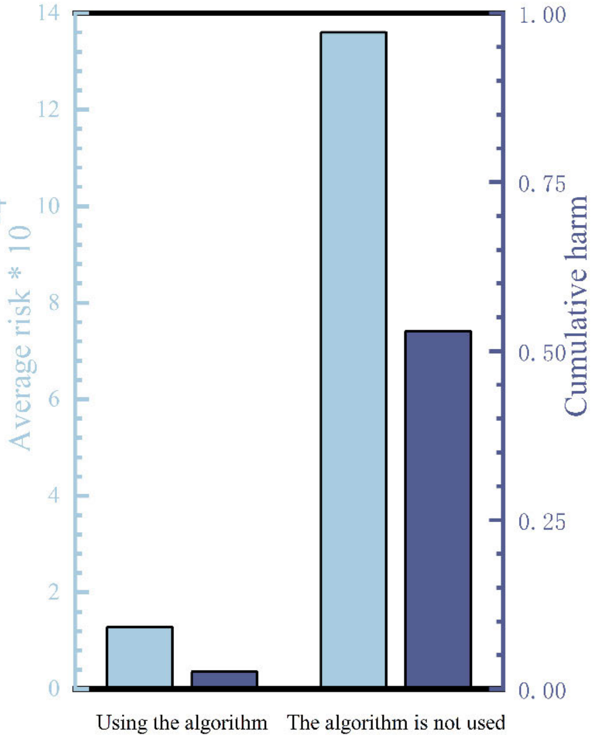

FIGURE 6. Comparison of the average risk and cumulative harm for all road users in typical scenarios with and without the usage of the algorithm.

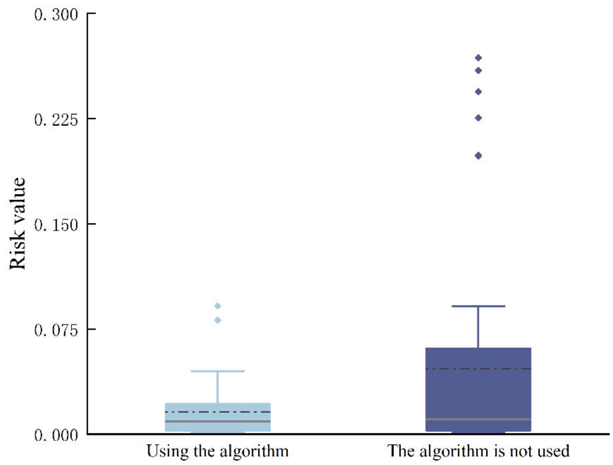

FIGURE 7. The distribution of the top 100 highest-risk values. Dotted lines represent mean values, while solid lines represent median values.

commonroad scenario library to quantitatively calculate the value at risk. The library consists of 2000 scenarios. These scenarios come from all over the world (e.g., China, the USA, and many European countries). The library contains various road conditions (e.g., city roads, highways, etc.). These scenarios include real scenarios and some important scenarios produced by hand. From these, this work selects six typical scenarios for empirical evaluation. The typical scenarios are real-world scenarios that adhere to traffic laws and regulations and reflect most road conditions in daily life. This work utilizes a point mass model of the vehicle in the scenario simulation runs, taking into consideration longitudinal constraints, lateral acceleration, steering constraints, and collision angles. In the simulation, the behavior of all road users is specific and they don't react behaviorally to AVs. Ultimately, this work still emphasizes guiding the path planning of AVs according to the cost values calculated by a cost function based on the maximum acceptable risk.

In this evaluation, this work analyzes the differences in risk among different planning methods from qualitative analysis and empirical assessment.

A. QUALITATIVE ANALYSIS

This work utilizes two typical scenarios involving a pedestrian crossing the roadway and an overtaking scenario to demonstrate the logic and benefits of the algorithm.

Figure 3 illustrates AVs are moving along a city road, steadily nearing a pedestrian crossing the street ahead. The two white vehicles can identify the pedestrian simultaneously but exhibit distinct actions. The vehicle, which lacks the algorithm, is heading at a velocity of 34.92 km/h with an acceleration of -0.04 m/s^2 at t=2.2 s. The vehicle equipped with the algorithm has a velocity of 29.59 km/h and an acceleration of -6.80 m/s^2. Their relative positions are 0.74 m apart. In the subsequent time, the vehicle without the algorithm could not make an effective trajectory prediction and collided at t=2.7 s because it was too late to slow down and change lanes. The vehicle using the algorithm makes a deceleration and changes lanes to deal with it after fully considering the velocity cost and risk cost. Figure 2 displays a graph comparing the velocity and acceleration of AVs with and without the algorithm throughout the whole scenario.

Figure 5 illustrates a scenario where AVs are driving on a city road with a bicycle traveling in front of them, and a car approaches in relative motion. The vehicle, which lacks the algorithm, is heading at a velocity of 63.12 km/h with an acceleration of -1.18 m/s^2 at t=1.1 s. The vehicle equipped with the algorithm has a velocity of 40.3 km/h and an acceleration of -10.66 m/s^2.When the AV approaches a bicycle, it will use the algorithm to actively apply a significant deceleration due to excessive risk until the velocity is lower than the bicycle. The AV will not engage in overtaking behavior. The AV that does not utilize the algorithm cannot perform effective deceleration behavior. The AV will engage in overtaking behavior without considering the risk. Figure 4 displays a graph comparing the velocity and acceleration of AVs with and without the algorithm throughout the whole scenario.

Also, further experiments have illustrated that the range of trajectory planning is also a more important parameter: If the range of trajectory planning is too short, being 1s instead of 2 s here, the risk of slowing down ahead of time and making a detour behavior cannot be submitted in time to trajectory planning. AVs can fail to estimate risky situations in advance.

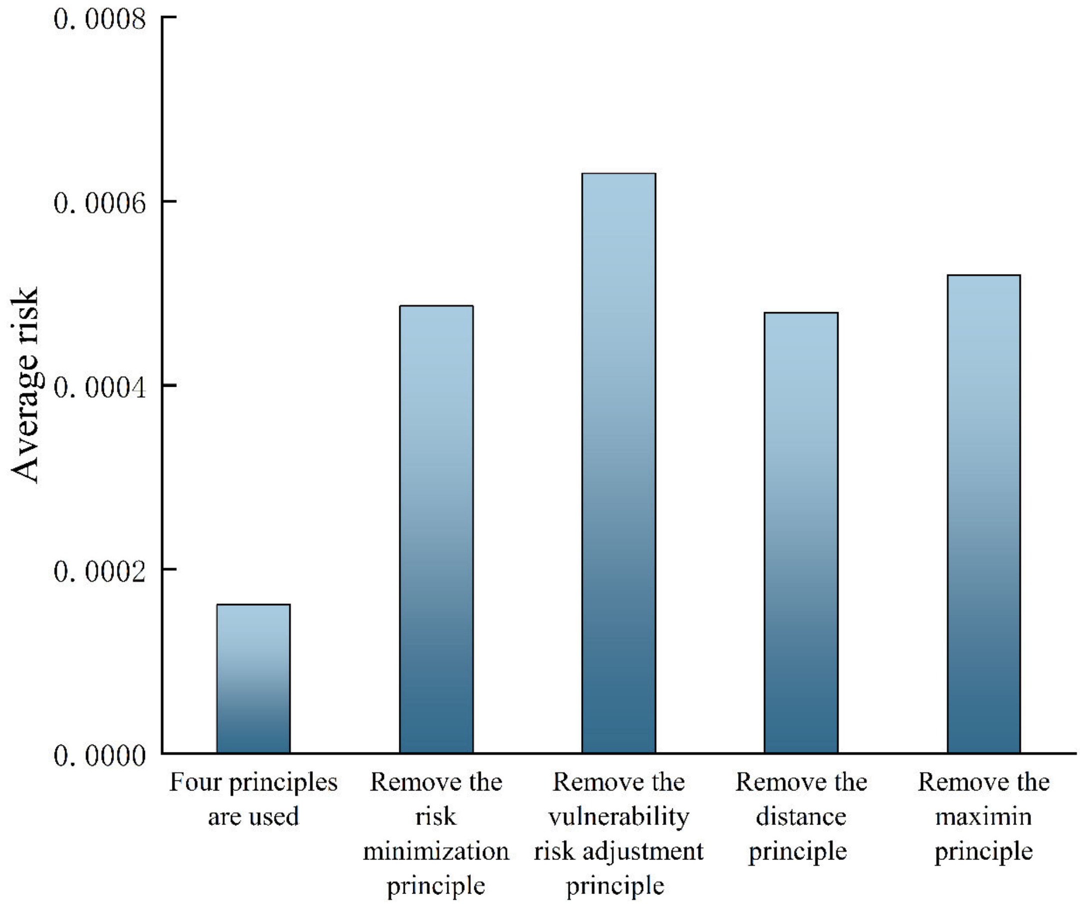

FIGURE 8. The average value of risk for five different situations. No matter which algorithm is removed, the average risk in the scenario rises. This illustrates that all four algorithms can be used simultaneously and each holds its utility.

B. EMPIRICAL EVALUATION

The algorithm described in the above examples affects the behavior of AVs in various scenarios. This work next evaluates it from a data perspective. Experiments have illustrated that explicit consideration of risk in trajectory planning is effective in reducing risk for all road users. To reduce the potential risk to road users, this work utilizes the maximum evaluated trajectory risk as the risk value for risks arising from trajectories. This work extracts the risk values and obtains the average risk values. This work also analyzes the accidents that occurred in typical scenarios and obtains the cumulative harm. In typical scenarios, Figure 6 illustrates that the AV equipped with the algorithm has a 90.6% decrease in its average risk value and a 95.18% decrease in cumulative harm compared to the AV without the algorithm.

This work then extracts the risk values for each moment in all typical scenarios and ranks the risk values from highest to lowest. Figure 7 illustrates a comparison of the top 100 highest-risk values while using and not using the algorithm. This work focuses on the top 100 risk values due to the abundance of risk values near 0 in all situations. Strong correlations exist among all high-risk values. The result illustrates that the usage of the algorithm does significantly decrease road risk.

Detailed data, which are used to compare the ethical algorithm used in a study with the algorithm in this work [25], are presented in Table 1. If the total harm is averaged for the number of typical scenarios and then multiplied by the number of scenarios in that study, the cumulative harm is reduced by 45.27% in comparison. This work compares the average of the top 100 highest-risk values and demonstrates that the algorithm in this work reduces it by 76.04% compared to the ethical algorithm.

TABLE 1. Performance comparison of the ethical algorithm with the algorithm in this work.

	Ethical algorithm	Our algorithm
Cumulative harm	15.53	8.5
Average of the top 100 highest-risk values	0.06576684	0.01575838

TABLE 2. **The average risk value corresponds to different maximum acceptable risk values.**

Maximum acceptable risk value	10^{-4}	10^{-3}	10^{-2}	10^{-1}	1
average risk value	6.0×10^{-6}	6.2×10^{-5}	3.1×10^{-3}	1.5×10^{-2}	1.5×10^{-2}

This work changes the weighting parameter values for the four principles and maximum acceptable risk parameter values. In the case of changing the weighting parameters of the four principles individually, Figure 8 illustrates that using all four principles in parallel works optimally. Experiments have illustrated that pre-setting different maximum acceptable risk values results in different average risks. During the experiment, the weight parameters of the four principles are zero. In the typical scenario shown in Figure 3, collisions occur when the maximum acceptable risk value exceeds 0.1. This reveals that it is better to set the initial value below 0.01. (As shown in Table 2.) By increasing the weight parameters of the vulnerability risk adjustment principle and the risk minimization principle while keeping the weight parameters of other principles constant, the AV will excessively consider risk when approaching the pedestrian, leading to excessive deceleration. As the combined weight of these two principles approaches 100%, it will result in AV stopping. The AV significantly increases the safe distance to the pedestrian when the weights of the distance principle and the maximin principle are increased.

V. CONCLUSION

In this research, this work proposes a multi-module joint algorithm focusing on the risk of VRUs. The algorithm utilizes the notion of maximum acceptable risk. Valid trajectories are evaluated in real-time based on road boundary and collision checks. The optimal trajectory is chosen by combining a cost function that includes smoothness, safety, and velocity. In the methods, the graded consideration of vulnerability is realized, which is more in line with the mainstream thinking of society. When there is no valid trajectory, this work makes safety the primary focus and focuses only on the risk cost to make safe trajectory planning. The risk cost includes the four principles presented in the previous paragraphs. The evaluation of the results illustrates a significant decrease in average risk, cumulative harm, and highest risk on the road after using the algorithm. The algorithm is applicable to a wide range of typical traffic scenarios, such as intersections, urban roads with pedestrians, highways, etc.

However, the research specifies cost weighting parameters and maximum risk values. Different parameters cause AVs to perform different driving behaviors. According to the needs of different scenarios, the values of the weighting parameters should be adjusted appropriately. This work will try to seek an inherent balance between them. Meanwhile, incorporating a fact-based online legal driving behavior monitoring system may make AVs safer [27].

CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare that are relevant to the content of this article.

AUTHOR CONTRIBUTIONS

All authors reviewed the manuscript. Xiangyu Li: conceptualization, methodology, writing—original draft preparation, visualization; Jielin Li: conceptualization, software, formal analysis; Kai Gao: conceptualization, writing—review and editing, supervision.

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