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Novel Motion Planning Strategy with Fuzzy Logic for Improving Safety in Autonomous Vehicles in Response to Risky Road User Behaviors

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ABSTRACT

This study aims to propose a new motion planning strategy for autonomous vehicles (AV) using fuzzy logic to improve safety. The strategy mitigates risky behaviors of other road users, such as zigzagging vehicles, sudden braking, pedestrians emerging from blind spots, and responding to sudden lane changes. The proposed method combines a novel fuzzy inference system and a configuration space map with adaptive dynamic object bounding boxes. These bounding boxes adjust in size according to the risk level of the dynamic object's movement. The simulation test was conducted using four scenarios involving risky behavior from other road users. The proposed method was compared with conventional methods, with safety costs used to measure performance. The results showed that the proposed algorithm achieved better safety costs across all four scenarios; this improvement is due to the integration of the fuzzy system with the adaptive configuration space map, which accounts for uncertainties. These findings suggest that the proposed method improves AV motion planning safety in dynamic and unpredictable environments. This research contributes to developing safer, more reliable autonomous driving systems.

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1. INTRODUCTION

Autonomous vehicles (AVs) are equipped with technology to perceive their surroundings. These vehicles can make real-time decisions and perform driving tasks independently without human intervention (Aria, 2019b). The rapid development of AVs has the potential to improve the quality of transportation. Among them are improving safety, efficiency, and accessibility. (Gu *et al*., 2023; Nascimento *et al*., 2019; Zheng *et al*., 2023). However, the transition to full AVs is fraught with significant challenges. One of them is motion planning in a dynamic and unpredictable environment. AVs must be able to operate safely together with other road users, namely human drivers and pedestrians. These human road users are likely to exhibit unexpected and risky behaviors, such as sudden stops, zigzags, unexpected lane changes, and sudden crossing of the road (Ma *et al*., 2015; Wang *et al*., 2023). These behaviors can increase the risk of accidents and compromise the safety of AVs. This problem is one of the main obstacles to implementing AVs in real-world road environments. Therefore, AV motion planning algorithms that can anticipate and adapt to risky behaviors are essential for AVs to integrate into real-world traffic successfully (Trauth *et al*., 2023; Valiente *et al*., 2022). This AV motion planning algorithm determines the vehicle's path and speed to navigate safely (Pan *et al*., 2024; Zhang *et al*., 2021).

Several studies have investigated motion planning strategies for AVs to handle risky road behaviors. Trauth *et al*. (2023) and Debada *et al*. (2020) studied path planning that is aware of occlusions or areas that AV sensors cannot cover. However, they focused only on risky objects emerging from blind spots and no other risky scenarios. Dávid *et al*. (2019) proposed a behavior-planning method to handle other vehicles' sudden lane changes and zigzag movements. However, the method did not cover sudden braking or pedestrians emerging from blind spots. Likewise, Fu *et al*. (2020) only focused on decision-making strategies for emergency braking. Pohan & Utama (2023b) proposed an algorithm for AVs to respond to various traffic scenarios but did not analyze the presence of risky road user behavior. Studies on speed planning using fuzzy neural networks by Li *et al*. (2022), Wang *et al*. (2021), and Xue *et al*. (2019) also did not address responses to risky road user behavior. Ma *et al*. (2015) suggested motion planning for limited static and dynamic situations, such as overtaking, but their work did not address strategies to handle various risky road user behaviors. To the best of the authors' knowledge, no comprehensive AV path planning algorithm approach can mitigate various dangerous road user behaviors, such as handling sudden braking, unexpected lane changes, sudden crossing, and zigzagging maneuvers. This gap highlights the need for advanced motion planning strategies to improve the AVs' safety in unpredictable environments.

Overlay visualization of bibliometric analysis related to AV studies is shown in **Figure 1** (Al Husaeni & Nandiyanto, 2022; Nandiyanto *et al*., 2024; Nandiyanto & Al Husaeni, 2021). Based on this analysis, it can be concluded that research on AV is still in its infancy, as indicated by the lighter colors on the visualization. Although the use of fuzzy rules and safety improvements in AVs has begun to be carried out by researchers, these areas are new and still under development. This area is still under development, as reflected by the relatively low density of connections between fuzzy rules, safety, and AVs.

This study aims to address the previously discussed research gap by proposing a novel motion planning strategy to improve the safety of autonomous vehicles in response to dangerous behaviors by other road users. The novel motion planning strategy combines lane and speed planning methods that can dynamically adapt to unexpected road user actions, such as sudden braking, zigzagging, sudden lane changes, and pedestrians emerging from

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blind spots. The novelty of this study lies in two main contributions: (1) designing a configuration space map that has adaptive dynamic object bounding boxes based on the risk level of vehicle movement and (2) proposing a novel fuzzy inference system (FIS) capable of handling four dangerous road user behaviors simultaneously, namely, cars moving in a zigzagging manner, sudden braking, pedestrians emerging from blind spots, and sudden lane changes. This adaptive approach enables autonomous vehicles to make faster and safer navigation decisions in real-time. Our methodology has been tested through simulations in four different scenarios representing various dangerous behaviors of other road users. Comparative analysis with conventional motion planning algorithms shows that our approach results in better safety costs. These results demonstrate the potential of our proposed strategy to improve the safety of autonomous vehicles. This research helps support autonomous vehicles operating in natural traffic environments and contributes to developing autonomous driving technology.

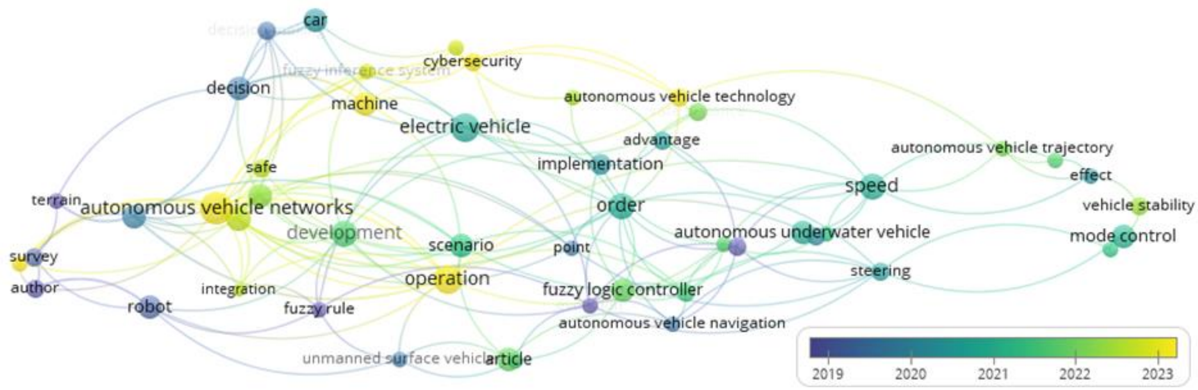

Figure 1. Overlay Visualization of Bibliometric Analysis on AVs

2. METHODS

The general architecture of the AV system consists of several modules that work together to enable the vehicle to operate safely and efficiently. As shown in **Figure 2**, this architecture consists of four main components: Input Sensor Data Module; Perception, Localization, and Mapping Module; Planning and Decision-Making Module; and Actuator. The Planning and Decision-Making Module is divided into Global Planning, Behavior Planning, Motion Planning, and Low-Level Control. This study focuses on the development of the Motion Planning module, which consists of path planning and speed planning.

2.1. Path Planning

In this study, we design a path planning algorithm developed in previous studies, namely the RRT-ACS algorithm (Pohan *et al*., 2021), Bi-Directional Rule Templates, and Time-Space Configuration, referred to as the RRT+BRT+CTS algorithm (Pohan & Utama, 2023a). The RRT+BRT+CTS algorithm has been successfully applied in various unmanned system applications (Aria & Utama, 2023; Pohan & Utama, 2023b).

The RRT+BRT+CTS algorithm works using the principle of bidirectional rule templates, as depicted in Figure 3. This method uses two template trees: one from the starting node (depicted as the red tree) and the other from the destination node (depicted as the blue tree). These two trees grow towards each other to try to connect. If the connection is established, the process ends, and the path planning is successful. If the trees cannot be connected, the RRT-ACS algorithm is applied to help both the red and blue trees connect. The result is a smooth path depicted by the green curve in **Figure 3**. The complete process of the RRT+BRT+CTS algorithm is explained in detail in the reference (Pohan & Utama, 2023b).

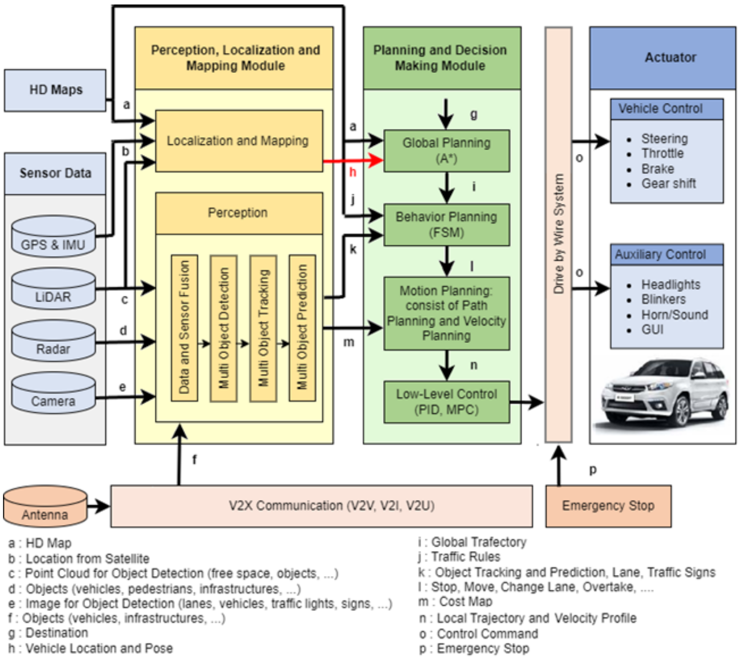

Figure 2. AVs system architecture.

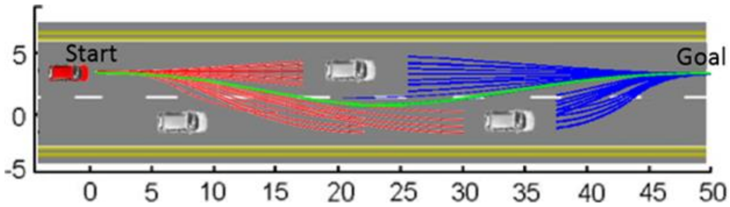

Figure 3. Path planning with bi-directional rule templates.

2.2. Velocity Planning in Configuration Space

Speed planning in AVs dynamically adjusts the vehicle speed based on environmental conditions and detected objects. A perception module detects static and dynamic objects. The static and dynamic objects are then mapped into the configuration space (C-space). In C-space, the bounding box size of the dynamic object adapts to the uncertainty of its movement. This uncertainty includes both longitudinal motion uncertainty and lateral motion uncertainty, as shown by the yellow box around the social vehicle in **Figure 4**. In the figure, the planned path for the ego vehicle is depicted by the red arrow. The brown arrow shows the movement of the social vehicle. If the movement of the social vehicle is predictable (e.g., moving in a straight line, as in **Figure 4a**), the yellow bounding box is small. This small yellow bounding box allows the ego vehicle to plan further forward movement. On the other hand, if the movement of the social vehicle is unpredictable (e.g., moving in a zigzag pattern, as in **Figure 4b**), the yellow bounding box becomes larger. This big yellow bounding box limits how close the ego vehicle can approach.

The uncertainty in longitudinal motion (D) is measured using the standard deviation of the uncertainty in longitudinal motion. It compares the predicted and actual longitudinal positions of the dynamic object. The uncertainty in longitudinal motion also considers the minimum braking distance considering the current speed of the ego vehicle. The uncertainty in lateral motion (L) is measured similarly. It uses the standard deviation between the dynamic

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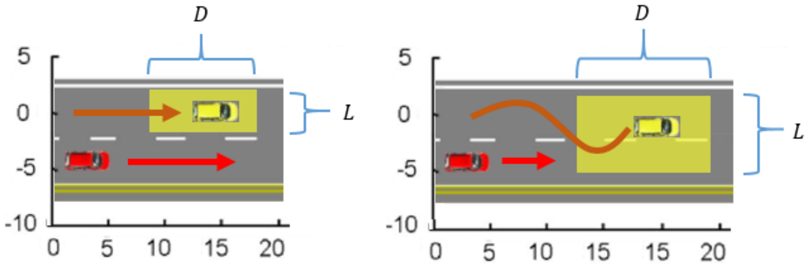
object's predicted and actual lateral positions. The uncertainty in lateral motion also takes into account the width of the vehicle and its current speed. If the nearby vehicles are moving in a zigzag pattern, the width of their bounding box increases. This sizeable yellow bounding box ensures safe navigation around unpredictable objects. Likewise, high-speed vehicles are potentially at higher risk of sudden and unpredictable maneuvers. Therefore, the yellow bounding box will be enlarged for high-speed vehicles. In this configuration space, speed planning is done using fuzzy logic.



(a) (b)

Figure 4. Configuration space with uncertainty-based bounding boxes for dynamic objects

2.3. Velocity Planning using Novel FIS

To handle various risky behaviors, we propose a new FIS. The risky behaviors to be handled include vehicles zigzagging, sudden braking, pedestrians exiting blind spots, and sudden lane changes. Our FIS builds on the work of Wang *et al.* (2021). In Wang's model, three separate FIS models are used, each with two inputs. These models handle three different traffic scenarios.

In contrast, we propose a single FIS. Our FIS uses three inputs: Distance, Speed, and Relative Speed. This FIS has one output: Acceleration. This FIS allows us to handle the four risky road user behaviors mentioned above. The membership functions for these variables are the same as in Wang's model. However, by integrating all three variables into one FIS, our system can handle risky behavior more efficiently.

The membership functions for these variables are the same as those discussed by Wang. We then designed the rule base for this novel FIS. Example rules for the proposed FIS are shown in **Table 1**. This approach leverages the established benefits of fuzzy logic (Amelia *et al*., 2019; Aria, 2019a; Khairudin *et al*., 2020).

Table 1. Example Rules for the Proposed FIS in Handling Risky Road User Behaviors

Input Variables			Output
Distance	**Velocity**	**Relative Velocity**	**Acceleration**
Far	Low	Negative	Strongly Accelerate
Far	Low	Zero	Accelerate
Far	Low	Positive	Maintain Speed
Far	High	Negative	Accelerate
Far	High	Zero	Maintain Speed
Far	High	Positive	Slightly Decelerate
Near	Low	Negative	Accelerate
Near	Low	Zero	Maintain Speed
Near	Low	Positive	Slightly Decelerate
Near	High	Negative	Strongly Decelerate
Near	High	Zero	Strongly Decelerate
Near	High	Positive	Strongly Decelerate

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3. RESULTS AND DISCUSSION

3.1. Experimental Setup

The proposed strategy's performance was evaluated in four simulated scenarios: zigzagging vehicles, sudden braking, pedestrians emerging from blind spots, and sudden lane changes. These scenarios replicated the testing conditions described by (Dávid *et al*., 2019; Debada *et al*., 2020; Fu *et al*., 2020; Trauth *et al*., 2023). Simulations ran on a 3.4 GHz Core i3 CPU with 4 GB RAM using LabVIEW 7.1.

Five configurations per scenario were used, varying the ego vehicle's state (position, speed), and surrounding risk vehicle behavior (position, hazardous movement, speed). **Figures 5-8** show one example per that scenario. This comprehensive evaluation ensures the robustness of the proposed strategy.

The proposed strategy's performance was benchmarked against two approaches: FIS (Li *et al*., 2022) and RRT-CL (Taheri *et al*., 2019). As the evaluation metric, we used safety cost as defined in equations (1-4). **Tables 2-5** summarize the results, presenting each method's best, worst, and average safety costs and standard deviations.

$$C_{safety} = \sqrt{\frac{1}{T}\int_{t_1}^{t_2} (AFP)^2\, dt} \tag{1}$$

$$AFP = \frac{c_1}{\left(\frac{\Delta d}{\Delta v + c_2} - c_3\right)^{c_4}} \tag{2}$$

$$\Delta d = \sqrt{(x,y)_{riskV}^2 - (x,y)_{egoV}^2} \tag{3}$$

$$\Delta v = v_{egoV} - v_{riskV} \tag{4}$$

In equations (1-4), Δd represents the distance between the ego vehicle and the risk vehicle, Δv represents the difference in speed between the ego vehicle and the risk vehicle, $(x,y)_{riskV}$ represents the position of the risk vehicle, $(x,y)_{egoV}$ represents the position of the ego vehicle, v_{egoV} represents the ego vehicle's speed, and represents the risk vehicle's speed.

3.2 Testing Scenarios and Results

This section evaluates the proposed motion planning strategy's performance in response to four distinct risky road user behaviors: zigzagging vehicles, sudden braking by other vehicles, pedestrians emerging from blind spots, and sudden lane changes by other vehicles. **Figure 5** illustrates an example configuration of the zigzagging vehicles scenario. The ego vehicle (red) attempts to overtake a leading vehicle (yellow) by performing a hazardous zigzag maneuver. The proposed strategy excels in such scenarios, as shown in **Table 2**. This is due to its ability to dynamically adjust speed and maintain a safe distance using fuzzy logic, thereby reducing the safety cost significantly compared to conventional methods.

Figure 6 depicts a scenario in which the ego vehicle encounters a vehicle (yellow) that suddenly brakes. The proposed strategy allows the ego vehicle to react promptly and safely, minimizing the risk of a rear-end collision (**Table 3**). This improvement stems from the fuzzy logic system's dynamic risk assessment and quick adaptation to sudden environmental changes.

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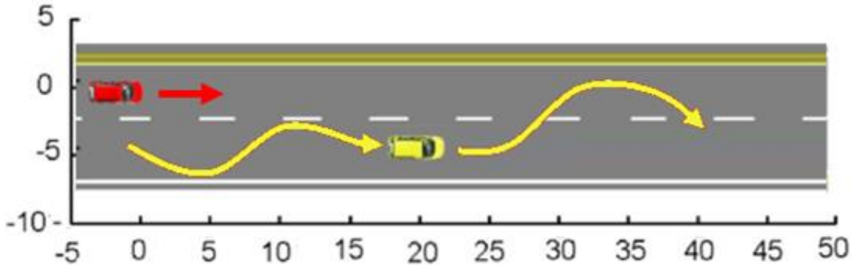

Figure 5. Zigzag maneuver by leading vehicle (example configuration).

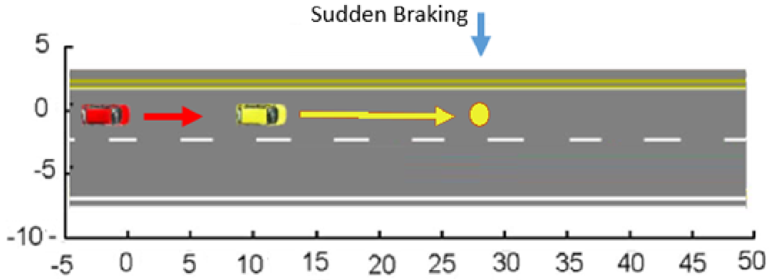

Figure 6. Sudden braking by another vehicle (example configuration).

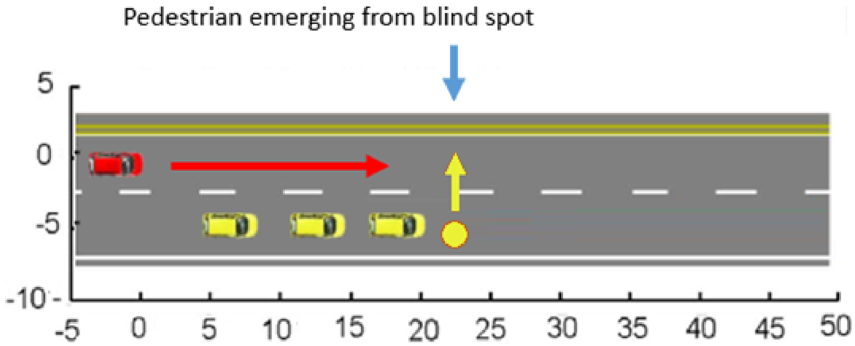

Figure 7. Pedestrians (example configuration).

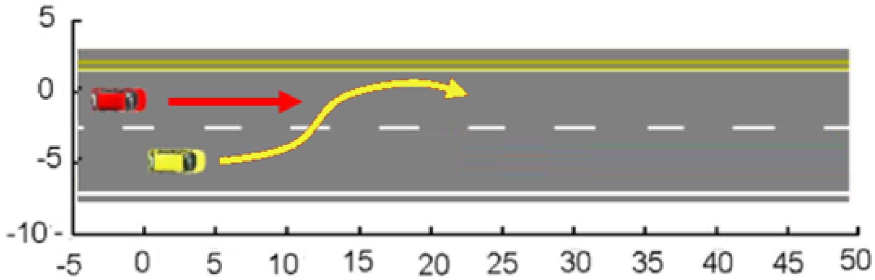

Figure 8. Abrupt lane change by another vehicle (example configuration).

Figure 7 showcases a scenario where pedestrians emerge from blind spots. The proposed fuzzy logic system effectively updates risk levels and adjusts the ego vehicle's path for safe navigation (**Table 4**). This approach outperforms traditional methods regarding safety cost, highlighting its robustness in handling unpredictable pedestrian movements.

One of the configurations in **Figure 8** demonstrates an abrupt lane change by another vehicle. The proposed strategy successfully predicts such maneuvers and adjusts the ego vehicle's path accordingly (**Table 5**). This consistent reduction in safety cost across all scenarios underscores the method's effectiveness in managing both longitudinal and lateral movement uncertainties.

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Table 2. Performance metrics for the zigzag maneuver scenario

Configuration	Methods	Best	Worst	Average
First Configuration	Proposed	-7.85	-5.05	-3.10
	FIS	18.10	28.75	43.70
	CL-RRT	49.10	95.45	260.25
Second Configuration	Proposed	-9.83	-6.30	-3.87
	FIS	23.21	36.41	1.27
	CL-RRT	63.15	122.36	7.60
Third Configuration	Proposed	-9.45	-6.09	-3.73
	FIS	21.43	34.79	1.20
	CL-RRT	59.43	114.97	7.14
Fourth Configuration	Proposed	-6.10	-3.92	-2.41
	FIS	14.06	22.59	0.78
	CL-RRT	39.39	76.66	4.75
Fifth Configuration	Proposed	-15.72	-10.12	-6.21
	FIS	35.67	56.26	1.96
	CL-RRT	97.82	188.53	11.73

Table 3. Performance metrics for sudden braking scenario

Configuration	Methods	Best	Worst	Average
First Configuration	Proposed	-13.40	-8.05	-4.20
	FIS	18.55	34.75	55.60
	CL-RRT	65.35	139.925	291.75
Second Configuration	Proposed	-10.78	-6.46	-3.38
	FIS	14.93	27.49	44.29
	CL-RRT	54.20	114.66	240.58
Third Configuration	Proposed	-12.82	-7.69	-4.02
	FIS	18.06	33.24	53.37
	CL-RRT	62.89	133.98	280.05
Fourth Configuration	Proposed	-10.99	-6.59	-3.44
	FIS	15.32	28.19	45.39
	CL-RRT	55.23	117.39	245.74
Fifth Configuration	Proposed	-10.84	-6.50	-3.39
	FIS	15.03	27.66	44.53
	CL-RRT	52.41	111.36	233.44

Table 4. Performance metrics for pedestrians emerging from blind spot scenario

Configuration	Methods	Best	Worst	Average
First Configuration	Proposed	-23.25	-14.15	-7.85
	FIS	21.25	38.80	61.15
	CL-RRT	160.40	207.80	439.075
Second Configuration	Proposed	-18.23	-11.09	-6.16
	FIS	17.51	31.46	49.70
	CL-RRT	131.32	169.42	358.39
Third Configuration	Proposed	-23.43	-14.28	-7.92
	FIS	21.99	40.17	62.88
	CL-RRT	163.40	212.21	448.74
Fourth Configuration	Proposed	-19.21	-11.70	-6.49
	FIS	17.89	32.38	51.09
	CL-RRT	137.42	177.81	375.92
Fifth Configuration	Proposed	-17.90	-10.90	-6.05
	FIS	16.40	29.54	46.84
	CL-RRT	123.88	159.62	338.15

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Table 5. Performance metrics for abrupt lane change scenario.

Configuration	Methods	Best	Worst	Average
First Configuration	Proposed	-17.70	-11.15	-6.75
	FIS	13.20	20.60	29.55
	CL-RRT	108.95	141.15	281.3
Second Configuration	Proposed	-15.50	-9.75	-5.91
	FIS	11.54	18.00	25.84
	CL-RRT	95.54	125.50	248.39
Third Configuration	Proposed	-17.82	-11.22	-6.79
	FIS	13.28	20.74	29.75
	CL-RRT	110.90	144.13	287.06
Fourth Configuration	Proposed	-14.23	-8.96	-5.43
	FIS	10.62	16.56	23.75
	CL-RRT	88.40	114.69	228.50
Fifth Configuration	Proposed	-13.32	-8.38	-5.08
	FIS	9.92	15.46	22.20
	CL-RRT	81.62	107.33	211.95

3.3. Statistical Analysis of the Simulation Results

We conducted statistical analysis to verify the proposed motion planning strategy's performance improvement. The analysis covered all simulation scenarios. We used an independent sample t-test to assess the statistical significance of the performance difference between our method and the benchmark algorithms. **Tables 6 - 9** show the t-test results, with p-values for each comparison. A p-value below 0.05 indicates a statistically significant difference. The proposed strategy shows statistically significant improvement in most scenarios. This improvement is evident from the low p-values in **Tables 6 - 9**. These results are consistent with previous studies (Pohan & Utama, 2023b; Wang *et al.*, 2021).

The results indicate that the RRT+BRT+CTS and fuzzy algorithms outperform the benchmark algorithms. These findings further confirm the effectiveness of the proposed method in improving the safety of autonomous vehicles in dynamic and unpredictable environments.

Table 6. Statistical analysis for zigzag maneuver scenario (p-values).

Configuration	Proposed method compared to FIS	Proposed method compared to CL-RRT
First configuration	0.009287	0.093825
Second configuration	0.060396	0.098962
Third configuration	0.061251	0.098303
Fourth configuration	0.061159	0.099531
Fifth configuration	0.059240	0.097683

Table 7. Statistical analysis for sudden braking scenario (p-values)

Configuration	Proposed method compared to FIS	Proposed method compared to CL-RRT
First configuration	0.015365	0.059207
Second configuration	0.015109	0.059463
Third configuration	0.015020	0.059244
Fourth configuration	0.015103	0.059468
Fifth configuration	0.015067	0.059340

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Table 8. Statistical analysis for pedestrians emerging from blind spot scenario (p-values)

Configuration	Proposed method compared to FIS	Proposed method compared to CL-RRT
First configuration	0.010979	0.030029
Second configuration	0.010902	0.030109
Third configuration	0.010863	0.030307
Fourth configuration	0.010875	0.030181
Fifth configuration	0.010851	0.030005

Table 9. Statistical analysis for abrupt lane change scenario (p-values)

Configuration	Proposed method compared to FIS	Proposed method compared to CL-RRT
First configuration	0.004426	0.023461
Second configuration	0.004434	0.023548
Third configuration	0.004437	0.023619
Fourth configuration	0.004416	0.023548
Fifth configuration	0.004433	0.023365

By addressing the safety concerns surrounding risky road user behaviors, this research can serve as a reference for addressing current challenges related to vehicle automation and urban environments, as discussed in earlier studies (Al-Obaidi *et al*., 2021; Bakar, 2021; Bhosale *et al*., 2022; Eftekhari *et al*., 2020, Eftekhari *et al*., 2022; Eftekhari & Al-Obaidi, 2019; Husain *et al*., 2023; Imaduddin *et al*., 2021; Khaleel *et al*., 2024; Setiyo *et al*., 2019). There are several recommendations for future research. This study utilized the RRT+BRT+CTS algorithm, which integrates the RRT and ACS algorithms for path planning. Future work could explore the integration of the RRT algorithm with PSO (Malik & Pohan, 2022), as reported by Pohan *et al*. (2024), that the integration of the PSO algorithm with variants of the RRT algorithm (specifically informed RRT*) demonstrates superior performance compared to the RRT and ACS integration. Additionally, this research employed Type-1 fuzzy logic; thus, future studies could investigate the use of Type-2 fuzzy logic, where (Pohan *et al*., 2023) indicated that Type-2 fuzzy logic controllers exhibit superior performance compared to Type-1 fuzzy controllers. Moreover, beyond RRT-based algorithms, future research could consider using variants of RRT and PRM-based algorithms (Aria, 2020, Aria, 2021; Pohan & Utama, 2024). In particular, it has been reported that the informed PRM algorithm exhibits better convergence speed. Future research could also consider using machine learning methods (Abdulazeez & Ageed, 2024; Mohammed & Abdulazeez, 2024; Soegoto *et al*., 2022; Taher & Abdulazeez, 2023) as well as deep learning techniques (Ali & Abdulazeez, 2024) to detect dangerous vehicles.

4. CONCLUSION

This study introduces a new motion planning strategy for autonomous vehicles. This strategy uses fuzzy logic to improve safety in response to risky road user behavior. By combining path and speed planning with a novel fuzzy inference system, this method addresses the challenges of erratic actions, including zigzag vehicles, sudden braking, and sudden lane changes. Simulation results show that this strategy outperforms conventional methods in terms of safety costs. This improved performance is due to the fuzzy system's ability to handle uncertainty in movement and stopping distance. These findings demonstrate

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the potential of this approach to advance the development of safer autonomous driving systems, which can promote smart and sustainable transportation solutions.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

7. REFERENCES

Abdulazeez, A. M., and Ageed, Z. S. (2024). Face emotion recognition based on machine learning: A review. *International Journal of Informatics, Information System and Computer Engineering (INJIISCOM)*, *5*(1), 53–87.

Al Husaeni, D. F., and Nandiyanto, A. B. D. (2022). Bibliometric using Vosviewer with Publish or Perish (using Google Scholar data): From step-by-step processing for users to the practical examples in the analysis of digital learning articles in pre and post Covid-19 pandemic. *ASEAN Journal of Science and Engineering*, *2*(1), 19–46.

Ali, N. N., and Abdulazeez, A. M. (2024). Facial emotion recognition based on deep learning: A review. *International Journal of Research and Applied Technology (INJURATECH)*, *4*(1), 21–34.

Al-Obaidi, A. S. M., Al-Qassa, A., Nasser, A. R., Alkhayyat, A., Humaidi, A. J., and Ibraheem, I. K. (2021). Embedded design and implementation of mobile robot for surveillance applications. *Indonesian Journal of Science and Technology*, *6*(2), 427–440.

Amelia, N., Abdullah, A. G., and Mulyadi, Y. (2019). Meta-analysis of student performance assessment using fuzzy logic. *Indonesian Journal of Science and Technology*, *4*(1), 74–88.

Aria, M. (2019a). New fuzzy logic system for controlling multiple traffic intersections with dynamic phase selection and pedestrian crossing signal. *Journal of Engineering Science and Technology, 14*, 1974–1983.

Aria, M. (2019b). New Sampling based planning algorithm for local path planning for autonomous vehicles. *Journal of Engineering Science and Technology Special Issue on INCITEST 2019*, 66–76.

Aria, M. (2020). Path planning algorithm using informed rapidly exploring random tree*-connect with local search. *Journal of Engineering Science and Technology Special Issue on INCITEST*, 50–57.

Aria, M. (2021). Optimal path planning using informed probabilistic road map algorithm. *Journal of Engineering Research, ASSEEE Special Issue*, 1–15.

Aria, M., and Utama, J. (2023). An autonomous parking system using the hybridization of the rapidly-exploring random trees star and ant colony system. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *31*(1), 291–297.

Bakar, M. A. (2021). Understanding of collective decision-making in natural swarms system, applications and challenges. *ASEAN Journal of Science and Engineering*, *1*(3), 161–170.

Bhosale, T., Attar, A., Warang, P., and Patil, R. (2022). Object detection for autonomous guided vehicle. *ASEAN Journal of Science and Engineering*, *2*(3), 209–216.

Dávid, B., Láncz, G., and Hunyady, G. (2019). Real-time behaviour planning and highway situation analysis concept with scenario classification and risk estimation for autonomous vehicles. *Designs*, *3*(1), 4.

Debada, E., Ung, A., and Gillet, D. (2020). Occlusion-aware motion planning at roundabouts. *IEEE Transactions on Intelligent Vehicles*, *6*(2), 276–287.

Eftekhari, H., Al-Obaidi, A. S. M., and Eftekhari, S. (2020). The effect of spoiler shape and setting angle on racing cars aerodynamic performance. *Indonesian Journal of Science and Technology*, *5*(1), 11–20.

Eftekhari, H., Al-Obaidi, A. S. M., and Eftekhari, S. (2022). Aerodynamic performance of vertical and horizontal axis wind turbines: A comparison review. *Indonesian Journal of Science and Technology*, *7*(1), 65–88.

Eftekhari, S., and Al-Obaidi, A. S. M. (2019). Investigation of a cruising fixed wing mini unmanned aerial vehicle performance optimization. *Indonesian Journal of Science and Technology*, *4*(2), 280–293.

Fu, Y., Li, C., Yu, F. R., Luan, T. H., and Zhang, Y. (2020). A decision-making strategy for vehicle autonomous braking in emergency via deep reinforcement learning. *IEEE Transactions on Vehicular Technology*, *69*(6), 5876–5888.

Gu, Z., Gao, L., Ma, H., Li, S. E., Zheng, S., Jing, W., and Chen, J. (2023). Safe-state enhancement method for autonomous driving via direct hierarchical reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, *24*(9), 9966–9983.

Husain, S. S., Kadhim, M. Q., Al-Obaidi, A. S. M., Hasan, A. F., Humaidi, A. J., and Al Husaeni, D. N. (2023). Design of robust control for vehicle steer-by-wire system. *Indonesian Journal of Science and Technology*, *8*(2), 197–216.

Imaduddin, I., Ramadhan, D. F., and Noor, R. A. M. (2021). Effect of voltage, current, and power on revolutions per minute in the brushless direct 3000-watt current motor on e-Gokart. *ASEAN Journal of Science and Engineering*, *1*(3), 221–228.

Khairudin, M., Refalda, R., Yatmono, S., Pramono, H. S., Triatmaja, A. K., and Shah, A. (2020). The mobile robot control in obstacle avoidance using fuzzy logic controller. *Indonesian Journal of Science and Technology*, *5*(3), 334–351.

Khaleel, H. Z., Ahmed, A. K., Al-Obaidi, A. S. M., Luckyardi, S., Al Husaeni, D. F., Mahmod, R. A., and Humaidi, A. J. (2024). Measurement enhancement of ultrasonic sensor using pelican optimization algorithm for robotic application. *Indonesian Journal of Science and Technology*, *9*(1), 145–162.

DOI: https://doi.org/10.17509/ajse.v4i3.75343
p- ISSN 2776-6098 e- ISSN 2776-5938

Li, R., Deng, S., and Hu, Y. (2022). Autonomous vehicle modeling and velocity control based on decomposed fuzzy PID. *International Journal of Fuzzy Systems*, *24*(5), 2354–2362.

Ma, L., Xue, J., Kawabata, K., Zhu, J., Ma, C., and Zheng, N. (2015). Efficient sampling-based motion planning for on-road autonomous driving. *IEEE Transactions on Intelligent Transportation Systems*, *16*(4), 1961–1976.

Malik, A., and Pohan, M. A. R. (2022). The development of a path planning algorithm combining the rapidly-exploring random tree algorithm and the particle swarm optimization algorithm. *Journal of Engineering Science and Technology*, *17*(6), 3742–3754.

Mohammed, A. J., and Abdulazeez, A. M. (2024). Healthcare diseases classification based on machine learning algorithms: A review. *International Journal of Informatics, Information System and Computer Engineering (INJIISCOM)*, *5*(2), 218–252.

Nandiyanto, A. B. D., Al Husaeni, D. F., and Al Husaeni, D. N. (2024). Introducing ASEAN Journal for Science and Engineering in Materials: Bibliometric analysis. *Journal of Advanced Research in Applied Mechanics*, *112*(1), 102–113.

Nandiyanto, A. B. D., and Al Husaeni, D. F. (2021). A bibliometric analysis of materials research in Indonesian Journal using VOSviewer. *Journal of Engineering Research - ASSEEE Special Issue*, 1–16.

Nascimento, A. M., Vismari, L. F., Molina, C. B. S. T., Cugnasca, P. S., Camargo, J. B., de Almeida, J. R., Inam, R., Fersman, E., Marquezini, M. V., and Hata, A. Y. (2019). A systematic literature review about the impact of artificial intelligence on autonomous vehicle safety. *IEEE Transactions on Intelligent Transportation Systems*, *21*(12), 4928–4946.

Pan, H., Luo, M., Wang, J., Huang, T., and Sun, W. (2024). A safe motion planning and reliable control framework for autonomous vehicles. *IEEE Transactions on Intelligent Vehicles*, *9*(4), 4780–4793.

Pohan, M. A. R., and Utama, J. (2023a). Efficient autonomous road vehicles local path planning strategy in dynamic urban environment using RRTACS bi-directional rule templates and configuration time-space. *Journal of Engineering Science and Technology*, *18*(5), 2388–2397.

Pohan, M. A. R., and Utama, J. (2023b). Efficient sampling-based for mobile robot path planning in a dynamic environment based on the rapidly-exploring random tree and a rule-template sets. *International Journal of Engineering*, *36*(4), 797–806.

Pohan, M. A. R., and Utama, J. (2024). Smart probabilistic road map (smart-PRM): fast asymptotically optimal path planning using smart sampling strategies. *Jordanian Journal of Computers and Information Technology*, *10*(2), 45–61.

Pohan, M. A. R., Taufiqurrahman, D. R., Fernando, S., and Fitriani, V. R. L. (2023). Odour pollution control using type-2 fuzzy logic controller. *Journal of Engineering Science and Technology*, *18*(1), 48–57.

Pohan, M. A. R., Trilaksono, B. R., Santosa, S. P., and Rohman, A. S. (2021). Path planning algorithm using the hybridization of the rapidly-exploring random tree and ant Colony systems. *IEEE Access*, *9*, 153599–153615.

Pohan, M. A. R., Trilaksono, B. R., Santosa, S. P., and Rohman, A. S. (2024). Path planning using combined informed rapidly-exploring random tree star and particle swarm optimization algorithms. *IEEE Access*, *12*, 56582–56608.

Setiyo, M., Widodo, N., Purnomo, B. C., Munahar, S., Rahmawan, M. A., and Luthfi, A. (2019). Harvesting cooling effect on LPG-Fueled vehicles for mini cooler: A lab-scale investigation. *Indonesian Journal of Science and Technology*, *4*(1), 39–47.

Soegoto, E. S., Ananta, H., Zaki, I., and Ranau, M. I. N. (2022). Implementation of management information system using machine learning technology. *International Journal of Research and Applied Technology (INJURATECH)*, *2*(2), 220–228.

Taher, H. A., and Abdulazeez, A. M. (2023). Machine learning approaches for heart disease detection: A comprehensive review. *International Journal of Research and Applied Technology (INJURATECH)*, *3*(2), 267–282.

Taheri, E., Ferdowsi, M. H., and Danesh, M. (2019). Closed-loop randomized kinodynamic path planning for an autonomous underwater vehicle. *Applied Ocean Research*, *83*, 48–64.

Trauth, R., Moller, K., and Betz, J. (2023). Toward safer autonomous vehicles: Occlusion-aware trajectory planning to minimize risky behavior. *IEEE Open Journal of Intelligent Transportation Systems*, *4*, 929–942.

Valiente, R., Toghi, B., Pedarsani, R., and Fallah, Y. P. (2022). Robustness and adaptability of reinforcement learning-based cooperative autonomous driving in mixed-autonomy traffic. *IEEE Open Journal of Intelligent Transportation Systems*, *3*, 397–410.

Wang, D., Fu, W., Zhou, J., and Song, Q. (2023). Occlusion-aware motion planning for autonomous driving. *IEEE Access*, *11*, 42809–42823.

Wang, M., Chen, J., Deng, Z., and Xiang, Y. (2021). Velocity planning method base on fuzzy neural network for autonomous vehicle. *IEEE Access*, *9*, 19111–19126.

Xue, H., Zhang, Z., Wu, M., and Chen, P. (2019). Fuzzy controller for autonomous vehicle based on rough sets. *IEEE Access*, *7*, 147350–147361.

Zhang, L., Zhang, R., Wu, T., Weng, R., Han, M., and Zhao, Y. (2021). Safe reinforcement learning with stability guarantee for motion planning of autonomous vehicles. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(12), 5435–5444.

Zheng, H., Chen, C., Li, S., Zheng, S., Li, S. E., Xu, Q., and Wang, J. (2023). Learning-based safe control for robot and autonomous vehicle using efficient safety certificate. *IEEE Open Journal of Intelligent Transportation Systems*, *4*, 419–430.

DOI: https://doi.org/10.17509/ajse.v4i3.75343
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