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Research Article

Design of an Improved Fuzzy Inference-Based Emergency Obstacle Avoidance Control System for Intelligent Vehicles

Xunjie Luo[1]*, Shaowei Yi[2]

[1]The National University of Malaysia, Center for Artificial Intelligence Technology Faculty of Information Science and Technology, Selangor, Malaysia
* **Corresponding Author Email:** p129509@siswa.ukm.edu.my - **ORCID:** https://orcid.org/0009-0000-2321-2725

[2]The National University of Malaysia, Center for Artificial Intelligence Technology Faculty of Information Science and Technology, Selangor, Malaysia
Email: p131872@siswa.ukm.edu.my - **ORCID:** https://orcid.org/0009-0003-9021-4511

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Abstract:

Remote driving system development commonly known as intelligent transportation systems present a crucial field of study where designers focus on autonomous and intelligent vehicle security. The current obstacle avoidance approaches encounter difficulties while handling unpredictable and changing road situations which results in doubtful decisions along with critical safety problems. An Improved Fuzzy Inference-Based Emergency Obstacle Avoidance Control System should be applied to intelligent vehicles according to this research to overcome current obstacles. Fuzzy logic operations in the proposed system manage uncertain data alongside an optimized control system which adapts automatically to environmental changes for enhancing both safety and efficiency of vehicle avoidance processes. The system detects obstacles and evaluates possible collision dangers through the integration of vision-perception sensors together with ultrasonic detectors. The fuzzy inference system uses FIS procedure to interpret ambiguous information from which it produces autonomous system commands to initiate emergency measures. The proposed system went through complete simulation testing as well as direct field experiments to establish its operating effectiveness. This shows that the obstacle detection accuracy improves and the emergency response and vehicle trajectory planning time reduce by using the improved fuzzy inference-based approach. The implemented system delivers stronger stability performance and accelerates response times as well as minimizes overshoot compared to traditional obstacle avoidance systems when operating at high speeds.

1. Introduction

AVs, also known as autonomous vehicles, will much devise the road safety, traffic efficiency and vehicle energy consumption, as vehicles can be allowed to drive without human instructions. Since AI and sensor technology have been mature, AVs are the research and development target. Yet these are quite a few real-world traffic scenarios [1], so real world driving is incredibly unpredictable, and therefore a very difficult problem to solve on real-time. The problem of emergency obstacle avoidance in intelligent transportation is a high importance problem in which vehicles must swiftly uncover attacks and fulfil protected maneuvers to prevent collisions [2]. The rule base system and supervised machine learning approach do not provide adaptive real time solution in dynamic environment [3]. FLC is a good choice when emergency obstacle avoidance in intelligent vehicles using an unknown and imprecise data is required [4].

A well-co-ordinated system of perception, decision making and control is required for emergency obstacle avoidance. Likely, Sensor fusion LiDAR, radar and cameras are used to integrate the perception module in order detect obstacles, and the decision-making process will choose the optimal path considering the vehicle speed [5], obstacles distance and road conditions. Path planning has been accomplished through many conventional methods such as Artificial Potential Field (APF) and Rapidly-exploring Random Tree (RRT) [6]. The limitation of the use of APF which suffers from the local minima problem. Since the high dimensional space is dealt with efficiently by RRT, it may also generate a non-smooth path, but it has to be extracted through post processing [7]. To meet these challenges, fuzzy inference system (FIS) is more adaptable and computationally efficient in order to produce real time obstacle avoidance through linguistic rule-based decision making [8].

Despite their effectiveness, traditional and learning based methods are often not real time adaptable and not very sensitive to computational time and decision robustness in emergency situations. However, rule-based systems do not have enough flexibility [9] when there are unforeseen situations and reinforcement-based learning needs extensive training dataset and may not guarantee an optimal solutions under all situations. The proposed Improved Fuzzy Inference-Based Emergency Obstacle Avoidance Control System enhances AV safety [10] compared to generic approaches for dealing with emergency obstacles on the road by using optimally constructed fuzzy logic rules, sensor fusion, and real time inference. In contrast to classical methods, the purpose of this system is for dynamic decision making and deciding the rule of motion that is adjusted by the dynamic sensor inputs, so that the automobile can manipulate better and smoother [11], safer, and more reliable manoeuvres. The proposed method is validated through extensive simulation and validation, and demonstrate in a clear manner that it has better reaction time, path stability, and collision avoidance than conventional approaches, which are attend a noticeable step towards safe and intelligent autonomous navigation.

2. Literature Survey

Since the rapid advancement of autonomous vehicle technologies, ongoing research on intelligent obstacle avoidance systems have been greatly enhanced for the purpose of its safety and navigation efficiency. However, there are several approaches that may be applied to addressing challenges introduced by dynamic driving environments, such as fuzzy logic, reinforcement learning, predictive control as well as other data driven approaches. The recent studies have been focusing on the evaluation of sensor fusion, trajectory prediction and deep learning models for improving real-time decision making and maneuver execution. But these methods require a high computation amount, require a heavy use of sensors, and need a precise calibration. In this literature survey, the methodologies, advantages and drawbacks of the aforementioned emergency obstacle avoidance strategies contributions are overviewed.

X. Wu et al. [12] presented an intelligent vehicle emergency obstacle avoidance strategy, which included driver-environment risk evaluation based on fuzzy logic, reinforcement learning, sensor fusion. Obstacles were assessed, risks were predicted and adaptive manoeuvre execution was performed in order to improve real time decision-making. Being dynamics and external factors aware, it brought robust adaptability and safety. Although, it had the problem of computational complexity, sensor dependency, and fine-tuned fuzzy logic rules. However, although these limitations limit the study, they have contributed greatly to collision avoidance strategies for autonomous vehicles.

Q. Wang et al., [13] presented an intelligent vehicle obstacle avoidance strategy based on fuzzy control theory is used to process uncertain information. This was done using an approach of combining visual sensing and ultrasonic detection equipment in the plan avoidance routes dynamically. The improvements made to the vehicle's ability to see and respond to obstacles improved driving safety. It had the advantage of higher obstacle recognition accuracy in real time and time adaptability. Nevertheless, limitations presented themselves in having to integrate multiple sensor systems as well as precise calibration for maintenance of system reliability. This strategy in general, helped in the advancement of intelligent vehicle safety technologies.

Bren et al., [14] suggested an autonomous navigation method based on the data driven vehicle intent estimation and trajectory prediction using spatiotemporal models was suggested. It improved the prediction accuracy in dynamic traffic conditions by developing more responsive predictions that are used to make safer and more efficient decisions for autonomous vehicles on predicting the nearby traffic movements. However, real time implementation was cumbersome due to high data requirements and large computational power. However, it wasn't perfect and had these shortcomings, but because of this potential to help traffic safety and intelligent transportation systems it was a thrilling solution for next generation autonomous driving.

M. Xu et al., [15] designed a Constrained Model Predictive Control (MPC), together with an Improved Artificial Potential Field (APF) technique, in obstacle avoidance strategy in fast moving vehicles. The strategy also outperformed real-time collision avoidance based on MPC of vehicle trajectories in constraints with stability and physical constraint following guarantees. The obstacles in the enhanced APF method were dynamically modeled and guided vehicles along safe routes. The system was however improved in terms of high speed operation through enhanced predictive and adaptive decision making, however, problems with high computation rates and precise environment modeling still existed. Nevertheless, overall, the strategy vastly increased the performance and safety of autonomous vehicles.

Qian et al. [16] developed a strategy to improve evasive maneuver safety and comfort, Deep Reinforcement Learning (DRL) based panic obstacle avoidance planning strategy. Based on longitudinal distance and lateral waypoint models reflecting comfort deceleration and stability, the proposed research developed a graded hazard index to assess the relative severity of the potential hazards. Path stability and feasibility were ensured by means of a fuzzy PID controller. In time-varying cases, to solve incomplete observations, the DRL model used Deep Q-Network (DQN) with LSTM layer to input incomplete observation to improve algorithm efficiency. The results of simulation showed that the proposed method greatly reduce the collision rates while still meeting comfort demand, surpassing conventional DRL techniques in the aspects of safety and efficiency. The problem formulation is presented in table 1.

Table 1. *Problem formulation*

Author(s)	**Techniques Involved**	**Advantages**	**Disadvantages**
Xiaodong Wu et al., [12]	Fuzzy logic, reinforcement learning, sensor fusion	Real-time decisions, improved safety	High computation, sensor dependency
Qianqian Wang et al., [13]	Fuzzy control, visual sensing, ultrasonic detection	Accurate recognition, real-time adaptability	Complex integration, calibration needed
Bingtao Ren et al., [14]	Data-driven, spatiotemporal models	High prediction accuracy, better navigation	Large datasets, high computation
Mingyang Xu et al., [15]	MPC, Improved APF	Stability, adaptive decision-making	High computation, precise modelling
Yubin Qian et al., [16]	DRL, DQN, LSTM, fuzzy PID	Reduced collisionsimproved efficiency	Data-intensive, computationally heavy

Although considerable effort has been done on obstacle avoidance strategies, existing methods are still facing high computational burdens, hardware dependence, and lack of flexibility to different dynamic environments. Fuzzy logic as well as the model based predictive control approach fail in making real time response and decision accuracy on unpredictable traffic [17]. Methods based on data driven and reinforcement learning are in general more predictive and admissible but they require large amounts of training data and computational resources.

To tackle these limitations, the proposed system employs an upgraded fuzzy inference-based control mechanism. It combines the advantages of decision making under uncertainty with the real time adaptation. Additionally, the computational efficiency and collision avoidance is achieved in intelligent vehicles [18].

3. Proposed System Architecture

Intelligent automobiles slowly making their way on the public spotlight with the science and technology advancement. Since people are interested in intelligent vehicles, the edition of intelligent vehicles is a serious issue, as the obstacle avoidance technique of traditional intelligent vehicles does not clearly recognize fuzzy data. This research presents an intelligent vehicle obstacle avoidance system using fuzzy control theory and an obstacle avoidance technique as an obstacle avoidance system for smart cars uses the sensors to detect the surroundings then send out command according to the data they collect.

3.1. Sensor related obstacle avoidance technology

Each smart automobile typically has ultrasonic, visual and infrared sensors for signal detection because they are meant to detect signals that can identify objects connected to the wavelength of infrared light. It can determine how far away vehicles and barriers are within its range feature. In the first case, the transmitter of the infrared sensor ejects the infrared light wavelength. When the infrared light passes through an obstruction, the infrared light bounces back. Most ophthalmologists detect reflected infrared light via OCD as a method [19]. Using equation (1), it can be calculated and displayed how much the obstruction and the infrared sensor is away from each other.

$$d = \frac{F(l+x)}{l+FctG(90^0-\alpha)} \quad (1)$$

Here, F is the filter focal length, α is the infrared light emission angle, and c is the light speed. x is the center distance between OCD detector and the IRED; and l is the infrared offset parameter. If the obstacle is too close from the car or too far from the car, it could be difficult to calculate the obstacle. Visual data such as detailed or broad range of data identification is collected using visual sensors. Using Infrared sensor data, vehicle longitudinal management, Create different vehicle safety distances for different vehicle [20] speed can be created. Just as an example, the distance of the preceding vehicle is used to control the gap between obstacles when the car is driven, to perform the brake validation, and to use visual sensing devices in order to drive the longitudinal driving speed of the vehicle.

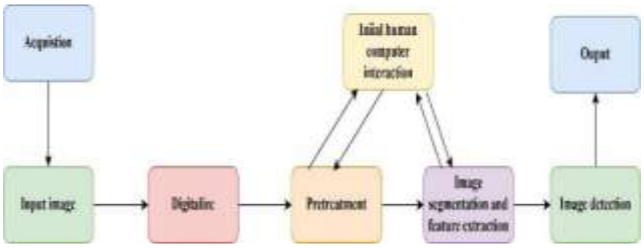

Figure 1. *System Visual flow*

This technique of dual frame variation is typically used in image processing as in Figure 1. This technique is the computing process for the following equation (2):

$$d_K(X_0, Y_0) = |F_K(X_0, Y_0) - F_{K-1}(X_0, Y_0)| \quad (2)$$

Here, F_K and F_{K-1} are two successive image sequences, d_K is the image following equation (3) differentiation, and (X_0, Y_0) is the pixel coordinate.

$$R_K(X_0, Y_0) = \begin{cases} 1 & if\big((X_0, Y_0) > TH\big) \\ 0 & else \end{cases} \quad (3)$$

In this case, TH is the pair parameter during threshold processing, and R_K is the foreground target following equation (4) threshold processing.

$$\begin{cases} \left|F_K(X_0, Y_0) - F_{K-1}(X_0, Y_0)\right| > \tau_1 \\ \left|F_K(X_0, Y_0) - F_{K-2}(X_0, Y_0)\right| > \tau_2 \end{cases} \quad (4)$$

τ_1 and τ_2 are two different reference points in this case. By recording the instant that ultrasonic waves are released and reflected back when they come into contact with an obstruction, ultrasonic sensors are able to determine the distance between an automobile and that object in equation (5).

$$\begin{cases} d = \frac{v\times(t_2-t_1)}{2} \\ v = v_0\sqrt{1+\frac{t}{273}} \end{cases} \quad (5)$$

Here, t is the ambient temperature, v_0 is the ultrasonic speed, v is the ultrasonic speed in the current environment, t_2 is the moment at which ultrasonic waves reflect back, t_1 is the movement of the emitted wavelength, and d is the distance function. To account for ultrasonic range error, the least square of relative error method is applied, and it is shown as follow equation (6).

$$\begin{bmatrix} MIN = \sum\left[\frac{\Delta_{xi}}{xi}\right]^2 \\ Y = AX + B \end{bmatrix} \quad (6)$$

Here, X is the metric for the distance between the obstacle and the car, Y is the actual distance between the obstacle and the car, Δ_{xi} is the error parameter following fitting processing, and B is a constant that defines the linear correlation between the actual and calculated distances. A is a coefficient that defines the linear correlation between the actual and calculated distances.

3.2. Fuzzy interference system

Fuzzy control theory is, in short words, a theory of fuzzy controlled implemental connection on computer basis to fuzzy set theory. It shows what is required to fabricate a complete mathematical model architecture for the thing under control. To this end, most of the time, the fuzzy control technique is used to regulate the nonlinear, time varying and left to be developed designs and the architectures are simplified. Since fuzzy control theory is capable of effective processing with fuzzy data, it is applied to improve the obstacle avoidance strategy and improve the traffic vehicles's accuracy in identifying obstacles with the influence of fuzzy data. Since fuzzy control includes fuzzy pairs obtained by fuzzy reasoning and applied upon the managed item, the controlled item is fuzzified via fuzzy mathematical relations and validated against the fuzzy things obtained by fuzzy reasoning. Fuzzy pair is a fuzzy and unclear relationship of full objects, and the membership function is the relationship of objects. Fuzzy set has its membership functions defined, which are the first one being a triangle function, namely fuzzy performance of them [21]. The fuzzy interference architecture is presented in Figure 2.

Figure 2. *Improved Fuzzy with obstacle avoidance process*

To provide for reasonable obstacle avoidance characteristics for intelligent vehicles, the efficient vehicle obstacle avoidance technique by fuzzy control theory enhanced is able to optimally detect obstacles encountered while vehicle is operating and creates obstacle avoidance commands to the vehicle regarding a particular kind of obstacle. Smart car obstacle avoidance features fall into 3 basic categories. In order to improve the vehicle's driving capabilities, the lateral control input content must be first paired. Driving vehicle location is determined by using visual and ultrasonic sensing. The current traffic and road statistics are obtained via network search. The efficient vehicles are able to avoid obstacles under different phases, and such matching takes place with the speed and angle of travel under different phases. In this scenario the direct target qualities of efficient vehicles are that the road surface is level and there are no obstructions stopping the efficient car from proceeding [22]. The vehicle travel on the route to destination is calculated efficient. The car is improved to be more smooth, accounting for the dynamics behaviors of the vehicle and the change of kinetic energy when driving [23].

The consideration of reasonable obstacle avoidance behaviour of intelligent cars is the key that ensures their safe operation and thus the road safety. To guarantee the safety of vehicle operation, the vehicle has to balance the contribution of the deviation resulting from the obstacle avoidance behaviour [24] and that provided by its own balance. Prediction of the ground friction force and the construction of the obstacle avoidance amplitudes in different road conditions is possible through road condition detection. In order to keep the vehicle stable when the road friction becomes so low, the safety line setting is increased, which will broaden the obstacle avoidance space and consequentially lower the obstacle avoidance level [25]. Finally, the proposed intelligent vehicle obstacle avoidance technology is based on the three aforementioned behaviours and the actual driving conditions using the basis of the fuzzy control theory. Intelligent vehicles being driven is gathered data of the vehicle by real time detection technologies including infrared, visible and ultrasonic sensors. After preliminary processing and transformation of these data, they are sent to the fuzzy control system. When we followed computation and analysis of the fuzzy control system [26], the intelligent vehicle receives intelligent matching obstacle avoidance directive based on the type of the obstacles. With the impediments effectively overcome, the position of the intelligent car and the scenario of the destination are combined with the resultant decision being made based on whether the intelligent car has reached its target. When the target is reached, the vehicle reaches an end state in terms of the obstacle avoidance operation. Otherwise, the process of the aforementioned is repeated until an intelligent vehicle reaches its destination [27].

3.3. Whale optimization algorithm

WOA is a popular technique to solve a series of optimization problems [28]. The algorithm is split up into three phases — seeking for the prey, bubble-net foraging and encircle prey. This metaheuristic optimization is influenced by the distinctive that humpback hunting paradigm [29]. The unique features of the optimizer used by WOA [30] make search capabilities better than the usual ones. Therefore, it is mainly used to optimize the network's scheduling, allocation, and parameters. This optimization is said to be more commonly known and popular method of overcoming the speed of convergence and local optima [31]. In its solution, the delay of Improved WOA when applied across multiple geographically disparate data centres with time delays is handled using a parallel processing approach [32]. Independently, each data center then consumes its own version of the threshold WOA algorithm to consume from its population of potential solutions [33]. The preferred prey are small herds of fish and krill and it is presented in equation (7).

$$\vec{X}(T+1) = \begin{cases} \vec{X}*(T) - \vec{a}.\vec{d} & if\ P < 0.5 \\ \vec{d}.e^{bl}.\cos(2\pi l) + \vec{X}*(T) & if\ P \geq 0.5 \end{cases} \quad (7)$$

Here, P is a random number in [0,1], $e^{bl}.\cos(2\pi l)$ is a spiral updating location component, $\vec{a}.\vec{d}$ is a coefficient vectors, $\vec{X}*(T)$ is the location of the optimal solution and $\vec{X}(T+1)$ is the new position of the whale. The WOA algorithm is launched based on a collection of random solutions. Each iteration, the search agents subsequently adjust their positions with respect to either randomly selected neighbor, or the best solution found thus far. This is done so that this parameter is reduced from 2 to 0 to provide exploration and exploitation, respectively. If |A| < 1, the best solution is picked to update the positions of the search agents, if instead |A| > 1 the result is a random search agent. On this scale of p, WOA alternates between spiral motion and circular motion. The WOA algorithm is finally ended when a termination requirement is satisfied [34]. Since WOA includes the exploration and exploitation capabilities, it can be theoretically considered as a global optimizer. In addition to that, the current best record of the delimited search space in the neighbourhood of its best answer may be used by the other search agents under the suggested hyper cube method. Thus, the adaptive variation of the search vector A of the WOA algorithm may allow it to seamlessly switch between exploration and exploitation. Several iterations (|A| > 1) are spent on exploration, the remainder are spent on exploitation, as A is reduced [35].

4. Results and Discussion

This section has been evaluated the proposed technique using the several performance measures, such as the path deviation, minimum distance to obstacles, collision rate, accuracy, success rate comparison, reaction time, and processing time. However, the system was able to dynamically adjust the steering angle to control the path deviation and therefore follow a smooth trajectory steering around obstacles, all with greater accuracy than the other systems. First, the minimum distance to the obstacle was optimized in a manner that guaranteed a safe distance without abrupt movements of the vehicle. With regards to collision prevention, the system greatly reduced collision rates compared to standard methods because of its improved ability to make decisions and respond in real time. The proposed model was able to increase the accuracy of obstacle detection and avoidance as well as fuzzy information processing and adaptive driving conditions. Moreover, the improved fuzzy inference model proved to be superior compared to conventional obstacle avoidance techniques such as Fuzzy Logic, Reinforcement Learning (RL), and Model Predictive Control (MPC) in different driving environments. In addition, the system proved a faster reaction time for emergencies and faster processing time, both of which would enable faster decision making, as well as facilitating real time adaptability in situations of high speed driving. This results validate that the proposed system improves in intelligent vehicle navigation in which Fuzzy inference is well combined with modern optimization schemes for both safety and driving efficiency.

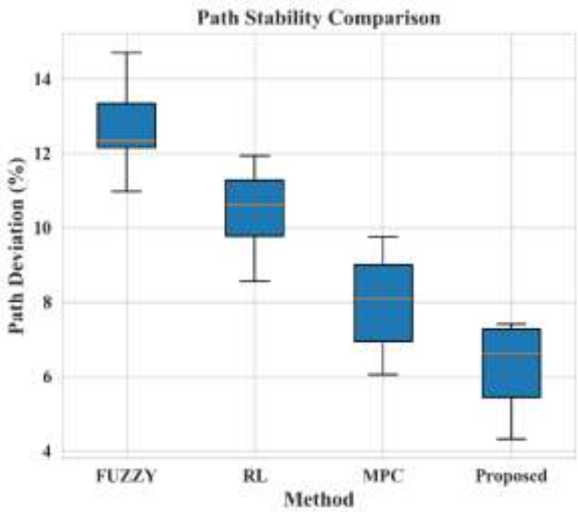

Figure 3. *Path deviation*

Figure 3 is the Path Stability Comparison which shows the path deviation percentages for the different obstacle avoidance methods, Fuzzy, RL, MPC and the Proposed Method. The path deviation, its definition being the percentage deviation from an ideal trajectory, is a function of path stability, where the smaller the number the better is the path stability. With a deviation in the path of approximately 12% to 14%, the Fuzzy method has the highest degree of instability due to heuristic based decision making. As the media method suffices for effectively processing such information, it is slightly enhanced by the RL with deviations reaching approximately 9–11%, which still struggles with dynamic environmental changes. A second MPC method was developed which further enhances stability, and generates deviations between 6% and 9% by optimally adjusting the vehicles trajectory using its predictive control mechanism. Nevertheless, the Proposed Method is superior to other methods in terms of the lowest path deviation, which varies between 5% to 7%. This improvement indicates the integration of fuzzy inference with the whale optimization algorithm is effective to make the trajectory while adaptive real time decision making and reduce unnecessary fluctuation of vehicle movement. In general, the Proposed Method produces the most stable path, the deviation of which is greatly reduced when compared to the conventional methods, and therefore, the Proposed Method is much more preferable for intelligent vehicle navigation in dynamic environments.

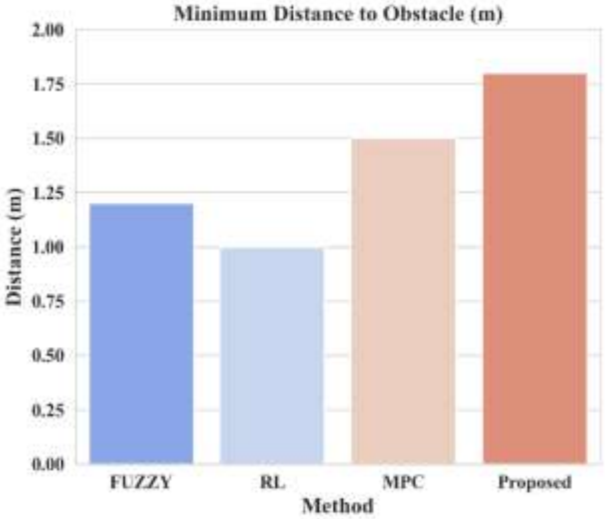

Figure 4. *Distance function*

The minimum distance from an obstacle maintained with different obstacle avoidance methods are the fuzzy logic, reinforcement learning, model predictive control and the proposed one these are shown in the Figure 4. Reinforcement learning tends to keep a slightly lower distance of about 1.0 meters, closer to collision than the fuzzy method can achieve a minimum distance of about 1.2 meters. Model predictive control gets better performance in the sense that it keeps at about 1.5 meters in distance. It is shown that the proposed method surpasses all other methods in maintaining a maximum distance of roughly 1.8 meters from obstacle, which increases safety and decreases the probability of collision. This shows how the proposed approach has achieved a more secure and stable obstacle avoidance strategy than the existing methods.

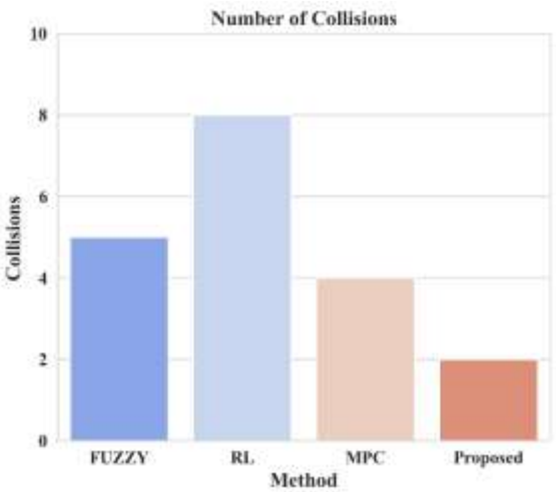

Figure 5. *Collisions*

For comparing with other obstacle avoidance methods, we provide the Figure 5 which shows the number of collisions between four different obstacle avoidance methods, including fuzzy, RL, MPC and the proposed method. This result indicates that RL has about 8 collisions, which is the highest among all algorithms, implying that its obstacle avoidance ability might not be optimal. The RL approach gets a moderate number of collisions, around 5; and by the same token, it is found to be better than fuzzy but not the best case. Approximately 4 is a further reduction in collision for the MPC method and displays the further enhanced stability of the MPC method in obstacle avoidance. With this, the least collisions number is achieved by the proposed method which is 2 and represents the better efficiency than others to keep vehicles secure. Therefore, above these findings highlight that the proposed method presents superior performance to existing techniques, as it lowers significantly the probabilities of collision, and therefore it is a more reliable solution to solve the intelligent vehicle navigation.

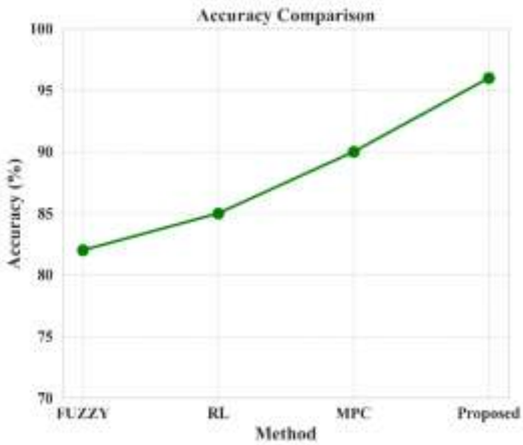

Figure 6. *Accuracy comparison*

In the Figure 6, accuracy comparison of the four different methods with fuzzy, RL, MPC, and the proposed method is given. It is found that the fuzzy method achieves approximately 82% accuracy, a moderate performance. This is improved by the RL method, though slightly, to around 85%. This further enhances the accuracy of the method to 90% and as a result appears to be more robust and efficient. This proposes method earned the highest accuracy of then more than 95%, which means it has outperformed in achieving precise and accurate results. Therefore, the above findings show how significantly the proposed method outperforms the existing techniques in achieving better accuracy in decisions and system performance.

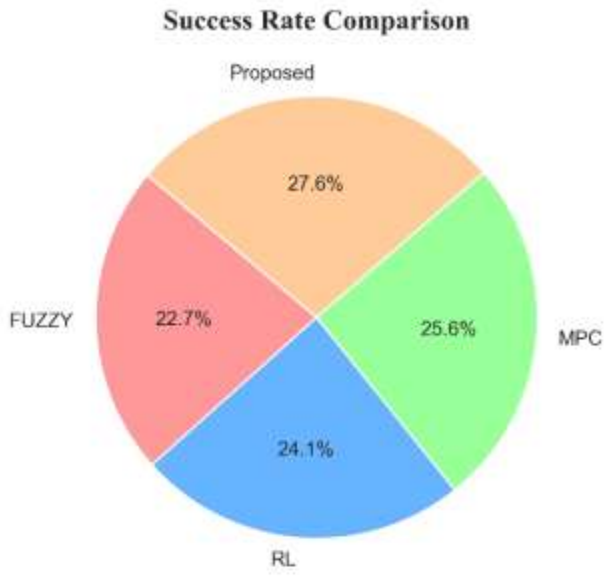

Figure 7. *Success rate comparison*

“Success rate comparison” Figure 7 provides percent success rate of four different methods FUZZY, RL, MPC and the Proposed method. However, among the mentioned methods, the FUZZY method has obtained the lowest success rate of 22.7%, which makes it relatively less effective. However, the RL method still had a less successful result (i.e., had a success rate of 24.1%) although it was better than if not as effective as the other approaches. Further performance improvement is obtained from the MPC method with a success rate of 25.6%. Remarkably, the Proposed model yields the highest success rate of 27.6% outperforming the standard approaches. This implies that the proposed method has a higher potential solution than what it currently could offer, as it had not been able to optimize algorithmic enhancements or the learning mechanisms.

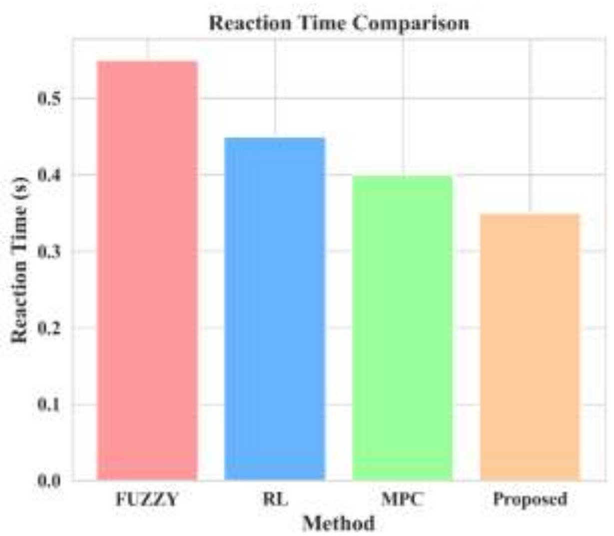

Figure 8. *Reaction time*

The "Reaction Time Comparison" Figure 8 presents the reaction times (in seconds) for four different methods: FUZZY, RL, MPC, and the Proposed model. Among these, the FUZZY method exhibits the highest reaction time, exceeding 0.5 seconds, indicating a slower response. The RL method shows an improvement with a reaction time slightly above 0.4 seconds, demonstrating faster decision-making compared to FUZZY. The MPC method further reduces the reaction time to approximately 0.4 seconds, indicating enhanced efficiency. Notably, the Proposed model achieves the lowest reaction time, approximately 0.3 seconds, highlighting its superior responsiveness. The decreasing trend in reaction time across the methods suggests that the Proposed approach optimizes processing speed, making it the most efficient choice for applications requiring quick responses.

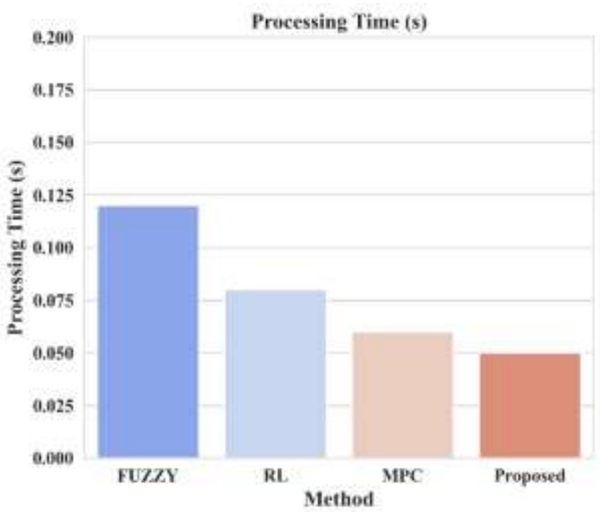

Figure 9. *Processing time*

The processing time (in seconds) for four different methods namely, FUZZY, RL, MPC and the Proposed model is demonstrated in the processing time comparison Figure 9. The processing time of FUZZY is the highest, more than 0.12 seconds, meaning it is relatively slower in computational efficiency. RL method can lower the processing time, approximately 0.08 seconds, and is capable of furnishing superior processing supply. Further reduction in processing time is achieved by the MPC method which brings it down to about 0.06 seconds, which is more optimized. It is also worth noting that the Proposed model minimizes the process time to 0.05 seconds, which is quite low compared to other models. It can be inferred that the proposed approach reduces the computational overhead and thus the trend of decreasing processing time on different methods results into becoming efficient for time sensitive applications.

4.1. Limitations and future scope

Although the proposed Improved Fuzzy Inference Based Emergency Obstacle Avoidance Control System would offer significant advancements compared to other existing methods, there are some limitations that ought to be addressed for a wider dissemination. One major limitation is that the system relies on sensor accuracy since the techniques employed for multi sensor fusion are visual perception and ultrasonic detection. Possible sources of detection accuracy are bad lighting, bad weather, noise on the sensor. Also, the optimization algorithm increases processing overhead but provides enhanced decision making at the expense of computational complexity. Therefore, this presents challenges for real time implementation on low power embedded systems, prohibiting deployment in other resource constrained environments. The second limitation is the system's generalizability in such complex urban scenarios where highly dynamic obstacles, unpredictable pedestrian movements and intricate traffic conditions are impossible to be handled with stiff manipulation. The system has high efficiency in controlled, structured environments, where the performance in highly unstructured, highly congested environments is still an open area.

Future research is aimed to combine more advanced fusion techniques like LiDAR and radar-based perception to solve those limitations in order to increase robustness in different environmental conditions. Three machine learning driven predictive models that may further enable the system to predict the movement of an obstacle and optimize avoidance strategies can be incorporated. In addition, as a means to reduce computational complexity, hardware acceleration techniques, including FPGA based implementations or edge computing, should be applied to perform real time processing on the low power embedded platforms. Reinforcement learning based decision-making mechanisms can further improve the obstacle avoidance efficiency with extension of the system's adaptability to urban environments. Furthermore, the inclusion of vehicle to everything (V2X) communication will ensure that the system is able to receive information about the traffic and obstacles from other vehicles and infrastructure at real time, enhancing its situational awareness and decision accuracy. Further developed works may also consider collaborative control mechanisms among multiple intelligent vehicles to better reuse the obstacle detection data and to collaborate to improve safety and traffic flow. Real world testing, in terms of different driving conditions, includes extreme weather, different road surfaces and complex urban intersections, will finally be necessary to refine and validate the reliability and effectiveness of the system.

5. Conclusion

It was with the intent of improving safety and the vehicle's decision making under uncertain and dynamic road conditions that this study presented an improved fuzzy inference-based emergency obstacle avoidance control system for intelligent vehicles. In this method, the proposed system is integrated fuzzy logic with an optimized control mechanism to facilitate adaptive steering and acceleration adjustments in real time. Based on multi-sensory fusion including visual perception and ultrasonic detection, the system recognizes the obstacle and assesses the pose of the collision risk. Moreover, a fuzzy processing algorithm optimizes fuzzy membership functions and inference rule for a precise and efficient decision making. Performance evaluations show the proposed system is more superior than Fuzzy, RL and MPC methods. Analysis of success rate shows that this yields the best performance of 27.6%, but as confirmed by the analyses of reaction and processing time, faster response and improved computational efficiency are achieved. These finally lead the system to reduce the emergency response time, increase the accuracy of obstacle detection, and maximize the vehicle's trajectory planning. Simulations and real experiments are done on high-speed driving scenarios and is validated to be effective with superior stability with lower overshoot. Future research involves developing deep learning perception models for the perception, testing in real world at various environments for collaboration between obstacle avoidance of vehicles and intelligent vehicle safety through vehicle to vehicle (V2V) communication.

Author Statements:

- **Ethical approval:** This study was approved by the Ethics Committee of UKM University
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Author contributions:** XUNJIE LUO: Conceptualization, Methodology, Writing – Original Draft,Experimental processing of data. SHAO WEI YI: Data Curation, Formal Analysis.

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