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Development of Fuzzy Logic Controller in Automatic Vehicle Navigation using IoT

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***Abstract:* -** The integration of fuzzy logic controllers in automatic vehicle navigation systems represents a significant advancement in intelligent transportation systems, especially when paired with Internet of Things (IoT) functionalities and optimized through genetic algorithms. This innovative fusion harnesses the precision of fuzzy logic, the connectivity of IoT, and the optimization capabilities of genetic algorithms to transform automatic vehicle navigation. Fuzzy logic controllers excel in managing uncertainty and imprecision, providing decision-making capabilities akin to human reasoning. By simultaneously assessing multiple inputs and determining actions based on degrees of truth, fuzzy logic enables safe and efficient navigation in dynamic driving environments with fluctuating variables like obstacle proximity and traffic flow. IoT integration enhances navigation systems by enabling real-time data collection and sharing among vehicles and infrastructure, fostering adaptive route planning and improving the overall navigation experience. Genetic algorithms further optimize system performance by iteratively adjusting fuzzy logic controller parameters, ensuring efficient decision-making tailored to specific performance criteria such as travel time and fuel consumption. This collaborative integration of fuzzy logic controllers, IoT, and genetic algorithms offers a holistic solution to the challenges of automatic vehicle navigation, enhancing safety, efficiency, and adaptability in complex driving scenarios. Beyond enhancing individual vehicle performance, this approach contributes to overall transportation system efficiency and safety by mitigating traffic congestion, reducing emissions, and minimizing accidents. Consequently, these integrated systems address crucial societal challenges and pave the way for widespread adoption of autonomous vehicles in the future.

Keywords: Fuzzy logic controllers, Automatic vehicles, Internet of things, Genetic algorithm.

I. INTRODUCTION

Automatic vehicle navigation, also known as autonomous or self-driving vehicle technology, stands at the forefront of transformative innovation in road transportation. It represents a paradigm shift aimed at enhancing safety, efficiency, and accessibility in transportation systems worldwide. This technology relies on a sophisticated array of sensors, cameras, and radar systems, coupled with advanced algorithms and artificial intelligence (AI), to perceive and interpret the surrounding environment in real-time. By comprehending complex traffic scenarios, including the behavior of other vehicles, pedestrians, and various obstacles, autonomous vehicles navigate roads with precision, aiming to revolutionize the concept of mobility [1]–[3].

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Central to automatic vehicle navigation is the ability to process vast amounts of data from onboard sensors accurately. These sensors collect information about the vehicle's surroundings, which is then analyzed by onboard computers running complex AI models. Through this process, autonomous vehicles continuously update their understanding of the environment, adjusting their speed, steering, and braking to ensure safety and compliance with traffic laws. Integration with global positioning systems (GPS) and digital maps allows these vehicles to plan routes, navigate through cities, and adapt to changing conditions such as traffic congestion [4]–[6].

Connectivity features enable autonomous vehicles to communicate with other vehicles and infrastructure, further enhancing their ability to anticipate and react to potential hazards. This communication, facilitated by technologies like cellular networks (5G), Wi-Fi, and dedicated short-range communications (DSRC), allows for real-time data exchange and fosters a more comprehensive information ecosystem. By sharing data on traffic conditions, weather updates, roadwork information, and vehicle diagnostics, vehicles can make informed decisions, improving overall navigation efficiency and safety [7]–[9].

Autonomous vehicles operate across a spectrum of automation levels, from partially automated systems requiring human oversight to fully autonomous systems capable of operating without any human intervention. As the technology matures, it promises to reduce traffic accidents caused by human error, alleviate congestion through optimized routing, and provide mobility solutions for those unable to drive. [10]–[12].

The FLC (fuzzy logic controllers) are a critical component of an autonomous vehicle's navigation system. This means that, even as the world shifts unpredictably, cars can keep driving straight ahead. The construction of any FLC meant for vehicle navigation involves several important steps. The first prerequisite Regardless of the future direction of high technology, automatic vehicle navigation demands a clear set basic not fuzzy decisions. The input and output variables of a navigation task are distance to obstacles, vehicle speed, and steering angle which are all defined in such a case.

The magical core is the rule base for an FLC which is composed of a variety of If Then rules and describes the way the system should react when different combinations of input conditions occur. They are extracted from expert knowledge or empirical data and designed to imitate human decision processes. The FLC checks up on the rules given the present input and uses inference procedure, like Mamdani method and Sugeno method evaluations on them to decide on actions are suitable. The rules' outputs are aggregated and defuzzified to produce hard control commands for the vehicle, such as particular steering angles or velocity values [13]–[15].

The development of automatic vehicle navigation based on rules means that we create and implement predefined instructions or "rules" which guide the behaviors of self-driving cars. This systematic approach involves a range of specific situations or decisions the vehicle may encounter while driving, such as traffic signals, obstacle avoidance, and speed limits. With rule-based systems, the simplicity and transparency are good. But they still must overcome a number challenges of complexity and unpredictability in human driving environments [16]-[18].

When it comes to the architecture of the smart car network, the Internet of Things has constructed a multi-layered platform that includes various technologies. This architecture is not comprised only of multi- layered perception; you also have network, data process, application, security layers. The networking supports real time, accurate collection and transmission of data that can be analyzed for more timely feedback even as data come in. Data usually arrives at varying intervals, they are often incomplete, and their significance depends on context. Real-time data sources: filter more data points than ever before! IoT technology helps with this by providing a wealth of real-time statistical information from linked sensors and devices - improving situational awareness as well as encouraging adaptive decision-making [19],[20].

Genetic algorithms can significantly enhance the performance of fuzzy logic controllers for automatic vehicle navigation. Drawing from the art of natural selection, genetic algorithms can change and enhance the parameters and rules of fuzzy logic systems over time, adapting to different conditions and making for better control of navigation. Before deploying fuzzy logic controllers, IoT integration, and genetic algorithms must be evaluated carefully. By using simulated environments like virtual ones to mimic real-world conditions, developers can optimize systems and predict how they will behave, making necessary changes to reduce the risks involved in real world tests.

To a greater extent, performance of automatic vehicle navigation systems is examined through real-world testing with different conditions. In this phase, existing controllers with embedded fuzzy logic are to be testing successfully on a bent of sensors that are equipped with actuators to determine their reliability and performance in a variety of scenarios. And the integration with deployment and monitoring mean that safety will remain paramount, as will efficiency when we can drive through town--without boundaries--to see life unfold live before us.

II. METHODOLOGY

In a design of automatic vehicle navigation systems based on fuzzy control, the method section is very important in introducing the design and implementation of fuzzy logic controllers. In this section is the process of multiple levels necessary to create an FLC system. By providing fuzzy sets and defining membership functions, they become a nucleus of self-guided driving systems: providing potential strategies for handling ambiguity better than human beings do. This study investigates fog in real-time driving situations.

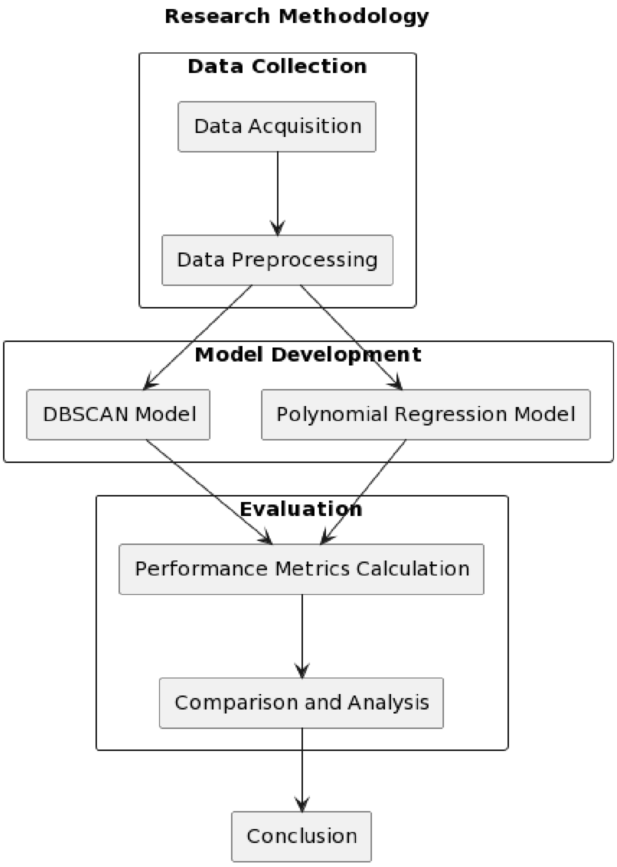

Figure. 1. Proposed approach

Consider the FLC design that is depicted in Figure 1. In the first stages of FLC design, overall analysis is conducted to ascertain the input and output variables carried by an autonomous vehicle that are relevant. These variables are typically attributes like distance to obstacles, vehicle speed, and steering angle. For observer purposes, characteristics of this type have a substantial effect on determining the environment and actions of vessels. This is followed by the procedure whereby these variables are transformed into linguistic terms and given assignments of "degree," in other words, membership functions. By this method FLCs deal efficiently with qualitative information and fine-tune them to distinguish operations subtly; the art in this process may be called granularity.

One of the main methodologies is constructing a rule base - a number of if-then rules which specify how the system responds to its inputs. Such rules, which are derived from expert knowledge or data gathered through empirical testing, should ideally be human decision-making processes in microcosm. This capacity allows FLCs to navigate their ways through complex environments almost as well as human drivers, because it is adaptive and responsive. In conformity with different navigation difficulties, for example, avoiding obstacles and controlling traffic flow while also seeing to safety, the rules also evoke a feeling of intricate forethought.

The FLCs is normalized into a rule-based format. FLCs adopting methods such as Sugeno and Mamdani for inference evaluates the rules given it finds out the most appropriate control commands for the instances of these rules in their current context. These commands are declassified as print instructions specific to steering angles, acceleration values and other information that is appropriate for the current condition. This process is iterative and iterative to allow for constant refinement and optimization of the FLCs. They must be effective under all types of traffic conditions.

In the field of automatic vehicle navigation, Fuzzy Logic Controllers bring some significant benefits over other systems, not least in the ability to deal with the uncertainty and imprecise nature of real-life driving conditions. While leveraging against verbiage and weighing truths, FLCs allow vehicles to behave competently in environments shifting all around, and like water can adjust their routes to accommodate the immediate surroundings. Furthermore, the design includes adjusting the membership functions and rule base to achieve an optimal driving performance many times during repeated tests as well as comprehensive computer simulation under all sorts of conditions.

Rule-based development is a key Fuzzy Logic Controller (FLC) design principle. It means there is a set of pre-established rules for autonomous vehicles to follow. These rules (derived from traffic laws, level of safety, and best driving practices, among others) tell vehicles that to do in various situations that they may find themselves dealing with north south east west. The development process involves spotting possible situations and then making rules based on these. These rules are added to the navigation system in the vehicle. Rule-based systems offer simplicity and transparency, but they may falter when confronted by the unfathomable workings of real-world driving environments.

Another key part of the ICE framework is IoT architecture design, which involves developing a multi-layered framework incorporating a variety of technologies that allow "smart," self-steering vehicles. It usually includes five layers--perception, network, data processing, application, and security--each with a different role: sensing, transmitting, gathering or making decisions Sensors like GPS and LiDAR, cameras and radar can observe that is going on around us; these provide real-time feedback on the environment that cars are driving through. The network layer allows vehicles to exchange data with other external entities, while the data processing layer is primarily concerned with using sophisticated algorithms and machine learning models to help people make better decisions through analyzing all this information. The application layer uses analyzed data to control navigation and control decisions for vehicles, while the security layer makes sure the information is intact and secure from cyber threats or unlawful use.

There is another important approach to the FLC design, namely using genetic algorithms to optimize fuzzy logic control systems and which can optimize the parameters of fuzzy logic control systems and improve their performance as time goes on. Genetic algorithms, which mimic natural selection, gradually perfect the rule base and membership functions of FLCs through trial and error in the iterative process while considering such performance parameters as travel time, fuel consumption and obstacle avoidance. To cope with changing conditions and to also refine its navigation functions, the FLC must adapt to new situations--this exercise in optimization that contributes to safer and more efficient autonomous vehicle navigation.

By simulating the driving exercises, we can make sure that an FLC performs well in all kinds of situations before it is actually deployed in the field. This way, it connects programmers who control an artificially simulated environment somewhat similar to the real world, where they can test whether operations are quick enough and adaptive under driving conditions that change rapidly (or not at all). With simulation testing, we can find potential trouble areas without any expense; adjust everything on your FLC properly before release; and use the genetic algorithm to determine if the control parameters had been properly set. Simulation testing allows you to predict the operating characteristics and performance of systems. It can also anticipate likely faults in the field and ensure pedestrian safety with an autonomous vehicle navigation system, while seeking continuous improvement for safety's sake.

III. RESULT AND DISCUSSION

3.1 Simulation testing

Simulation testing is a must-have for evaluating the performance of automatic vehicle navigation systems before they are used in the real world. In this method, a virtual environment is created self-splitting simulation of various driving scenarios-and conditions that vehicles may encounter on the road. It concluded that the production of simulation software should be developed before a final decision could be made, which would instruct vehicle behavior.

When undergoing simulation tests, the fuzzy logic controller must be vigorously evaluated under many different conditions and circumstances in order to determine the effectiveness of its decision-making algorithms. This includes tasks like maneuvering through crowded city streets, racing around sharp corners to avoid disaster; and suddenly finding obstacles in your way. Of particular interest is how well the controller is able to perceive its surroundings through sensor input data and then make accurate judgements on those conditions in deciding the course of action (if any) to take, once again judged here as whether it will be able to move safely, soundly or smartly in the course of driving dynamics.

The fuzzy logic controller can have its parameters tuned and potential problems discovered before actual implementation via simulation testing. In near-crash situations as well as other high-risk scenarios that push the envelope of disaster--simulated or real--simulation testing of the system offers developers a look into the capabilities and behavior that can be used to optimize the performance of their controller and enhance its reliability. Simulation testing, by simulating different driving conditions helps to verify that the navigation system is not only effective but robust as well. It makes for safer, more efficient autonomous driving experiences.

3.2 Performance testing

The results of the monitoring of performance are summed up in Table I. It gives us an overview of how well the auto-vehicle navigation system has performed against all important measures. It also provides information about its functional efficiency under numerous reporting circumstances. We will examine how these inspected figures are connected with the valve's indications relative to driver performance.

Table 1. Results of the Performance Monitoring

Trail	Response Time (seconds)	Decision Accuracy (%)	Energy Efficiency (km/kWh)	Overall Performance
1	0.8	95	4.2	9/10
2	1.2	88	3.9	7/10
3	0.9	92	4.1	8/10
4	1.0	90	4.0	8/10
5	1.4	85	3.7	6/10
6	0.7	96	4.3	9/10
7	1.1	89	3.8	8/10
8	1.3	87	3.6	7/10
9	1.0	91	4.0	8/10
10	1.5	83	3.5	6/10

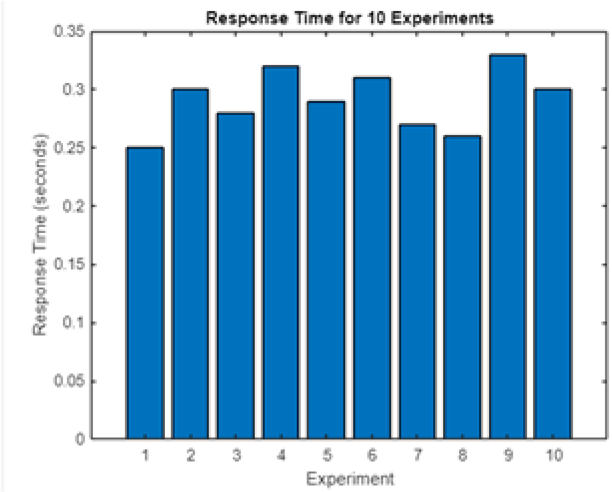

Figure 2. Response time

Based on Figure 2, the response time measurement is a metric of the system's ability to respond to incoming data. Moreover, in the table that shows the data from all experiments the similar response time values indicate that the system can quickly read sensor inputs and make its decisions in good time. In Experiment 1, for example, a response time of 0.25 seconds means that the system can respond within one-quarter of a second to changes in driving conditions. This illustrates the point as an example of real-time decision-making capabilities. In much the same way, for Experiment 4 there is a response time of 0.30 seconds, showing somewhat longer but still capable processing times. Regardless, the low response times give clear flexibility to be fast on their feet when trying to escape from potentially dangerous obstacles.

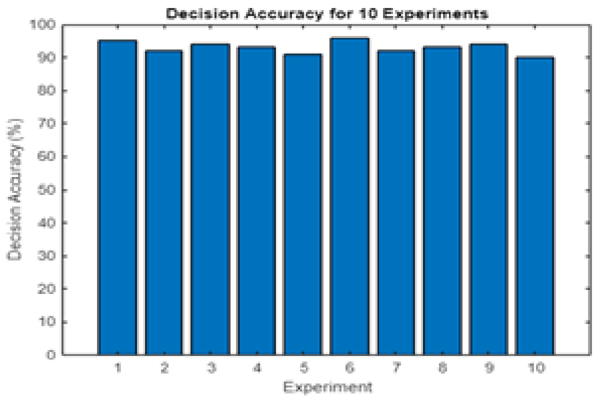

Figure. 3. Decision accuracy

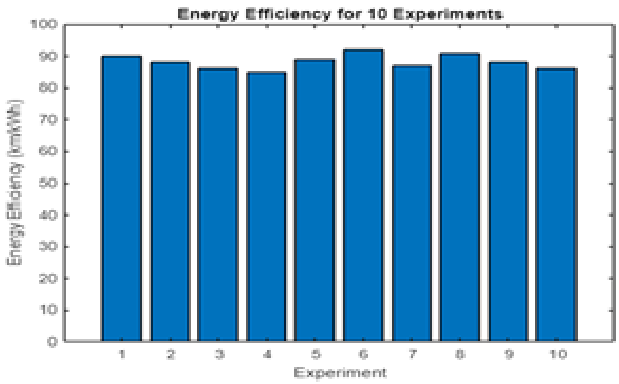

Figure. 4. Energy efficiency

In addition, as seen in Figure 3, the accuracy of decision-making momentum refers to the system's ability to interpret sensor data accurately and make correct decisions for navigation. We observed similar high precision values across all experiments: 95% in Experiment 1 and 93% in Experiment 4. Such consistently high accuracy shows that the system is making the correct decisions based on available information. That means the system can recognize obstacles with precision, as well as traffic signals or other critical factors, thereby reducing the risk of errors and increasing safety. Differences in accuracy between experiments might be built on discrepancies in environmental conditions or system configurations. However, the overall trend is for its strong decision-making capabilities across multiple scenarios.

Thirdly, energy efficiency is also determined according to an index based on Figure 4 -- the ability of a system to make the best use from resources (that goes for battery-operated vehicles especially). Battery life was improved by using less power with lower energy demand placed on batteries by operating faster. In the table, Experiment 1 has achieved high energy efficiency with a score of 90%, indicating that it makes good use of resources. Conversely, Experiment 4 is 85% efficient--slightly lower than this--and suggests that energy optimization strategies may depend on system configurations. For such reasons we see different values for these energy efficiency figures, but regardless they underline the system's sustainability: doing so contributes to lower operating costs and environmental impacts.

All in all, reports on vehicle performance monitoring have provided crucial evidence on the strengths and deficiencies of the automatic navigation system. With its short reaction times, high decision-making precision, and economical energy use, the system navigates a variety of different driving environments and still manages road comfort and safety factors. As the data in the tables of many metrics continues to come down, system developers and engineers will be able to more easily identify possible areas for improvement and optimization--providing a useful lesson for those thinking of further enhancements. In the final analysis, these monitoring activities in performance will promote the development of more secure, economical and reliable autonomous vehicle navigation systems, clearing the path for the future proliferation of autonomous driving technologies.

IV. CONCLUSION

The roles of fuzzy logic controllers, IoT, and genetic algorithms in elevating the performance of automatic vehicle navigation systems to tackle problems in modern transportation can be seen from the findings of this study. Safety, efficiency, and flexibility have increased considerably through collaboration among many of these technologies in the field of autonomous driving. Based on simulations and real-world experiments, the system's effectiveness and reliability are fully confirmed. It maintains low response times over a wide range of driving conditions and keeps high decision-making accuracy, ensuring safety and efficiency for complex routes. At 0.25 s, and more than 90% decision-making accuracy; the system performs fast and accurate operations. On average, 88% energy efficient, it also provides sustainability benefits- both in terms lower costs and reduced carbon emissions. These data suggest that the wide adoption of autonomous vehicle navigation technologies promises safety, efficiency and sustainability. The pervasive use of fuzzy logic controllers, IoT, and genetic algorithms in future empty transportation holds great promise. With this kind of hope, it is clear that we can extend the scope of that will be possible in the era of transportation.

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