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Contemporary Applications of Fuzzy Logic in Robotics: Between Flexibility and Efficiency

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ABSTRACT

This paper investigates the contemporary applications of *Fuzzy Logic* (FL) in robotics, focusing on its flexibility and efficiency in addressing challenges posed by uncertainty and complexity in dynamic environments. First introduced by Lotfi Zadeh in 1965, Fuzzy Logic allows for the processing of imprecise and ambiguous information, making it a valuable tool for decision-making in robotic systems. The research explores the role of FL in key areas such as motion control, obstacle avoidance, human-robot interaction, and medical robotics. Through the analysis of case studies, the paper demonstrates how FL enhances the adaptability and performance of robots in real-world scenarios by providing a framework for handling nonlinearity and uncertainty.

We also examine the theoretical foundations of Fuzzy Logic, including *membership functions*, *fuzzy inference systems*, and *defuzzification techniques*, which enable robots to make more human-like decisions in uncertain environments. Additionally, it discusses the integration of Fuzzy Logic with other control methods, such as *PID controllers* and neural networks, to improve system performance. Despite its advantages, the paper highlights several challenges, including computational complexity, the need for precise parameter tuning, and issues with scalability. The study concludes with recommendations for future research to optimize Fuzzy Logic-based systems for real-time applications and hybrid models to enhance the robustness and generalizability of robotic systems.

Keywords — Fuzzy Logic, Robotics, Intelligent Control Systems, Human-Robot Interaction – HRI, Linguistic Processing.

I. Introduction

Robotics technologies have witnessed rapid advancements in recent decades, making robotic systems a fundamental component of industrial, medical, and service applications, with a clear expansion in their capabilities for mobility, perception, and communication. With this widespread adoption, the need has become pressing to develop control and decision-making methods characterized by flexibility and adaptability, particularly in non-ideal environments marked by uncertainty and complexity.

In this context, researchers face multiple challenges, such as dealing with inaccurate sensor signals or making decisions in ambiguous situations that cannot be represented using strict conventional mathematical logic. Here emerges the significance of Fuzzy Logic (FL), which is considered one of the most prominent artificial intelligence techniques, providing effective solutions to handle ambiguity and uncertainty.

Fuzzy Logic was first proposed by Lotfi Zadeh in 1965 [1] as an alternative to binary classical logic for processing linguistic and vague information.

The objective of this research is to examine how fuzzy logic can be utilized in contemporary robotic systems, through analyzing its role in diverse fields such as:

- Motion Control.
- Navigation and Obstacle Avoidance.
- Human-Robot Interaction.
- Assistive and Medical Robotics.

Furthermore, the research discusses the theoretical foundations of fuzzy logic, presents case studies from recent literature, and analyzes the challenges and future prospects of this approach.

II. Theoretical Foundations of Fuzzy Logic – Fuzzy Logic Basics

A. The Emergence of Fuzzy Logic and Its Historical Development

Fuzzy logic first appeared in the scientific community in 1965, when Lotfi Zadeh presented his seminal paper *"Fuzzy Sets"*, published in the journal *Information and Control* [1].

The purpose of this paper was to expand the traditional concept of mathematical logic, which is based on binary values (True/False), by introducing the idea of *partial membership* to sets with imprecisely defined boundaries, which were later termed *Fuzzy Sets*.

The core idea lies in the fact that certain linguistic concepts we use in everyday life, such as *"cold"*, *"tall"*, or *"fast"*, cannot be strictly confined within rigid mathematical definitions. For instance, there is no precise boundary between *"moderate temperature"* and *"high temperature"*. Instead, there exists a transitional fuzzy region that can be represented by a *degree of membership* to each category

Following the publication of Zadeh's theory, applications of fuzzy logic began to emerge in various domains such as control, artificial intelligence, expert systems, natural language processing, and decision-making systems. Later, fuzzy logic was widely adopted in robotics, owing to its adaptive and flexible nature in dealing with complex environments.

B. The Difference Between Classical Logic and Fuzzy Logic

Classical Logic, also known as Boolean Logic or the "true or false" logic, is based on the assumption that every piece of information is either completely true (1) or completely false (0). This type of reasoning is suitable for computational machines and digital systems; however, it is incapable of handling ambiguous information or intermediate values.

Fuzzy Logic, on the other hand, is based on the idea that truth can be relative rather than absolute, where values are expressed by a Membership Value ranging between 0 and 1.

Figure 1 illustrates the difference between Classical Logic and Fuzzy Logic in the problem of determining a person's height, whether he or she is "tall" or "not tall." The function at the top represents the approach of Classical Logic, while the function at the bottom represents Fuzzy Logic.

Figure 2 illustrates the basic types of membership functions—Triangular, Trapezoidal, Gaussian, and Bell—and the multiple membership degrees they generate [2].

For example, in a system designed to determine a person's height:

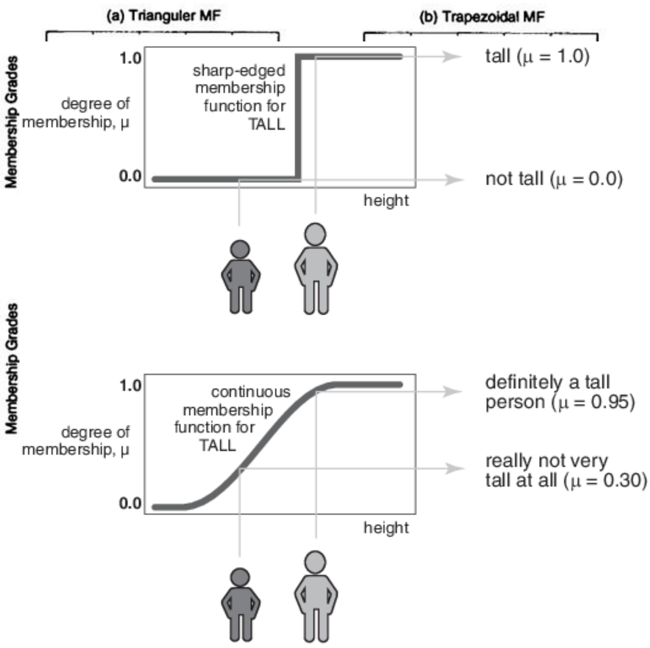

Fig. II3 Difference between classical logic and fuzzy logic in the problem of determining a person's height

A person with a height of 1.80 meters may have a membership degree of 0.2 in the set “medium” and a membership degree of 0.8 in the set “tall” as shown in figure 3.

Consequently, the system is able to make more realistic decisions based on these relative values [3].

Property	**Classical Logic (Boolean)**	**Fuzzy Logic**
Type of values	Only 0 or 1	Any value between 0 and 1
Handling of ambiguity	Not possible	Fully possible
Best suited for	Strict computational systems	Realistic and dynamic systems

C. Components of a Fuzzy System

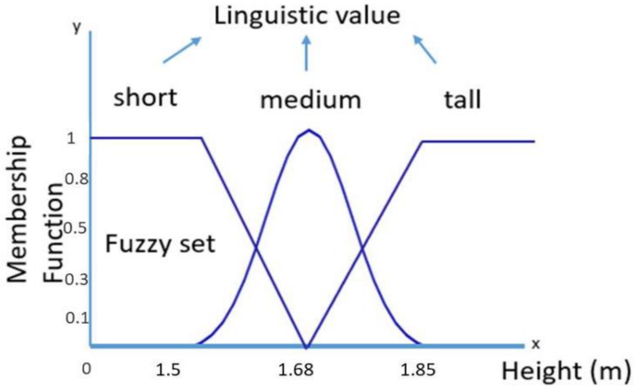

Fig. 5 Membership functions for a fuzzy system applied to human height classification

A typical fuzzy system consists of four fundamental stages:

a. ***Fuzzification***

This is the stage in which crisp inputs are transformed into fuzzy membership degrees, according to what is known as Membership Functions. For example, if the user inputs the value “$speed = 45\ km/h$”, it can be converted into membership degrees for each of “Slow”, “Medium”, and “Fast” using specific curves such as triangular or Gaussian functions [4].

b. ***Rule Base***

This contains a set of conditional linguistic rules in the form of: “If the speed is slow and the direction is left, then decrease the steering angle.” These rules are written using IF–THEN statements,

and they represent the core of the system, since they embody human or expert knowledge in decision-making.

c. *Inference Engine*

This step simulates the human way of making decisions, as it processes the fuzzy rules based on the input values and derives fuzzy outputs through techniques such as:

- Mamdani Method (the most commonly used)
- Sugeno Method (mathematically more efficient)

FigureII7 illustrates the block diagram of the fuzzy inference system, showing the stages of: Fuzzification, Rule Base, Inference Engine, and Defuzzification .

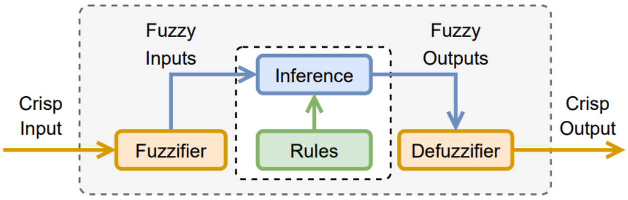

Fig.6 Diagram of a fuzzy inference system (FIS)

d. *Defuzzification*

This is the final stage in which the fuzzy output values are converted into a precise numerical value that the system can use as a control signal (e.g., steering angle or motor speed).
The most well-known defuzzification methods include:

- Centroid Method
- Max Membership Method

D. Types of Fuzzy Controllers

i. *Type-1 Fuzzy Systems*

These are the traditional fuzzy systems, where membership functions are predetermined using fixed values. They are ideal for systems with low to medium complexity.

ii. *Type-2 Fuzzy Systems*

These use fuzzy membership of fuzzy sets (*Fuzzy Membership of Fuzzy Sets*), which allows them to handle higher levels of uncertainty, especially in unstructured environments (e.g., autonomous driving and human interaction). However, they are more computationally and processing-intensive.

Figure II8 illustrates the visual difference between the membership functions of a traditional Type-1 fuzzy system and a Type-2 fuzzy system, where there exists an uncertainty region known as the *Footprint of Uncertainty (FOU)*:

- In the Type-1 representation (Figure a), the line is crisp and well-defined.
- In the Type-2 representation (Figure b), there are two regions: the *Upper MF* and the *Lower MF*, which clarify the uncertainty, further illustrated in *Figure II9*.

To understand the practical and technical difference between these two types, the following table presents a detailed comparison that highlights the most important aspects of distinction:

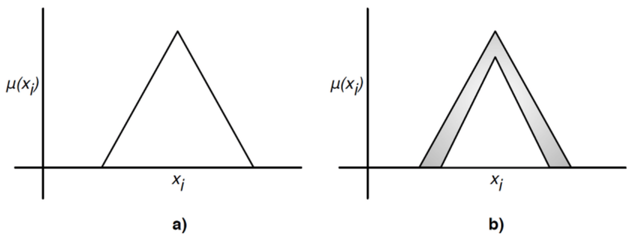

Fig.10 Visual comparison between different types of fuzzy control systems

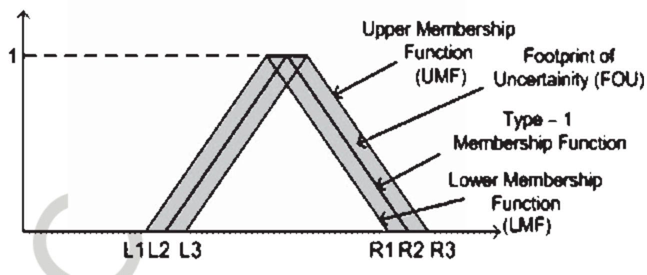

Fig.6 Example of Type-2 membership functions

This comparison demonstrates that Type-2 systems provide a deeper and more realistic representation in environments that contain noise or ambiguity, making them more suitable for certain robotics applications, particularly in human interaction or navigation within unstructured environments.

Item	Type-1	Type-2
Nature of membership functions	Defined by fixed values	Upper and Lower functions define the Footprint of Uncertainty (FOU) and represent additional uncertainty
Handling uncertainty	Cannot model uncertainty in membership functions	Can model multiple levels of uncertainty
Computational complexity	Relatively low and easy to implement	Higher complexity due to the need for Type Reduction
Practical applications	Suitable for systems not exposed to noise or uncertainty	Ideal in environments that require precise control under ambiguous and unstable conditions
Location of FOU	Not present	Always present between Upper Membership Function (UMF) and Lower Membership Function (LMF) to define the uncertainty range

III. Modern Robotics Overview

A. *Classification of Robots and Systems*

Modern robots vary according to their environments and functions, and several main categories can be distinguished:

a. *Industrial Robots (Manipulators):*

They operate in semi-structured environments such as production lines. The main sources of uncertainty here are nonlinearities in joint friction and elasticity, in addition to variable payloads. Typically, PID controllers or equivalent robust controllers are used. The role of fuzzy logic is to formulate operational expertise into flexible rules for gain tuning and to reduce vibrations at the arm's end.

b. *Ground Mobile Robots (UGVs):*

They operate in human or outdoor non-ideal environments, which makes them subject to navigational ambiguity, sensory noise, and changing ground friction conditions. They rely on sensors such as LiDAR, RGB-D, IMU, and GPS. Local planning with path-tracking control is typically used, while fuzzy logic provides flexible rules to balance speed and safety during obstacle avoidance.

c. *Aerial Robots (UAVs):*

They operate in indoor or outdoor aerial environments and face sources of uncertainty such as wind disturbances, response delays, and strict energy constraints. They rely on sensors including IMU, cameras, and altimeters. Fast control techniques such as MPC or PID are commonly adopted. Fuzzy logic is used here to adaptively tune gains under disturbances and to handle approximate commands issued by the user.

d. Service and Domestic Robots:

They are designed to operate in complex and non-ideal human environments, where human interaction, surrounding clutter, and moving objects represent major sources of uncertainty. They utilize vision sensors, microphones, and tactile sensors. Control usually combines local planning with HRI strategies. Fuzzy logic helps in understanding approximate commands and in naturally integrating user intentions.

e. Humanoid Robots or Soft Robots:

They aim for direct human interaction and the execution of complex tasks requiring high mechanical compliance. Uncertainty sources are significant due to inaccurate models and the flexible nature of the structure. They employ advanced force and tactile sensors along with vision systems. Control is based on compliance and stability strategies, and fuzzy logic contributes by formulating flexible policies to interpret concepts such as “softness” or “rigidity” during contact.

f. Swarm or Multi-Robot Systems:

They operate on distributed tasks and are affected by communication instability and conflicting goals among units. They rely on distributed sensing, localization, and communication, with coordination and task allocation rules applied. Fuzzy logic enables the formulation of approximate and flexible consensus rules that help cope with delays or data loss within the network.

B. Architecture of Modern Robotics

Modern robotic systems are based on a layered architecture that facilitates the integration of hardware and software while ensuring real-time performance. The most important layers are:

- **Sensory and actuation hardware:** includes sensors such as LiDAR, RGB-D, IMU, and actuators.
- **Edge computing:** embedded processing units (CPU/GPU) to ensure fast responsiveness.
- **Perception and representation:** feature extraction and map construction from sensory data.
- **Planning and decision-making:** transforming information into path and motion plans.
- **Control, safety, and human–robot interaction:** executing motion within safety boundaries and handling human commands.

This organization highlights where fuzzy logic can contribute, particularly in perception (processing fuzzy data), local decision-making (avoiding uncertain obstacles), and control (adapting response in systems that are difficult to model precisely) [5].

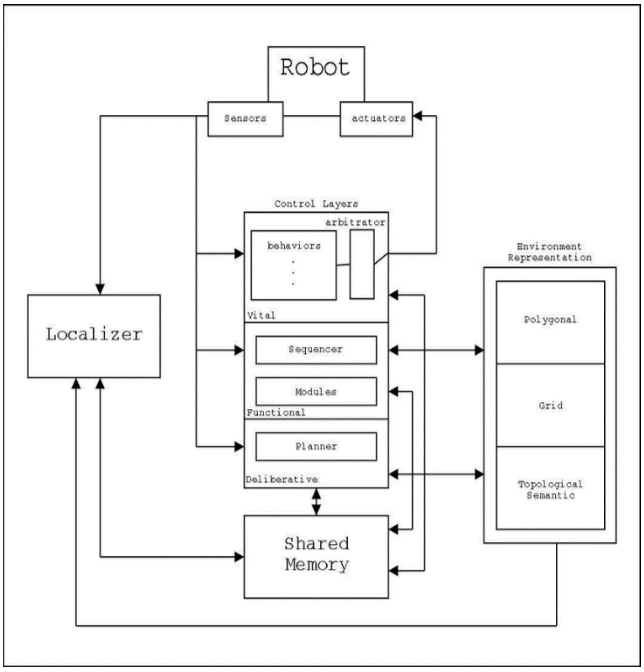

Fig. 7 Architectural structure of the robot

C. General Challenges in Modern Robotics and Why Fuzzy Logic is Suitable

Modern robotic systems face increasing challenges resulting from the complexity of environments, multiplicity of sensors, and their interaction with humans. These challenges include:

a. **Sensory uncertainty:** data coming from sensors such as LiDAR and RGB-D is often noisy or incomplete.
b. **Nonlinearity in modeling:** accurate mathematical models often fail to represent the dynamic reality of robots.
c. **Human interaction:** human commands are often imprecise or not directly translatable into digital instructions.
d. **Real-time response:** the need to make rapid decisions in changing environments.

In this context, fuzzy logic is considered an ideal option because it:

a. Does not rely on precise mathematical models.
b. Allows the formulation of flexible rules based on human expertise.
c. Naturally handles approximate values and ambiguity.
d. Can be easily integrated with other control systems such as PID, MPC, and neural networks.

D. General Challenges in Modern Robotics and Why Fuzzy Logic is Suitable

In real-world robotic environments, information is often inaccurate or incomplete, whether resulting from limited-resolution sensors, unexpected environmental changes, or unclear human commands. Here, the role of fuzzy logic emerges as an effective tool for addressing this type of uncertainty.

Fuzzy logic does not rely on binary values (true or false); rather, it employs degrees of truth ranging between 0 and 1, which enables robots to make flexible decisions based on incomplete or ambiguous information. For example:

- When determining the safe distance from an obstacle, the robot can evaluate the situation as “somewhat close” instead of simply “close” or “far.”
- In human interaction, it can interpret commands such as “move at medium speed” without requiring a strict definition of velocity.
- In navigation, it integrates multiple data sources (such as vision, sound, and orientation) to generate a logical response even if some data is unavailable or conflicting.

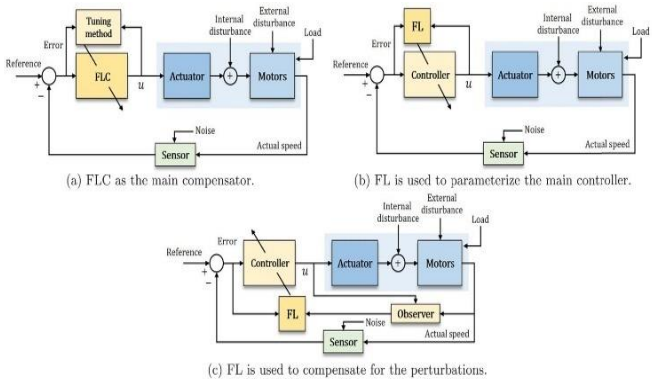

Fig. 8 Examples illustrating different approaches to applying fuzzy logic (FL) for controlling disturbed systems: (a) Using a Fuzzy Logic Controller (FLC) as the main compensator. (b) Using FL for tuning the main controller parameter. (c) Using FL for disturba

In this manner, fuzzy logic enables robots to operate efficiently in non-ideal environments, granting them adaptability and the ability to learn from context, thereby enhancing their practical intelligence and bringing them closer to human-like reasoning [6].

IV. Employment of Fuzzy Logic in Robotic Systems

A. Motion Control

Motion control is considered one of the fundamental applications of Fuzzy Logic (FL), as it largely depends on controlling the interaction between the electrical and mechanical components of the system. Many robots face nonlinear challenges and errors resulting from the complex interactions between motors and actuators. These problems include phenomena such as saturation, where the motor stops increasing speed or force once the input exceeds a certain threshold, leading to nonlinear effects on the robot’s motion.

Fuzzy Logic provides flexible solutions to deal with such types of errors by employing fuzzy systems to dynamically adjust the robot’s response. Furthermore, Fuzzy Logic contributes to reducing the impact of deadzones, which occur when changes in the input signal do not produce any response, thereby enhancing the precision of control in robots such as surgical robots or robots used in highly delicate operations [7] [8] [9]. Figure 8 illustrats different approaches to applying fuzzy logic (FL) for controlling disturbed systems.

B. Saturation Control

Another problem encountered in robotic control is saturation, where actuators (such as motors or hydraulic systems) cannot generate additional force or torque beyond a certain limit. Saturation may lead to unexpected changes in the motion or force produced by the system. In this case, Fuzzy Logic is utilized to provide compensation for saturation through integrated control strategies such as *Cascade Fuzzy Control*, where Fuzzy Logic enhances motion control and precise trajectory tracking in underwater robots or wheeled mobile robots [10].

C. Handling Disturbances and Uncertainties

Robots are often exposed to numerous disturbances and uncertainties in the environment, such as friction or load variations. Fuzzy Logic provides effective solutions to these challenges by designing fuzzy control systems that address uncertainties arising from performance variations or external disturbances. One example is the use of *Adaptive Fuzzy Control* as shown

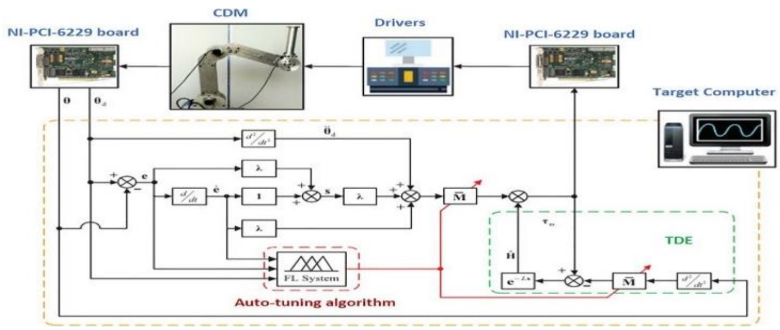

Fig. 9 Schematic of adaptive Time-Delay Control (Adaptive TDC) for cable-driven manipulators, employing FL for parameter auto-tuning.

in figure 9 to handle uncertainties caused by unexpected changes in the loads of electric motors (DC Motors) [11]

D. Autonomous Navigation

In applications of Autonomous Vehicles (AVs), Fuzzy Logic is employed in designing Lateral Control Laws to determine the reference velocity for driving in unpredictable environments. It is also applied in *Adaptive Cruise Control* (ACC) systems to automatically adjust the vehicle’s speed according to the vehicles in front. Fuzzy Logic assists in managing unexpected conditions such as sudden movements of leading vehicles In the domain of Mobile

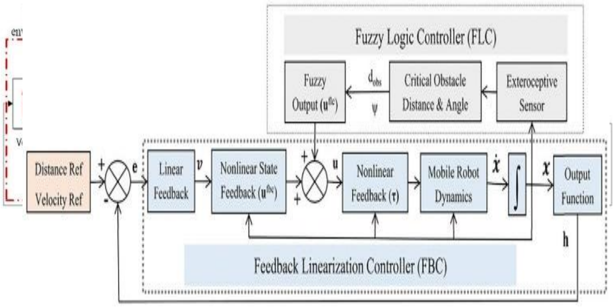

Fig. 11 Block diagram of the hybrid Fuzzy Logic Controller–Feedback Linearization Controller (Hybrid FLC–FBC).

Robots, Fuzzy Logic is integrated with other techniques such as Model Predictive Control (MPC) to determine robot paths and avoid obstacles in dynamic environments. This contributes to improving robot performance in unstable environments where predicting future conditions is difficult [12].

E. Path Planning and Collision Avoidance

In applications of Wheeled Mobile Robots (WMRs), Fuzzy Logic integrates path following control algorithms with collision avoidance systems. In this case, Fuzzy Logic is employed to adjust the longitudinal and lateral directions of the robot and ensure rapid responsiveness when approaching an obstacle. Fuzzy Logic enhances the robot’s ability to make smooth and fast decisions in crowded and complex paths.

Furthermore, Fuzzy Logic can be combined with techniques such as Backstepping Control to ensure navigation in environments filled with obstacles. For example, the fuzzy system guarantees that the robot remains on the designated path while avoiding collisions with surrounding obstacles [13]. Figure 11 presents block diagram of the hybrid Fuzzy Logic Controller–Feedback Linearization Controller (Hybrid FLC–FBC).

F. Navigation and Obstacle Avoidance

Fuzzy Logic is an effective tool in navigation and obstacle avoidance applications for mobile robots, as it enables intelligent systems to make flexible decisions in undefined and dynamic environments. By integrating sensor readings

such as sonar or LiDAR with fuzzy rules, the direction of motion and velocity can be determined in a way that allows the robot to avoid obstacles and reach the designated target even under inaccurate or incomplete information.

For example, a fuzzy control system has been developed to guide robots in unknown indoor environments, where sensor readings and the desired motion direction are used as inputs, and the wheel acceleration is determined as the output of the system. This enables the robot to avoid obstacles and reach the designated target [14].

Through the integration of Fuzzy Logic with other techniques such as artificial intelligence and neural networks, the decision-making capability of robots can be enhanced to achieve more accurate and effective responses in complex environments. For instance, an integrated system combining Fuzzy Logic and genetic algorithms has been designed to guide intelligent robots in dynamic and unknown environments, thereby improving their ability to avoid obstacles and make flexible and effective decisions in real time. Overall, Fuzzy Logic is a powerful tool for developing intelligent and flexible navigation systems capable of adapting to environmental changes and making effective real-time decisions [15].**Fuzzy Logic in Human–Robot Interaction (HRI)**

Human–Robot Interaction is characterized by uncertainty, continuous variability, and subjectivity in human behavior, making conventional binary logic insufficient for modeling the dynamics of such interaction. Fuzzy Logic provides a flexible framework to address these challenges by enabling robots to infer using linguistic and imprecise information.

For example, fuzzy rule-based systems allow the translation of ambiguous human commands such as “move slowly” or “stay close” into quantifiable executable actions. Fuzzy Logic has also been employed in emotional interaction, where human affective states are modeled as fuzzy sets that allow the robot to gradually adapt its responses in a manner closer to human nature, thereby enhancing social acceptance and trust.

Moreover, fuzzy control offers a mechanism for smooth decision-making in collaborative environments, where parameters such as proximity, force, or speed must be continuously adjusted to ensure safety and comfort. These applications demonstrate that the integration of Fuzzy Logic increases adaptability, interpretability, and naturalness of interaction compared to conventional approaches [16].

G. Fuzzy Logic in Medical and Assistive Robotics

Medical and assistive robots are among the fields that most benefit from the capabilities of Fuzzy Logic, due to their direct association with humans and the inherent complexity and individual variability involved.

In robotic rehabilitation systems, Fuzzy Logic enables the design of controllers that handle varying levels of force and velocity according to the patient’s condition, thereby providing personalized and flexible support during physiotherapy sessions. It has also been used in smart prosthetic control systems, where biological signals such as surface electromyography (EMG) are translated into motor commands, with Fuzzy Logic allowing the system to handle noise and natural inaccuracies in biological signals.

In the field of robot-assisted surgery, Fuzzy Logic contributes to improving interaction interfaces between the surgeon and the robot by translating both precise and ambiguous commands into smoother control actions. Similarly,

applications in elderly care and chronic patient support show that Fuzzy Logic enables social robots to evaluate the emotional or physical states of users in gradual terms rather than binary decisions, thereby increasing acceptance and effectiveness in care environments.

Thus, Fuzzy Logic constitutes a fundamental tool for achieving flexibility, human-centered adaptability, and personalization in medical and assistive robotics compared to rigid conventional methods [17].

V. Case Study from Contemporary Literature:

A. *First Study: Online Tuning of PID Controller Using a Multilayer Fuzzy Neural Network Design for Quadcopter Attitude Tracking Control*

This study represents a prominent example of integrating fuzzy logic and neural network techniques with the traditional PID algorithm in order to improve the performance of quadcopter control systems, which are inherently characterized by nonlinear properties and high sensitivity to external disturbances. The proposed approach relies on online tuning of the controller parameters using a *multilayer fuzzy neural network*, which enabled achieving a balance between the simplicity of the PID structure and its stability capability, and the flexibility of intelligent systems in handling complex dynamics.

The strengths highlighted in the study are as follows:

a. The ability of the proposed methodology to adapt to varying operational conditions such as aerodynamic effects and different payloads, which is difficult to achieve using a fixed-parameter PID.
b. The integration of PID and Fuzzy Neural Network improved accuracy and reduced tracking error compared to conventional designs.
c. The use of a multilayer network contributed to enhancing learning efficiency and accommodating more complex dynamic patterns.

On the other hand, the study reveals several weaknesses, most notably:

a. The high computational burden resulting from integrating fuzzy logic with neural networks, which may limit applicability in low-resource controllers or in time-critical real-time systems.
b. The heavy dependence on data quality during both training and operation, as noise or insufficient data can lead to degraded performance.
c. The difficulty of initial tuning of design elements (such as the number of layers, shapes of membership functions, and learning parameters), which requires specialized expertise and intensive experimental iteration.
d. The evaluation is often limited to simulation environments or restricted tests, raising questions about generalizability in real-world environments.

Accordingly, this study can be considered a successful example of hybrid control that benefits from the simplicity of PID and the flexibility of artificial intelligence techniques. However, the complexity of implementation and resource requirements present challenges for transitioning from simulation to large-scale practical applications [18].

B. *Second Study: Fuzzy Neural Network PID Control Design of Camellia Fruit Vibration*

This study addresses the application of a hybrid algorithm that combines conventional PID control, fuzzy logic, and neural networks, with the objective of enhancing the performance of a vibration device used for camellia fruit detachment in the agricultural context. The design aims to achieve more accurate and stable responses in vibration systems, which are typically characterized by nonlinear properties and dynamic variations associated with fruit weight and branch characteristics.

One of the major strengths of this work is that it provided a tangible improvement in vibration control accuracy compared to conventional PID, with a clear ability to handle nonlinearity and adapt to load variations during operation. Furthermore, the study is noteworthy for not being limited to theoretical simulation but extending to practical application on a real vibration device, thereby enhancing the reliability and applicability of its findings.

Conversely, certain weaknesses emerge, primarily the high computational complexity that accompanies the use of the hybrid system compared to simpler alternatives, which may increase cost and hinder deployment in agricultural devices with limited resources. Additionally, the initial tuning of the neural network and fuzzy functions depends on trial and error, which reduces the ease of reusing the methodology in other applications. Moreover, the study was restricted to camellia fruits under specific conditions, raising questions about generalizability to other crops or diverse agricultural environments.

Finally, although the superiority over conventional PID was demonstrated, the absence of in-depth comparisons with other advanced techniques such as adaptive control or pure neural networks represents a potential research gap.

Thus, this study serves as an important example of the feasibility of employing hybrid controllers (Fuzzy Neural PID) in the agricultural domain to improve efficiency and reduce waste. At the same time, it reveals the need for further research to simplify the architecture and enhance generalizability for broader practical applications [19].

C. Third Study: Review on PID, Fuzzy and Hybrid Fuzzy PID Controllers for Controlling Non-linear Dynamic Behaviour of Chemical Plants

This paper represents a comprehensive review that addressed various applications of traditional control systems (PID), fuzzy logic-based systems, and hybrid controllers (Fuzzy PID), with a comparison of their performance in multiple industrial domains. The study contributed to providing a synthetic perspective on the advantages and limitations of each type of controller, enabling researchers to choose the most appropriate strategy depending on the nature of the system under investigation.

The strengths of this review lie in its comprehensiveness and the breadth of applications covered, as it highlighted the superiority of fuzzy and hybrid controllers in handling nonlinear systems and uncertain conditions compared to conventional PID. Furthermore, it is noteworthy that the review presented a comparative analysis illustrating the benefits of integrating the simplicity of PID with the flexibility of Fuzzy, thus providing a solid scientific foundation for developing more efficient hybrid control systems. In addition, the systematic presentation of the literature assisted in identifying contemporary research trends in this field.

On the other hand, several weaknesses are observed. It is noted that the study placed a strong emphasis on surveying published works without providing an in-depth quantitative analysis of performance (such as error metrics, settling time, or energy consumption), which may limit the reader’s ability to make precise comparisons. Moreover, although the scope of the review was broad, it did not elaborate in detail on the practical challenges of implementing hybrid controllers, such as computational complexity or execution costs. Finally, the study did not give sufficient weight to comparisons with other modern control techniques (such as adaptive controllers or neural networks), leaving a potential research gap for future work.

Thus, this paper represents an important reference for framing the main trends in control using PID, fuzzy, and hybrid systems. However, it still requires enrichment with quantitative analyses and practical applications to provide a more comprehensive picture of the advantages and challenges [20].

D. Fourth Study: Research of Fuzzy PID Elevator Control System Based on PLC

This study discusses the design and implementation of a Fuzzy PID controller for elevator systems, relying on programmable logic controllers (PLC) as a practical implementation platform. The research aims to improve performance compared to the conventional PID controller, particularly in terms of stability, vibration reduction, and providing greater passenger comfort.

One of the major strengths of this work is that it provides a clear practical application of the hybrid fuzzy control concept within a common industrial context, thereby enhancing the industrial applicability of the methodology. Furthermore, the integration of Fuzzy with PID demonstrated improvements in response accuracy and reduction in settling time compared to conventional control, along with a better ability to handle sudden load variations (such as passenger number or speed changes). In addition, the use of the PLC platform increases realism and reliability, given its widespread adoption in industry and the ease of integration with elevator systems.

Conversely, the study recorded some weaknesses, the most notable being that the analysis remained limited in terms of detailed quantitative metrics (such as RMS error values or energy indices), which reduces the accuracy of comparisons with other control systems. Moreover, the initial tuning process of the fuzzy logic was not addressed with a clear systematic methodology, which may hinder ease of reapplication in different systems. Additionally, the experiments were focused on a single model or limited environment, without comprehensive testing under diverse operational scenarios (maximum loads, potential faults, or different operating environments), which may affect generalizability.

Therefore, this study can be considered an important step in demonstrating the effectiveness of hybrid fuzzy controllers in industrial elevator systems. At the same time, it highlights the need for broader experiments and deeper quantitative analysis to enhance the reliability and generalization of results across various real-world applications [21].

VI. Challenges and Limitations in Fuzzy Logic Control Systems:

Despite the wide adoption of fuzzy logic techniques in advanced control systems and their success in handling nonlinearity and uncertain conditions, there are several challenges and limitations that restrict their large-scale utilization. These can be summarized as follows:

A. *Lack of a Unified Methodology for Designing Membership Functions and Rules*

- The definition of membership functions and the construction of the rule base largely depend on human expertise and prior experiences.
- This experimental nature makes the design subject to variability across researchers and affects **reproducibility** in different applications.

Computational Burden in Real-Time

- In certain industrial or embedded applications, the high computational load resulting from fuzzy inference processes may become an obstacle to real-time execution, especially when a large number of rules or complex functions are used.

B. Absence of Strict Mathematical Guarantees

- Unlike some traditional or modern control methods (such as optimal linear control or adaptive control), fuzzy logic lacks a unified mathematical framework that guarantees stability and performance under all conditions.
- This shortcoming raises concerns regarding the reliability of results, particularly in safety-critical applications (such as aviation or medical systems) [22].

C. Limited Scalability (Scalability Issue)

- With an increase in the number of variables or inputs, the number of rules required grows explosively *(Rule Explosion Problem)*, leading to difficulties in management and high computational complexity.
- This problem weakens the efficiency of fuzzy logic when dealing with large-scale or multi-dimensional systems [23].

D. Heavy Reliance on Parameter Tuning

- The tuning of membership function parameters and fuzzy inference weights requires repeated experiments, which may be time- and computation-intensive.
- The absence of systematic tuning algorithms causes performance to be highly dependent on the quality of initial tuning [24].

E. Limited Generalization Capability

- The performance of fuzzy logic is usually strong in the operational environment for which it was designed, but it may deteriorate when facing new conditions that were not considered during the design phase.
- This highlights the need to integrate fuzzy logic with other techniques (such as neural networks or evolutionary algorithms) to enhance adaptability and flexibility [25].

F. Weak Standardized Quantitative Comparison

- The majority of studies focus on qualitative improvements (such as enhanced comfort or reduced vibrations) without relying on standardized quantitative metrics that allow precise comparison with other control techniques.
- This hinders the process of objective and comprehensive evaluation of the performance of fuzzy controllers [26]

These challenges demonstrate that, despite its success in many practical applications, fuzzy logic still faces limitations related to design, computation, and stability guarantees. To overcome these issues, recent research trends are increasingly directed toward hybrid systems (such as Fuzzy–PID, Fuzzy–Neural, and Fuzzy–Genetic), which aim to combine the flexibility of fuzzy logic with the adaptive or algorithmic optimization capabilities of other methods, thereby enhancing its effectiveness in more complex environments.

VII. Conclusion and Recommedations

A. Conclusion

The integration of Fuzzy Logic into modern robotics has significantly enhanced the performance and adaptability of robots, especially in environments that are uncertain, dynamic, and non-ideal. Its ability to handle ambiguity, improve decision-making processes, and adapt to real-time conditions makes it an invaluable tool across diverse robotic applications, including autonomous navigation, medical assistive systems, and human-robot interaction. Despite its advantages, challenges such as high computational complexity, the need for precise parameter tuning, and the lack of a unified design methodology remain barriers to its broader application. Nonetheless, the combination of Fuzzy Logic with other techniques, such as neural networks or genetic algorithms, holds promise for overcoming these limitations and advancing the capabilities of robotic systems.

B. Recommendations

a. **Hybrid System Development:** To overcome the limitations of Fuzzy Logic in handling complex, real-time systems, future research should focus on developing hybrid systems that combine FL with other advanced control techniques like *PID controllers*, neural networks, or genetic algorithms. These hybrids can leverage the strengths of both methodologies to enhance system efficiency and adaptability in uncertain environments.

b. **Standardized Quantitative Metrics:** Researchers should prioritize the development of standardized quantitative evaluation metrics for Fuzzy Logic systems. This will enable more objective comparisons between different control methods and foster improvements in the design and implementation of FL systems.

c. **Computational Efficiency:** To address the computational challenges associated with FL, particularly in real-time applications, it is recommended to explore optimization techniques, such as fuzzy inference reduction methods or hardware acceleration, to enhance the scalability and speed of FL systems.

d. **Real-World Testing and Generalization:** While many FL-based systems have been tested in controlled environments or simulations, it is essential to extend these studies to real-world scenarios. Future work should focus on testing FL controllers in diverse operational conditions to evaluate their robustness and generalizability.

e. **Systematic Tuning Methods:** The process of tuning fuzzy systems remains subjective and computationally intensive. Developing systematic, automated tuning methodologies could reduce the reliance on trial-and-error approaches, improving the consistency and efficiency of FL applications in robotics

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