UNIVERSITY OF MISKOLC

FACULTY OF MECHANICAL ENGINEERING AND INFORMATICS

ETHOLOGICALLY INSPIRED FUZZY BEHAVIOUR BASED SYSTEMS

PHD DISSERTATION

Prepared by

Mohd Aaqib Lone

BACHELOR OF INFORMATION TECHNOLOGY

MASTER OF COMPUTER SCIENCE

JÓZSEF HATVANY DOCTORAL SCHOOL FOR COMPUTER SCIENCE AND ENGINEERING

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Head of Doctoral School

Prof. Dr. László Kovács

Full Professor

Scientific Supervisor

Prof. Dr. Szilveszter Kovacs

Full Professor

Miskolc 2025

ACKNOWLEDGMENTS

I would like to begin by expressing my sincere gratitude to the divine presence for granting me the strength and perseverance required to undertake and complete this academic journey.

I am especially grateful to my supervisor, Prof. Dr. Kovács Szilveszter, for his exceptional guidance, valuable insights, and unwavering support throughout the course of this research. His expertise and mentorship have been instrumental in shaping the direction and quality of this thesis.

I extend my deepest appreciation to my parents for their unconditional love, encouragement, and steadfast support. Their commitment to my education and personal growth has provided the foundation upon which my academic achievements have been built.

I would also like to thank my colleagues for their collaboration, encouragement, and collegial spirit. Their support and shared experiences have contributed significantly to the richness of this academic journey.

I am sincerely thankful to the faculty members and reviewers whose constructive feedback and critical evaluations have greatly contributed to the refinement and rigor of this work. Their dedication to academic excellence is truly appreciated.

Finally, I wish to acknowledge all those who have supported me in various ways during this doctoral research. Their contributions whether personal, academic, or administrative have been invaluable, and I am deeply grateful for their presence.

TABLE OF CONTENTS

Preface 1
Chapter 1: Introduction 3
1.1 Overview 3
1.2 History 4
1.3 Motivation 6
1.4 Methodology 7
1.5 Simulation Environment and Experimental Setup 8
Chapter 2: Ethology Inspired Fuzzy Behaviour Model 10
2.1 Ethology 10
2.2 Fuzzy Behaviour-Based Systems 10
2.3 Comparative Analysis with Existing Fuzzy and Bio-Inspired Controllers 14
2.4 Implementing the“Aggression” Behaviour 15
Chapter 3: The Fuzzy Model for the “Aggression” Behaviour 21
3.1 Model Overview and Implementation Guidelines 21
3.2 Trajectories for Simulating Aggressive Behaviour 31
3.2.1 Escape Behaviour 32
3.2.2 Attack Behaviour 34
3.3 Conclusion 37
3.4 Thesis I 38
3.4.1 Scientific Foundations 38
3.4.2 Mathematical Formalism 38
3.4.3 Simulation Based Evidence 41
3.4.4 Falsifiability and Testability 41
3.4.5 Novelty and Impact 42
3.4.6 Applications 42
Chapter 4: Embedding Aggressive Behaviour in Robotics 43
4.1 Embedded Model Overview 43
4.2 Methodologies for Biologically Inspired Behaviour Modeling in Robotics 44

4.2.1 Knowledge-Based Ethologically Influenced Behavioural Design 44
4.2.2 Situated Action-Based Behaviour Design 45
4.3 System Architecture and Implementation 47
4.3.1 Perception Layer 48
4.3.2 Behaviour Evaluation Layer 49
4.3.3 Fuzzy Inference Engine 49
4.3.4 Motion Execution Layer 49
4.3.5 System Synchronization and Communication Layer 50
4.4 Motivation for Integration 50
4.5 Behaviour Implementation 51
4.5.1 Implementing Escape Behaviour 53
4.5.2 Implementing Attack Behaviour 57
4.5.3 Classification Metrics and Empirical Benchmarking 61
4.6 Conclusion 63
4.7 Thesis II 64
4.7.1 Scientific Contribution 64
4.7.2 Mathematical and System Formalism 64
4.7.3 Empirical Validation and Simulation Based Evidence 65
4.7.4 Experimental Highlights 65
4.7.5 System Level Testability and Reproducibility 66
4.7.6 Applications and Ethical Implications 66
4.7.7 Novelty and Impact 67
Chapter 5: Fuzzy Behaviour Based Control Framewok with Virtual Force Field Navigation. 68
5.1 Introduction 68
5.2 Background 69
5.3 Fuzzy Behaviour Fusion 70
5.4 Virtual Force Field Navigation 71
5.5 Implementation of Fuzzy Behaviour-Based Control Framework with VFF 73
5.6 Conceptual Framework of VFF with Fuzzy Behaviour Control 77
5.7 Trajectories of Fuzzy Behaviour Control Framework with VFF 79
5.8 Simulation Environment and Evaluation in ROS 82

5.9 Classification Metrics and Empirical Benchmarking 88
5.10 Conclusion 90
5.11 Thesis III 91
5.11.1 Scientific Contribution 91
5.11.2 System Architecture and Mathematical Formalism 91
5.11.3 Empirical Validation and Simulation Based Evidence 93
5.11.4 Novelty and Impact 94
5.11.5 Application 94
Chapter 6: Conclusion and Future Work 95
6.1 Conclusion 95
6.1.1 Thesis I: Ethologically inspired Fuzzy Behaviour model of the Archer's "Aggression and fear in vertebrates" ethological model 95
6.1.2 Thesis II: Implementing Fuzzy State Machine for Behaviour control in robotic environment 95
6.1.3 Thesis III: Fuzzy Behaviour Based Control Framewok with Virtual Force Field Navigation 96
6.2 Future Work 96
6.2.1 Investigating Human-Robot-Animal Behavioural Parallels: 96
6.2.2 Advancing Machine Learning Integration 97
6.2.3 Exploring Ethical and Societal Implications 97
6.2.4 Expanding Sentiment and Behaviour Analysis Models 97
Chapter 7: Publications 98

References 100

LIST OF FIGURES, TABLES. ABBREVIATIONS AND SYMBOLS

List of Figures

Figure 1. The Applied Fuzzy Behaviour-Based System.. 11
Figure 2. The Architecture of Behaviour Arbitration 12
Figure 3. Archer Organization Model... 16
Figure 4. Fuzzy Behaviour Model for Animal Aggressive Behaviour 20
Figure 5. Graphical Representation of Behaviours 28
Figure 5(a). Level of Fear Behaviour... 28
Figure 5(b). Level of Attack Behaviour... 29
Figure 5(c). Level of Escape Behaviour 29
Figure 5(d). Level of Immobility Behaviour 30
Figure 6. Trajectories for Escape Behaviour, where colours of the paths are representing the level of the "Fear".. 33
Figure 7. Trajectories for Attack Behaviour, where colours of the paths are representing the level of the "Attack" 35
Figure 8. A Knowledge-Based Ethological Approach for Robot Behaviour Design 45
Figure 9. The Situated Action-Based Design 47
Figure 10. Basic Visualization of Escape Behaviour.. 52
Figure 11. Basic Visualization of Attack Behaviour 53
Figure 12. Escape Behaviour Simulation.. 54
Figure 12(a). Initial Position of Robots: Both Robots Start at Designated Positions... 54
Figure 12(b). Movement Stage: Robots Start Moving... 55
Figure 12(c). Detection and Fear Assessment: Robot_1 Detects Robot_2 and Assesses Fear Based on Proximity and Environment Unfamiliarity. 55
Figure 12(d). Robot_1 Escaping (Because of High fear and the Presence of an Escape Route).. 56
Figure 12(e). Robot_1 Successfully Presented Escape Behaviour 56
Figure 13. Attack Behaviour Simulation 57
Figure 13(a). Initial Position of Robots 57
Figure 13(b). Robot_1 Starts Moving Towards its Goal Task..................................... 58

Figure 13(c). Robots are Getting Close to Each Other (Robot_2 Identifies an Unknown Animal Robot is Approaching) 59
Figure 13(d). Robot_1 shows Aggression (Robot_2 Fear Level is Increasing and Starts to Leave)........ 60
Figure 13(e). Robot_1 Successfully Presented Attack Behaviour (Robot_2 is far from Robot_1)........ 60
Figure 14. Classification Metrics Report on Escape and Attack Behaviour........ 61
Figure 14(a). Escape Behaviour Classification Metrics 61
Figure 14(b). Attack Behaviour Classification Metrics 61
Figure 15. Fuzzy Behaviour Fusion Process........ 71
Figure 16. Virtual Force Field (VFF) Navigation........ 72
Figure 17. Conceptual Diagram of the Fuzzy Behaviour Control with VFF Navigation........ 78
Figure 18. Trajectories of Escape Behaviour Through Fuzzy Behaviour-Based Control Framework with VFF........ 79
Figure 19. Flowchart of Fuzzy Behaviour-Based Control Framework with VFF 80
Figure 20. Visualization of Hybrid (Fuzzy Behaviour-Based Control Framework with VFF) Architecture........ 83
Figure 21. ROS Simulations of Fuzzy Behaviour-Based Control Framework with VFF 84
Figure 21(a). Initial Stage of Robots........ 84
Figure 21(b). Robot_1 Starts to Move Towards its Goal........ 85
Figure 21(c). Robot_1 Detects Robot_2 86
Figure 21(d). Robot_1 Object identification........ 87
Figure 21(e). Robot_1 Successfully Achieved its Goal.. 87
Figure 22. Classification Metrics of Hybrid Model........ 88

List of Tables

Table 1. Mapping Ethological Observations to Fuzzy Rules 26

Table 2. Summary of Behavioural Responses Based on ADTA and EPE.. 31

Table 3. Fuzzy Behaviour Based Vs Baseline Controller... 62

Table 4. Comparison of Traditional and Fuzzy Ethological Control Systems 63

Table 5. Comparison of Fuzzy Behaviour-Based VFF with Traditional Reactive Controller 89

Table 6. Comparison of Traditional vs Proposed Fuzzy Behaviour-Based VFF Navigation................90

List of Abbreviations and Symbols

FBDL	Fuzzy Behaviour Description Language
FSM	Fuzzy State Machine
FLC	Fuzzy Logic Controller
FBBS	Fuzzy Behaviour-Based Systems
FRI	Fuzzy Rule Interpolation
AFTP	Animal Familiarity Towards Place
AFTA	Animal Familiarity Towards another Animal
ADTA	Animal Distance Towards another Animal
AFTO	Animal Familiarity Towards Object
ADTO	Animal Distance Towards Object
EPE	Escape Path Exists
PIWPE	Positive Impact With Respect to Previous Experience
ROS	Robot Operating System
LIDAR	Light Detection and Ranging
SLAM	Simultaneous Localization and Mapping
CD	Compute Distance
D	Critical Distance
AI	Artificial Intelligence
ML	Machine Learning
VFF	Virtual Force Field
HRI	Human-Robot Interaction
IMU	Inertial Measurement Unit

Preface

The development of intelligent machines capable of operating autonomously in complex, dynamic environments has long been a central pursuit in the fields of artificial intelligence and robotics. While significant progress has been made in mechanical control, sensory perception, and cognitive reasoning, the integration of affective and ethologically grounded behaviour in artificial agents remains a relatively underexplored and challenging frontier. This dissertation addresses this gap by investigating how ethologically inspired emotional constructs specifically fear, escape, and attack, as conceptualized in ethology can be computationally modeled, behaviourally expressed, and operationally deployed within autonomous robotic systems.

Drawing on Archer's ethological framework of aggression and fear in vertebrates, this research explores how these adaptive emotional responses can be meaningfully translated into robotic behaviour that is both functionally intelligent and socially interpretable. The central argument of this work is that embedding emotional constructs into machine behaviour not only enhances the realism and expressiveness of autonomous agents but also significantly improves their capacity to interact safely, intuitively, and adaptively with humans and dynamic environments. The dissertation is structured around three core contributions, each representing a progressive development in the conceptual, methodological, and technical integration of Archer's ethological model into artificial systems.

The research first introduces a novel framework that formalizes Archer's model using Fuzzy Behaviour Description Language (FBDL). This represents the first machine-executable and computationally interpretable model of ethologically defined aggression and fear, utilizing fuzzy linguistic variables and rule-based reasoning. The framework enables artificial agents to generate nuanced, context-sensitive emotional responses and is characterized by its dual interpretability being both human-readable and machine-operational. It supports real-time behavioural execution, visual tracking of emotion-driven behavioural trajectories, and adaptability through learning algorithms. This contribution lays the theoretical foundation for embedding affective dynamics into intelligent control systems.

Building on this foundation, the research then extends into embodied robotics by implementing an ethologically inspired fuzzy state machine within the Robot Operating System (ROS). Leveraging real-time sensory data (e.g., LIDAR), Simultaneous Localization and Mapping (SLAM), and fuzzy logic controllers, the system enables robots to exhibit behaviour patterns such as escape and attack in response to dynamically evolving environmental cues. Unlike conventional reactive systems based on deterministic rule sets, the proposed model accommodates uncertainty, allowing fluid transitions between behavioural states based on the situational appraisal of threat levels. The architecture supports both individual and multi-agent coordination, offering a scalable approach suitable for complex scenarios such as collaborative rescue missions, autonomous surveillance, and navigation in unstructured or hazardous terrains.

Further extending this work, the research introduces a hybrid framework that integrates Virtual Force Field (VFF) navigation with fuzzy emotional behaviour coordination. This system enables robots to evaluate spatial constraints alongside emotional variables such as perceived threat, environmental familiarity, and escape feasibility. By embedding affective logic into behavioural decision-making, the robot modulates its trajectory based on internal states like fear, rather than relying solely on geometric optimization. Implemented within the Robot Operating System (ROS) and enhanced by Simultaneous Localization and Mapping (SLAM), LIDAR, and sonar sensing, the framework allows real-time, adaptive navigation that mirrors ethological escape patterns. This biologically inspired architecture not only improves interpretability and responsiveness but also lays a foundation for emotionally intelligent agents in human-centric or safety-critical environments.

Together, these contributions form a unified theoretical and technical foundation for affective robotics, grounded in both ethological science and fuzzy logic control. This work advances current understanding of artificial emotional intelligence, affective behaviour generation, and autonomous navigation. Moreover, it provides practical tools and architectures for designing emotionally responsive and socially aware machines.

This dissertation is the result of an interdisciplinary inquiry, drawing upon theories and methods from behavioural ethology, cognitive science, robotics, control systems, and artificial intelligence. The journey was intellectually demanding and profoundly enriching. I extend my deepest appreciation to my supervisors, collaborators, and academic mentors, whose guidance, rigor, and insight shaped this work. I am equally grateful to my peers and loved ones, whose unwavering encouragement sustained me through the many phases of research and writing.

It is my hope that this work not only contributes meaningfully to the academic community but also serves as a practical blueprint for the development of the next generation of intelligent, adaptive, and emotionally responsive machines that reflect, in their behaviour, the nuanced complexity of the ethological systems that inspired them.

Chapter 1: Introduction

1.1 Overview

In recent years, there has been a growing connection between ethology the scientific study of animal behaviour and the fields of robotics and artificial intelligence (AI). This connection is driven by a shared goal: to build robotic machines that don't just work mechanically, but can adapt and behave intelligently, much like animals do. Ethology looks at behaviours like communication, self-defense, and aggression, both in nature and in controlled experiments. These studies offer important insights for building systems that can handle real-world complexity and unpredictability [1].

At the center of ethological modeling is the careful observation of how animals behave. From this, researchers build behaviour-based models structured systems that explain actions in terms of responses to specific situations [2]. These models are now helping engineers design intelligent robots by breaking down complex tasks into smaller, behaviour-focused modules. This cross-disciplinary field is known as Ethorobotics [3], combining ethology, robotics, and fuzzy logic. It forms the scientific foundation of this work by translating animal behaviour strategies into control systems for robots, helping bridge the gap between natural and artificial intelligence.

This research presents a innovative methodology called the Fuzzy Behaviour Description Language (FBDL) [4], which is used to describe and analyze models of aggression based on animal behaviour, especially following Archer's ethological framework [5]. FBDL uses fuzzy logic and fuzzy set theory to handle the complexity of aggression how it emerges from internal states, outside stimuli, and the situation an agent is in.

Before going further, it's important to clarify that "behaviour" in this context means the full range of actions and reactions that animals or robots show in response to their environment [6]. By using behaviour-based architecture, robots can tackle complex problems by combining simple behaviour modules [7]. For example, a robot navigating on its own may use separate modules for following a path, avoiding obstacles, and reaching a goal. Each module works independently but is part of a well-coordinated system. This design makes the robot more flexible and adaptable, allowing it to perform well in changing and uncertain environments across different tasks.

1.2 History

Ethology offers valuable perspectives for designing intelligent robotic systems by analyzing how animals behave and adapt to their environments [8]. One of the most influential contributions to this field comes from Nikolaas Tinbergen, who formulated four essential questions to understand behaviour: function, mechanism, evolution, and ontogeny [9]. Though originally intended for studying animal behaviour, these questions have been successfully adapted to guide robotics research and behaviour modeling.

In robotics, the question of *function* concerns the role a behaviour plays in achieving operational goals, such as efficient navigation, threat avoidance, or mission completion. For example, aggressive behaviour in a security robot may serve to deter intruders or defend territory. The *mechanism* question examines the internal and external triggers that initiate behaviour. In robotic systems, this often involves interpreting sensory data such as proximity or motion detection using fuzzy logic to transition between behavioural states like warning, retreat, or attack. These fuzzy variables help manage uncertainty and allow the robot to respond flexibly.

The *evolutionary* dimension relates to how robotic behaviours are refined over time or generalized across different platforms. A behaviour developed for land-based navigation, for instance, can be adapted for aerial or underwater systems through abstraction and iterative testing. Lastly, *ontogeny* refers to the development of behaviour through learning or environmental interaction. In robotic terms, this involves updating behavioural rules based on experience, allowing the robot to refine its responses such as distinguishing between familiar and unfamiliar entities through repeated encounters.

Applying these ethological dimensions enables the creation of adaptive, goal-driven control models in robotics. Complex dynamics like predator-prey interactions or dominance hierarchies can be translated into control rules for navigation, conflict resolution, or escape maneuvers. Specific behavioural domains such as aggression, communication, and defense provide rich templates for designing realistic and responsive robotic behaviour [10].

This research applies fuzzy logic and fuzzy behaviour modeling to simulate aggression patterns observed in animals. Fuzzy logic handles uncertainty by assigning degrees of truth to inputs, enabling robots to respond with greater flexibility than rigid, rule-based systems [11]. A key implementation of this approach is the Fuzzy State Machine (FSM), which incorporates fuzzy rules into robotic decision-making to navigate uncertainty in dynamic environments [12]. Unlike traditional finite state machines that use fixed state transitions, FSMs allow for smooth, gradual changes between behaviours, reducing abrupt shifts and improving both resilience and adaptability [13].

Robotic behaviour is commonly structured through control architectures such as deliberative, reactive, hybrid, and behaviour-based systems [14]. Fuzzy logic, known for its effectiveness in handling uncertainty, is often integrated into these frameworks to support flexible and adaptive decision-making. In *deliberative* control, also known as "Think Then Act," robots analyze current sensory inputs along with past experiences to plan their actions. This approach requires building internal symbolic models of the environment, enabling high-level reasoning and long-term planning [14]. While it supports optimized decision-making, its reliance on computation and planning time may reduce responsiveness in fast-changing environments. In contrast, *reactive* control or "Don't Think, Just Act" maps sensory inputs directly to motor outputs without relying on internal models. Robots using this method follow predefined rules to generate immediate responses, making it well-suited for unpredictable or rapidly evolving situations [15]. Its simplicity allows for quick reactions, though it often lacks strategic depth and adaptability over time.

Hybrid control combines the strengths of deliberative and reactive paradigms [16]. Known as "Simultaneously Think and Act," it enables robots to respond immediately to environmental stimuli while also planning complex behaviours when time allows. Typically, this is implemented through a layered architecture, where a deliberative layer manages long-term planning, and a reactive layer handles real-time interaction. Effective coordination between these layers ensures cohesive behaviour, even under unexpected conditions. Another important control paradigm is the *behaviour-based control* approach [17]. This method organizes robotic systems into multiple distributed modules, known as behaviours, that operate concurrently and interact dynamically. Following the principle "Think the Way You Act," these modules operate concurrently and interact dynamically based on sensory inputs. This architecture allows robots to adapt through environmental interaction, supporting learning and robustness in complex, real-world scenarios [18] [19].

Building on these frameworks, this study models robotic aggression based on Archer's ethological framework [5]. The aim is to replicate key patterns observed in animals, such as fear, flight, attack, or freezing, and to encode responses to familiar versus unfamiliar stimuli. For instance, encountering an unfamiliar agent may trigger a fear-based retreat, while recognition of a familiar one could lead to reduced aggression. These behaviours can be translated into robotic rules that drive realistic threat responses. To support this, recognition algorithms are integrated to distinguish between known and unknown entities, and combined with navigation and mapping systems, they allow the robot to adapt its behaviour based on environmental familiarity. By fusing these perceptual and behavioural modules, the system can simulate complex aggression dynamics in diverse scenarios, ensuring both functional performance and ethological credibility.

1.3 Motivation

The motivation for Implementing Ethologically Inspired Fuzzy Behaviour-Based Systems stems from the desire to make robotic systems behave more naturally, especially when responding to danger, navigating unfamiliar environments, or engaging in social interactions. Traditional robotic systems often rely on binary decision-making simple yes/no logic which lacks the flexibility required to operate effectively in dynamic, real-world conditions. In contrast, animals exhibit a broad range of adaptive behaviours such as fleeing, freezing, or displaying aggression that are context-sensitive and shaped by evolutionary pressures. These behaviours reflect not only mechanical reactions but also emotional and situational assessments that enhance survival. The goal is to design robots that act not only efficiently but also naturally, adjusting their actions in real time based on what they perceive.

This study draws from ethological frameworks, particularly Archer's theory of aggression and fear, to enable robots to interpret and respond to their environment in ways that mimic animal decision-making under stress. Building on this foundation, the research integrates principles from ethology, fuzzy behaviour-based control, and Virtual Force Field navigation. This combination allows robots to make graded decisions based on continuous variables such as perceived threat levels, proximity, and environmental familiarity rather than relying on rigid rules.

Beyond technical innovation, this work aims to develop emotionally aware, context-sensitive robotic systems. Such systems are especially valuable in applications like search and rescue, where quick, instinct-like responses are crucial, or in human-robot interaction, where socially intelligent behaviour enhances trust and safety. Additionally, by simulating emotional behaviour computationally, the research supports ethical advancements by potentially reducing reliance on animal-based behavioural studies. Ultimately, the goal is to create robotic systems that fuse computational precision with the adaptive fluidity of biological intelligence.

1.4 Methodology

To develop an emotionally aware and behaviourally intelligent robotic system, this research integrates core principles from animal behaviour science, fuzzy logic, and robotic control systems [Aaqib1- Aaqib7]. The framework is primarily grounded in Archer's ethological model of aggression and fear [5], which offers a conceptual basis for modeling stress-responsive behaviours. Additional behavioural cues are drawn from human-animal interaction studies [20], ensuring the system reflects real-world, socially relevant contexts. At the center of the design is a fuzzy behaviour-based control architecture, inspired by Archer's model. This architecture processes environmental variables such as distance to other agents, familiarity with the environment or individuals, and availability of escape routes to determine both the intensity and direction of behavioural responses. Instead of rigid, binary decisions, the system uses fuzzy logic to assess how strongly the robot should react in different scenarios, selecting behaviours like escape, attack, or immobility based on contextual input.

Behavioural decisions are encoded using the Fuzzy Behaviour Description Language (FBDL) [4], a modular, human-readable framework for defining fuzzy rules that support adaptive, real-time decision-making. FBDL replaces static, pre-programmed responses with context-sensitive evaluations. The methodology follows a structured three-step process. First, Archer's model is translated into a fuzzy rulebase using FBDL, capturing key variables such as proximity, familiarity, and perceived threat level. Its modular structure allows for the addition of further behaviour categories such as social bonding, cooperation, or mating making FBDL a flexible tool for biologically inspired control.

In the second step, the fuzzy framework is implemented within a Fuzzy State Machine (FSM) to allow smooth transitions between behavioural states. The system is developed and tested in the Robot Operating System (ROS) environment, with simulations conducted in Gazebo and real-time visualization via RViz. LIDAR sensors provide real-time obstacle detection and distance estimation, while Simultaneous Localization and Mapping (SLAM) enables the robot to build and continuously update an internal map of its surroundings. This multi-modal sensory input feeds directly into the fuzzy control system, ensuring ongoing context-awareness.

The third step integrates the fuzzy behavioural architecture with a Virtual Force Field (VFF) navigation mechanism. Behavioural outputs inform the computation of attractive and repulsive force vectors, where attractive forces guide goal-seeking and repulsive forces promote threat avoidance. A key innovation is the dynamic scaling of repulsive forces based on internal emotional states, such as fear or aggression. For example, higher fear levels increase the magnitude of repulsion, prompting robots to retreat more quickly and decisively. This emotion-weight navigation enhances the realism and safety of robotic behaviour in complex and uncertain environments.

The methodology presents a biologically grounded yet computationally robust approach to robotic control. By integrating fuzzy logic, ethological theory, and advanced simulation platforms, this study enables artificial agents to exhibit emotionally nuanced and context-sensitive behaviours, establishing a new benchmark in the design of intelligent, adaptive robotic systems.

1.5 Simulation Environment and Experimental Setup

The ethologically inspired fuzzy behaviour-based control system was developed and tested using the Robot Operating System (ROS), which served as the middleware framework for integrating sensing, decision-making, and navigation. ROS provides a modular, publish-subscribe architecture that enables real-time communication between the fuzzy logic controller, sensors, and actuators making it particularly suitable for behaviour-based robotic control. Its flexibility, scalability, and seamless integration with tools such as Gazebo and RViz align well with the modular structure of the proposed system. Furthermore, ROS's support for real-time processing enhances the system's capability for adaptive, emotionally informed decision-making. Overall, ROS provides a robust and extensible platform for developing and validating biologically inspired robotic architectures.

Simulations were conducted using ROS-integrated tools. The primary simulation environment was Gazebo, a physics-based robotics simulator capable of modeling dynamic interactions such as collisions, object behaviour, and terrain response. Gazebo was selected for its ability to replicate realistic operational conditions for mobile robots, especially in behaviour-intensive scenarios. To monitor and debug behavioural states during runtime, RViz a 3D visualization tool within ROS was used to display real-time sensor data, trajectory planning, and active behaviour modules. Sensor simulation was achieved using ROS-compatible plugins for LIDAR, which provided obstacle detection and proximity measurements. These data were processed through a Simultaneous Localization and Mapping (SLAM) module, enabling the robot to build and update an internal map of its surroundings. This mapping capability was essential for assessing environmental familiarity, a key contextual variable influencing behavioural arbitration within the fuzzy logic system.

The experiments were conducted in a structured yet dynamic environment containing both static and variable obstacle placements. Two robot agents, R1 and R2, were used, with the primary focus on R1, which was responsible for executing aggression-related behaviours. To evaluate the robustness and generalizability of the system, approximately 50 simulation trials were performed under varying initial conditions. These included different starting positions, dynamic obstacle layouts, proximity and recognition of robot agents, and differing levels of environmental familiarity. Each trial was designed to activate different combinations of behaviour modules such as escape, attack, or immobility ensuring that the fuzzy logic controller encountered a wide range of interaction scenarios. These trials provided empirical validation of the system's ability to transition between behaviours in real time, influenced by factors such as spatial proximity, inter-agent recognition, and familiarity with the environment.

For benchmarking, a baseline control system was implemented using traditional reactive logic, both with and without fuzzy behaviour modulation. This comparison allowed the evaluation of the proposed fuzzy control architecture against a simpler rule-based approach. Key performance metrics recorded included task completion time, number of collisions, behaviour switching latency, and adaptability in unfamiliar environments. The results quantified using classification metrics such as precision, recall, F1-score, and accuracy demonstrated that the fuzzy-based system achieved greater behavioural flexibility, improved contextual awareness, and smoother transitions between competing behaviours when compared to the baseline system.

All experiments were conducted entirely in simulation. No physical robots were used during the development or testing phases. However, the complete control architecture including fuzzy behaviour modules, SLAM integration, and behaviour coordination is fully ROS-compatible, making it directly deployable to physical robotic platforms with minimal modification. Based on the promising simulation results, future work will aim to implement and validate the system on real-world robots such as TurtleBot3 or Clearpath Husky, particularly in applications involving human-robot interaction and mobile navigation in unstructured or dynamic environments.

Chapter 2: Ethologically Inspired Fuzzy Behaviour Model

2.1 Ethology

Ethology, the scientific study of animal behaviour, focuses on how animals interact with their environment and with one another [1]. Ethological models are critical for understanding and predicting behaviour patterns and have become foundational elements for developing behaviour-based robotic control systems. These models operate on the principle that natural selection favors behaviours that are best adapted to specific environmental challenges, thereby ensuring their transmission across generations. Additionally, ecological models, such as predator-prey dynamics, provide essential insights into species interactions within natural ecosystems.

In robotics, ethologically inspired models are increasingly employed to overcome the limitations of traditional behaviour systems. Pioneering ethologists such as Baerends, Tinbergen, and Lorenz developed foundational frameworks for describing animal behaviours, frameworks that have now found direct application in robotic design and control. This interdisciplinary convergence enables roboticists to create adaptive systems based on biologically grounded models, while offering ethologists a new experimental platform to test and refine behavioural theories through synthetic implementations [Aaqib1].

Although ethology and robotics share common components such as the concepts of sensors, actuators, and navigation their methodologies differ. Ethology relies on systematic observation and empirical analysis of natural behaviours, whereas robotics seeks to recreate and operationalize these behaviours within artificial agents using synthetic sensors, actuators, and control architectures. Despite these differences, the synergy between the two disciplines significantly enriches both fields, enhancing the understanding, validation, and application of behaviour models in both biological and synthetic systems [2].

2.2 Fuzzy Behaviour-Based Systems

One effective approach to implementing ethologically inspired behavioural models in robotics is through Fuzzy Behaviour-Based Systems [21]. These advanced computational systems utilize fuzzy logic to govern the operations of robots and autonomous agents within complex and dynamic environments. By managing degrees of truth or membership values, fuzzy logic enables systems to make nuanced, context-sensitive decisions rather than relying on rigid binary outcomes. This adaptability is critical for replicating behaviours observed in animals such as avoidance, aggression, and exploration. Individual behaviour units control these actions, and fuzzy rules integrate their outputs to ensure coherent system performance. A Fuzzy

Behaviour-Based System is essentially constructed upon a framework of fuzzy rule-based systems, which are particularly effective for modeling animal behaviour and designing autonomous systems that must adapt to evolving environments [22], [23]. A fuzzy rule-based system is an expert system where knowledge is represented as production rules, typically structured as **If** *[condition]* **Then** *[action]* statements. For instance, a behavioural model's "Fear" level can be defined using fuzzy logic, as demonstrated in the following example:

If AFTP = *Low* **And** AFTA = *Low* **And** ADTA = *Low* **Then** FEAR = *High*

Here, AFTP represents Animal Familiarity Toward Place, AFTA denotes Animal Familiarity Toward Another Animal, and ADTA indicates Animal Distance Toward Another Animal. Such structures allow robots to simulate complex emotional states and behaviour transitions based on environmental conditions.

The architecture of a Fuzzy Behaviour-based System [24] comprises several key modules, including Behaviour Coordination (or Arbitration), Behaviour Fusion, and individual Component Behaviours. Each module and its respective behaviours are implemented as fuzzy rule-based systems, also called Fuzzy Logic Controllers (FLCs), as depicted in Figure 1.

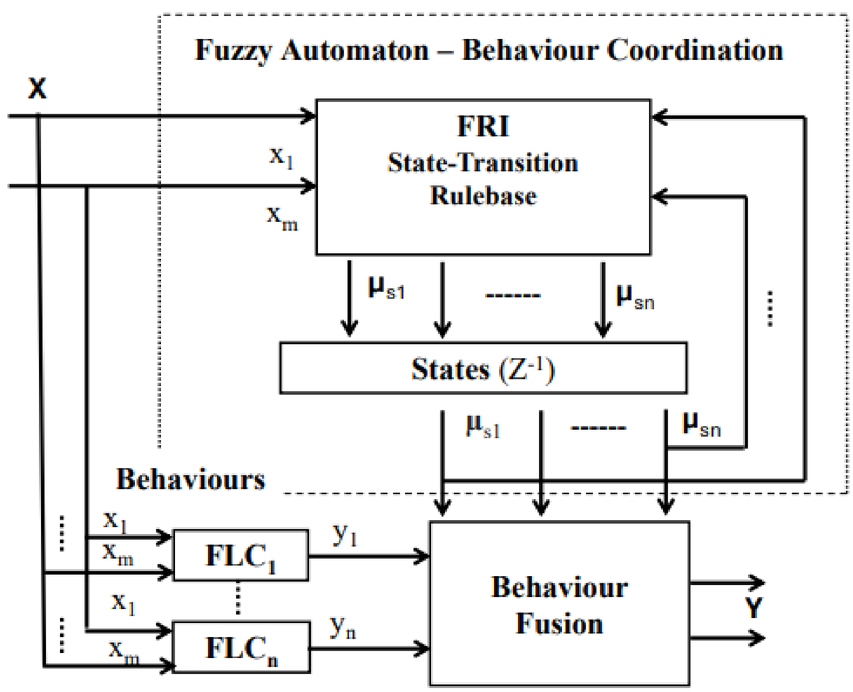

Figure 1. The Applied Fuzzy Behaviour-Based System [24]

Behaviour Coordination also known as arbitration, plays a pivotal role in fuzzy behaviour-based systems, especially when multiple behaviours are activated simultaneously and may produce conflicting outputs. In real-world scenarios, autonomous robots frequently operate in complex environments where behavioural modules such as exploration, obstacle avoidance, aggression, and retreat can be triggered concurrently. Arbitration mechanisms are responsible for resolving these conflicts, ensuring that the robot responds in a coherent and contextually appropriate manner. As illustrated in Figure 2, sensory input received through exteroception, and proprioception activates multiple behaviours. The arbitration strategy then evaluates the situation and assigns control weights to each behaviour [25]. These weights are processed through a Command Fusion unit, which blends or selects outputs to produce the final control signal.

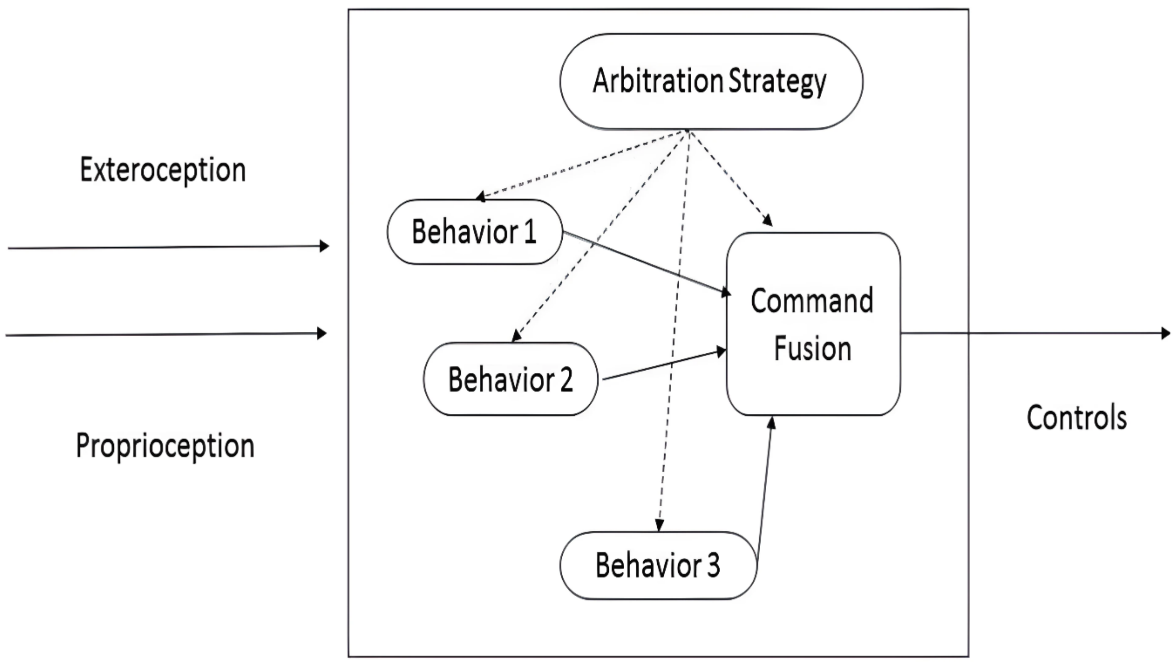

Figure 2. The Architecture of Behaviour Arbitration [25]

Traditional behaviour-based architectures often use a hierarchical arbitration strategy, where behaviours are prioritized in a predefined order. For example, in a surveillance robot, obstacle avoidance may be ranked above exploration. If the robot encounters an obstacle while navigating a corridor, the arbitration system suppresses the exploration behaviour and activates the avoidance routine. Once the obstacle is bypassed, control reverts to the exploration module. This ensures that safety-critical behaviours take precedence, maintaining operational reliability.

In contrast, fuzzy arbitration supports more flexible and adaptive decision-making by evaluating the degree of activation for each behaviour using fuzzy logic. Instead of relying on binary switching, fuzzy arbitration blends behaviour outputs proportionally. For instance, during a navigation task, if a robot is tracking a target while simultaneously detecting an obstacle, the fuzzy coordination module may assign a high priority to obstacle avoidance (e.g., 0.9) and a moderate priority to goal-seeking (e.g., 0.6). The resulting behaviour blend enables the robot to cautiously advance toward the target while maintaining a safe distance from the obstacle. This form of arbitration allows context-aware decision-making and mimics biological survival responses, where multiple competing goals are pursued in balance rather than one being entirely suppressed. Such mechanisms contribute to more adaptive, ethologically grounded robotic behaviour.

Behaviour Fusion involves merging the outputs from behaviour coordination processes. For instance, if a robot navigating a path encounters an obstacle, the arbitration mechanism would prioritize obstacle avoidance. However, there are situations where behaviour fusion alone cannot fully resolve conflicts between behaviours. A fuzzy rule-based system can evaluate competing conditions and determine which behaviour to prioritize [26]. Fuzzy behaviour fusion is a behaviour fusion built upon the elements of fuzzy systems. It has wide applications in fields such as robotics, autonomous vehicles, and healthcare [27] [28]. More broadly, fuzzy behaviour fusion provides a versatile computational mechanism for synthesizing complex behaviour components, facilitating precise and flexible decision-making.

A behaviour-based system consists of interconnected modules, referred to as behaviours, that collectively define a robot's functionality and decision-making architecture. Each behaviour models a specific action or interaction scenario, enabling the robot to operate adaptively and intuitively within complex environments [29]. In the context of social robots, which are designed to engage naturally with humans, behaviours must be carefully designed to respond to nuanced social cues. These models often draw inspiration from human-dog interactions, where a dog's ability to interpret gestures, vocal tones, and proximity serves as a natural template for social engagement. Just as dogs adjust their behaviour across diverse contexts, social robots can be programmed to replicate similar interaction patterns. By systematically observing and documenting a dog's responses, researchers can infer the internal conditions driving these behaviours and translate them into robotic behaviour models. This approach enables robots to exhibit socially intelligent behaviour and engage with human users in a more natural and context-aware manner [11].

Developing ethologically inspired fuzzy behaviour-based systems to replicate animal aggressive behaviours in robotics requires an integrated and methodical approach. The process begins with an extensive literature review to establish a robust theoretical foundation, focusing on Archer's ethological model of aggression and fear in vertebrates, the fundamentals of fuzzy logic, and their application in behaviour-based robotics. Archer's model is then translated into a fuzzy logic framework, where key behavioural components are linked to fuzzy rules capable of managing the variability and uncertainty inherent in aggressive behaviours.

A fuzzy inference system is constructed to process sensory inputs and generate appropriate behavioural outputs [Aaqib2]. Integration of the Fuzzy Behaviour Description Language (FBDL) enables seamless communication between the robot's sensory systems and control architecture, allowing adaptive behaviour modulation. This research ultimately aims to develop a resilient and flexible robotic system capable of accurately simulating aggressive behaviours under varying environmental conditions. The system's performance and adaptability are evaluated through real-world application testing, validating the practical potential of ethologically inspired fuzzy behavioural models in robotics.

2.3 Comparative Analysis with Existing Fuzzy and Bio-Inspired Controllers

The proposed ethologically inspired fuzzy behaviour-based system builds upon established paradigms in autonomous robotics, particularly those involving fuzzy control and biologically motivated architectures. To contextualize its contributions, this section compares the system with three key approaches: Subsumption Architecture, Belief-Desire-Intention (BDI) models, and Neuro-Fuzzy Systems. The comparison focuses on four aspects: behaviour coordination, emotional modeling, environmental reactivity, and real-time adaptability.

The Subsumption Architecture, developed by Brooks [30], organizes robot behaviours into hierarchical layers in which higher-level behaviours can suppress or inhibit lower-level ones. Although effective for reactive, real-time responses especially in navigation and obstacle avoidance it lacks the capacity to model internal emotional states and cannot support graded behavioural transitions. By contrast, the proposed system uses fuzzy logic to represent emotions such as fear and aggression along a continuum. This facilitates nuanced behavioural blending, resulting in more ethologically realistic responses rather than simple binary suppression.

BDI models, which are prominent in deliberative agent design, use symbolic reasoning to select actions based on explicit representations of beliefs, desires, and intentions [31]. These models are powerful in structured environments that benefit from formal planning. However, they are computationally intensive and less adaptable to dynamic, unpredictable scenarios. In contrast, the proposed system avoids symbolic world modeling by grounding decision-making in fuzzy ethological rules. This results in faster, context-sensitive responses crucial for emotionally responsive and socially interactive environments.

Neuro-fuzzy systems combine the learning capabilities of neural networks with fuzzy inference to adapt rule structures over time [32]. While such systems can optimize behaviour through experience, they typically require extensive training datasets and often operate as "black boxes," limiting interpretability especially in safety-critical applications. The proposed system addresses this limitation by employing a transparent and interpretable rule base derived from Archer's aggression theory. This ensures that each fuzzy rule is biologically grounded and traceable, enhancing both ethical accountability and system adjustability.

While existing studies such as [22] which apply fuzzy logic to medical diagnosis in livestock, and [23], which focus on fuzzy control for obstacle avoidance and mobile robot navigation demonstrate the utility of fuzzy logic, they do not incorporate biologically grounded emotional behaviour. The current system advances the field by embedding emotion-driven, ethologically inspired behaviours directly into the control logic. As a result, the robot can exhibit survival responses such as freezing, fleeing, or aggression in ways that are contextually appropriate and biologically plausible.

2.4 Implementing the "Aggression" Behaviour

This research aims to develop a fuzzy behaviour-based model for simulating aggression, drawing upon Archer's ethological framework presented in "The Organization of Aggression and Fear in Vertebrates: Perspectives in Ethology" [5], as illustrated in Figure 3. Archer's model offers a theoretical foundation for analyzing the structure, function, and mechanisms of aggression and fear behaviours in vertebrates, providing key insights into their underlying motivations and decision-making processes. By integrating fuzzy logic, which is well-suited for managing imprecise and uncertain data [33], the model can better represent the complexity and variability inherent in animal aggression.

The combination of Archer's ethological principles with fuzzy behaviour-based system design enables the development of a more adaptable, scalable, and context-sensitive representation of aggressive behaviour. This integrative approach not only enhances the fidelity of robotic simulations but also deepens the understanding of the dynamic and often ambiguous nature of aggression and fear responses in vertebrates. It supports the modeling of fluid behavioural decisions that are influenced by environmental cues, internal states, and prior experiences.

Figure 3 illustrates the structure and decision-making flow of the implemented aggression model based on Archer's ethological framework. Each stage of the behavioural sequence represents a cognitive or reactive component that contributes to the animal's final response. A detailed explanation of each stage is provided below:

Expectation Copy: The animal forms expectations about the behaviour of another animal. These expectations are informed by prior experiences, general behavioural knowledge, and the animal's current internal state, such as its arousal level.

Sensory Input: The animal receives sensory information from other animals, including cues such as size, posture, movement, and other observable behaviours.

Orientation Response: After processing the sensory input, animal orients toward the other animal, assessing the situation based on the new sensory input.

Discrepancy: The animal compares the incoming sensory information with its established expectations. Any mismatch triggers increased arousal and may prompt a fight-or-flight response.

Decision Process 1 - Fear or Attack?: The animal evaluates whether to respond with Fear or initiate an attack. This decision depends on factors such as the degree of mismatch, hormonal levels, past experiences with conflict, and current emotional state.

Attack: If aggression is selected, the animal engages in an attack toward the opponent.

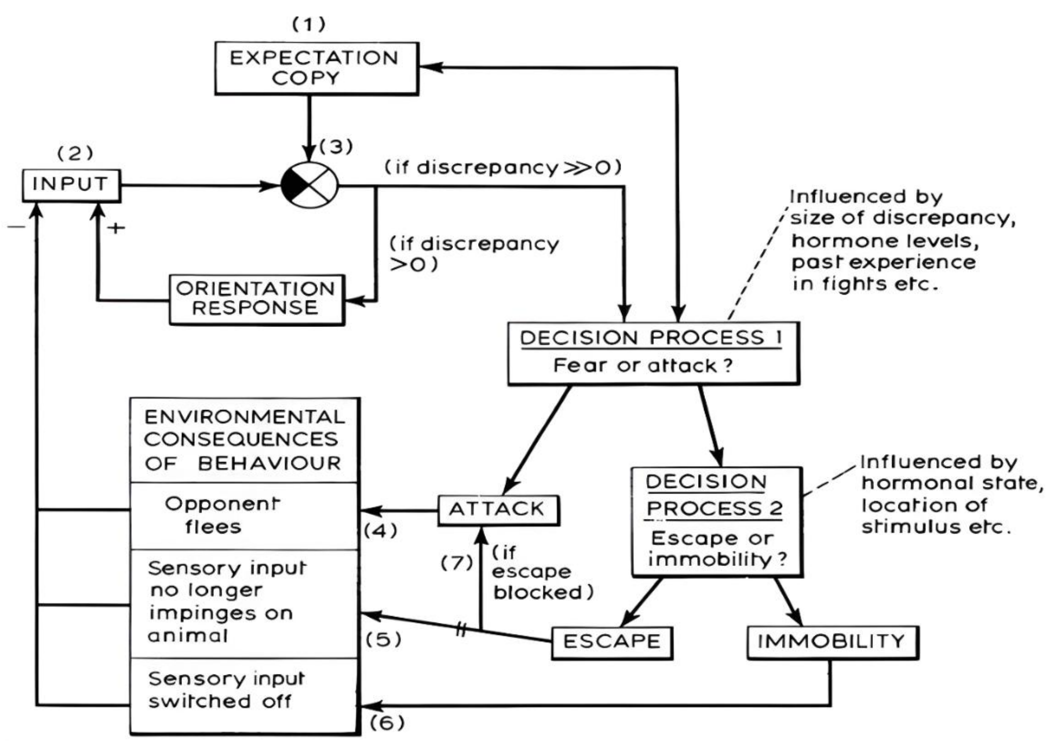

Figure 3. Archer Organization Model [5]

Environmental Consequences of Behaviour: The aggressive action may lead to various environmental changes, such as the retreat or submission of the other animal.
Decision Process 2 - Escape or Immobility?: If the animal decides not to attack during Decision Process 1, it proceeds to decide between escape or immobility. This choice considers variables like hormonal state, the position of the other animal, and the animal's perceived likelihood of successful Escape.
Escape: If the decision is to flee, the animal attempts to distance itself from the other animal.
Sensory input no longer impinges on the animal: If the animal chooses to escape, then the sensory input from the other animal no longer affects the animal's senses.
If Escape is blocked: If Escape is not feasible, the animal may switch to aggression and initiate an attack.
Immobility: If the animal neither attacks nor escapes, it enters a state of immobility. Which subsequently leads to the Sensory Input Switched Off.
Sensory Input Switched Off: The animal disengages from reacting to the sensory input provided by the other creature. In short, it means animals will not do anything at all.

The Archer Control Theory model provides a structured framework for understanding how biological systems regulate behaviour to achieve specific objectives. Within this model, animals govern their actions through the interplay of internal and external influences, particularly within motivational systems. A simplified version of the theory, focused on aggression and fear in vertebrates, posits that these behaviours are managed by two opposing systems: the aggression system and the fear/anxiety system. These systems operate dynamically, and the equilibrium between them determines the animal's behavioural outcome. The balance is influenced by a range of internal variables such as physiological state and emotional arousal as well as external environmental cues, which shift based on context and need.

The dynamics of aggression are typically expressed through three primary behavioural responses: Attack, Escape, and Immobility. Modeling these responses using Fuzzy State Machines (FSMs) allows for more biologically realistic representations, as FSMs accommodate the uncertainty, gradation, and imprecision inherent in animal behaviour [34]. The implementation process involves several core steps. First, the system states representing distinct behaviours like Attack, Escape, and Immobility are defined. Second, the system's inputs are identified, encompassing both internal factors (e.g., emotional state) and external stimuli (e.g., proximity to another animal or object). These inputs are modeled using fuzzy logic. For example, the input "presence of another animal" may be represented by a fuzzy set with levels such as Low, Medium, or High, based on familiarity.

Once the states and inputs are defined, fuzzy rules are established to govern state transitions. These rules represent probabilistic decision-making, reflecting the animal's ambiguous and context-dependent behaviour. A typical rule might be: "If familiarity with another animal is Low and familiarity with the environment is Low, then the likelihood of "Escape" is High." Terms such as High, Medium, and Low allow for nuanced interpretation of behaviour. Finally, outputs are determined based on the selected state. For instance, the output "Attack" might be triggered when the animal is unfamiliar with both its environment and another animal. This methodology provides a robust framework for simulating ethologically valid aggression responses in artificial systems.

To apply this ethologically inspired behaviour model, the process begins with categorizing scenarios that provoke aggression. The model identifies how such situations elicit behavioural responses like Fear, Attack, Escape, and Immobility. It then generalizes these conditions to formulate a broader theory of aggression and fear triggers. Internal variables such as physiological states, motivational drives, and memory of prior experiences are combined with external environmental factors to calculate the likelihood of specific responses. These elements are encoded using fuzzy logic to ensure the model accommodates the non-binary, fluid nature of real animal behaviour. Before implementation, specific terms and rules are defined and expressed using fuzzy logic to capture animal behaviour's nuanced and complex nature.

State Variables: The fuzzy "Aggression" behaviour model incorporates four primary state variables, as illustrated in Figure 4. Three of these "Attack," "Escape," and "Immobility" represent observable behavioural responses, while the fourth, "Fear," serves as a hidden state variable. Although "Fear" cannot be directly observed, it plays a critical modulatory role by influencing transitions among the observable states.

"Fear": This variable reflects an animal's internal physiological, emotional, and behavioural response to threatening stimuli. While fear is not directly observable, it often manifests through secondary indicators such as changes in posture or movement. Common signs include a lowered body and head, ears drawn back, widened eyes, and a tucked tail. In this model, Fear functions as a latent state, lacking a distinct behavioural output but exerting a significant influence on the decision-making dynamics between Attack, Escape, and Immobility.

"Attack": This state involves a rapid, targeted action directed at a specific stimulus, typically resulting in physical contact or harm. Examples include biting, striking, or pecking, and these behaviours are associated with aggression or defense, rather than predation or food acquisition.

"Escape": This variable encompasses behaviours intended to increase distance from a perceived threat. Escape responses are typical in life-threatening situations, such as evading predators or avoiding aversive stimuli, and may include running, flight, or evasive maneuvers.

"Immobility": Also known as "freezing", this state reflects a complete cessation of movement. It may occur as a conditioned fear response to a known threat or as a spontaneous reaction to sudden or ambiguous stimuli particularly those resembling predator presence. Immobility is often an adaptive strategy that reduces detection by predators.

Observations: Drawing from the ethological model of Aggression as outlined in [5], this simplified fuzzy behaviour model identifies a set of key observational variables that inform the system's state transitions [Aaqib2]. These variables reflect the animal's familiarity, proximity, past experience, and environmental context, serving as inputs to determine the likelihood of entering states such as Fear, Attack, Escape, or Immobility.

"Animal Familiarity Towards Place" (AFTP): Represents the extent to which an animal is familiar with its surroundings. It considers scenarios where an animal encounters familiar or unfamiliar environments. Fear is more likely to be triggered in unfamiliar environments. However, if a suitable target is present, aggressive behaviour may also occur even in unfamiliar settings.

"Animal Familiarity Towards another Animal" (AFTA): This captures the degree of familiarity an animal has with another animal. This applies across both familiar and unfamiliar territories. For example, encountering an unknown animal in a familiar space or entering another animal's known territory may result in fear or aggression.

"Animal Distance Towards another Animal" (ADTA): Refers to the physical proximity between two animals. For instance, when an animal is unfamiliar with another animal and environment, and the distance between them is in close range, and there is no available escape route, the likelihood of fear or aggressive behaviour increases significantly.

"Animal Familiarity Towards Object" (AFTO): Measures how familiar the animal is with an object. This situation occurs in an animal's familiar and unfamiliar environment, like when a moving object comes close to an animal or when the distance between the animal and the object decreases in an unfamiliar place. Also, when a novel object enters an animal's familiar place, these include the conventional territorial issue and a wide range of other scenarios such as Fear, Attack, and escape behaviours. This observation (and also ADTO) serves as a robotic extension of the original model by Archer by considering that the appearance of a non-living object causes territorial issues for robots.

"Animal Distance Towards Object" (ADTO): Measures the distance between an animal and an object. It considers situations where the animal may be unfamiliar with the place or object. For example, when an unfamiliar object comes too close in an unfamiliar place, the animal may exhibit Fear, aggression, or escape behaviours.

"Escape Path Exists" (EPE): Evaluates the availability of a clear and viable escape route. When approached by another animal or object, the presence of an escape path generally results in flight. In contrast, if escape is not possible, fear may escalate into aggression, particularly under conditions of stress or perceived threat.

"Positive Impact With Respect to Previous Experience" (PIWPE): Reflects how past experiences, whether positive or negative, influence current behavioural responses. For instance, prior exposure to threatening situations can predispose the animal toward defensive behaviours such as fear or aggression in similar future contexts.

Figure 4 presents the fuzzy model for simulating animal aggressive behaviour, integrating all previously defined inputs such as familiarity with place, other animals, objects, and spatial distance. The model uses these observations to generate context-dependent behavioural responses, emphasizing the interaction between environmental familiarity, social recognition, physical proximity, and experiential memory. By encoding these variables within a fuzzy logic framework, the system effectively captures the uncertainty and variability inherent in real animal behaviour. This enables a nuanced representation of behavioural dynamics influenced by both context and experience. Consequently, robotic systems built on this model can exhibit lifelike, adaptive responses to complex, multi-dimensional scenarios bringing biologically grounded realism to artificial behaviour modeling. defensive behaviours such as fear or aggression in similar future contexts.

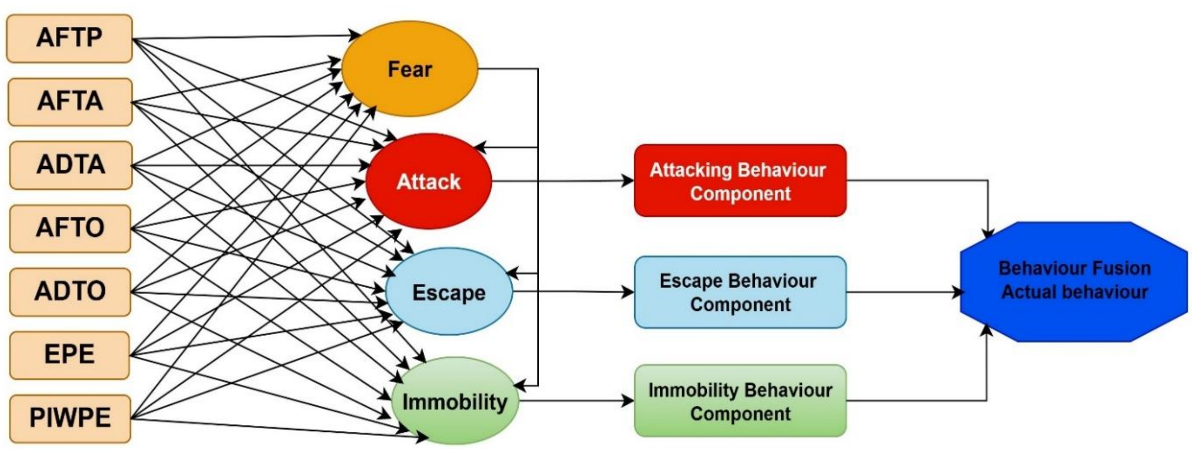

Figure 4. Fuzzy Behaviour Model for Animal Aggressive Behaviour

Chapter 3: The Fuzzy Model for the “Aggression” Behaviour

3.1 Model Overview and Implementation Guidelines

To implement the fuzzy behaviour model for “Aggression,” the Fuzzy Behaviour Description Language (FBDL) [4] is utilized. FBDL is based on fuzzy rule-based systems and Fuzzy Rule Interpolation (FRI) [35] [36] which facilitates the construction of behaviour components and their behaviour coordination. Its rule-based approach ensures that knowledge representation is self-explanatory for humans. Additionally, fuzziness and linguistic terms defined as fuzzy sets enhance human understanding, mainly when variables are expressed within continuous universes. Numerical evaluations can be performed directly with the fuzzy behaviour model defined in FBDL. The FBDL code can either be executed on a system as is or, with supplementary measurement data, applied as input for machine learning optimization algorithms.

The FBDL specifies input and state variable universes, their linguistic terms (fuzzy sets used in the rule-bases), and the fuzzy rule-bases. For instance, if we consider an observation such as the level of “Animal Familiarity to the Place,” which is an input universe with two linguistic terms, ‘Low’ and ‘High’, the variable can be represented with the symbol ‘AFTP’ in FBDL as follows:

```
universe “AFTP”
description “Level of the Animal Familiarity to the Place.”
    “low” 0 0
    “high” 1 1
end
```

An example fuzzy rule from the behaviour coordination to determine the level of the “Fear” hidden state variable based on factors such as animal familiarity with the place (AFTP), another animal (AFTA), and an approaching object (AFTO) could be expressed as:

If AFTP=*High* **And** AFTA=*High* **And** AFTO=*High* **Then** FEAR=*Low*

whereas the AFTP, AFTA, and AFTO are antecedent universes. FEAR is the consequent universe, *Low* and *High* are fuzzy linguistic terms in the corresponding universes.

In FBDL format, the same rule is written as:

Rule *“Low”* **When** “AFTP” is “*High*” **And** “AFTA” is “*High*” **And** “AFTO” is “*High*” **end**

The fuzzy model of the **“Aggression”** behaviour in FBDL format

The FBDL definition of the input and state variable universes are:

universe “*Universe label*”
“low” 0 0
“high” 1 1
end

where “*Universe label*” is “AFTP”, “AFTA”, “AFTO”, “ADTA”, “ADTO”, “PIWPE”, “EPE”, “FEAR”, “ATTACK”, “ESCAPE” and “IMMOBILITY”.

The FBDL based definitions of state rule bases are designed to address a range of ethologically relevant scenarios. These include the animal’s familiarity with its surroundings, objects, or other animals, as well as encounters involving spatial intrusion such as when a moving object or another animal approaches too closely. Another key scenario involves the entry of a novel object or unfamiliar animal into a known territory, potentially triggering territorial or defensive behaviours. Fear responses are particularly prevalent when animals enter unfamiliar environments, though even familiar objects in strange contexts can alter behavioural outcomes. Additionally, the valence of prior experiences especially the degree of positivity or negativity associated with past aggressive encounters plays a significant role in modulating current behaviour. Collectively, these scenarios provide a robust foundation for constructing the fuzzy state rule bases, enabling the model to dynamically represent behaviours such as Fear, Aggression, Escape, and Immobility in a context sensitive and interpretable manner.

In fuzzy rule-base format, the FEAR Fuzzy Rule-base ($\boldsymbol{R}_{\text{FEAR}}$) is the following:

If AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** FEAR=*High*
If AFTA=*Low* **And** ADTA=*Low* **And** EPE=*Low* **Then** FEAR=*High*
If AFTO=*Low* **And** ADTO=Low **And** EPE=*Low* **Then** FEAR=*High*
If AFTP=*Low* **And** EPE=*Low* **And** PIWPE=*Low* **Then** FEAR=*High*
If AFTP=*High* **And** AFTA=*High* **And** AFTO=*High* **Then** FEAR=*Low*
If AFTA=*High* **And** ADTA=*High* **And** EPE=*High* **Then** FEAR=*Low*
If AFTP=*High* **And** AFTA=*High* **And** EPE=*High* **And** PIWPE=*High* **Then** FEAR=*Low*

The same FEAR rule-base in FBDL format appears as:

RuleBase “FEAR”

Rule *High* **when** “AFTP” is *Low* **and** “AFTA” is *Low* **and** “AFTO” is *Low* **end**
Rule *High* **when** “AFTA” is *Low* **and** “ADTA” is *Low* **and** “EPE” is *Low* **end**
Rule *High* **when** “AFTO” is *Low* **and** “ADTO” is *Low* **and** “EPE” is *Low* **end**
Rule *High* **when** “AFTP” is *Low* **and** “EPE” is *Low* **and** “PIWPE” is *Low* **end**
Rule *Low* **when** “AFTP” is *High* **and** “AFTA” is *High* **and** “AFTO” is *High* **end**

Rule *Low* **when** “AFTA” is *High* **and** “ADTA” is *High* **and** “EPE” is *High* **end**

Rule *Low* **when** “AFTP” is *High* **and** “AFTA” is *High* **and** “EPE” is *High* **and** “PIWPE” is *High* **end**

end

where AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE are the antecedent universes. FEAR is the consequent universe, *Low* and *High* are fuzzy linguistic terms in the corresponding universes.

In fuzzy rule-base format the ATTACK Fuzzy Rule-base ($\boldsymbol{R}_{\mathrm{ATTACK}}$) is the following:

If AFTA=*Low* **And** ADTA=*Low* **And** EPE=*Low* **Then** ATTACK=*High*

If AFTO=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** ATTACK=*High*

If AFTP=*Low* **And** ADTA=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** ATTACK=*High*

If FEAR=*High* **And** EPE=*Low* **Then** ATTACK=*High*

If AFTP=*High* **And** AFTA=*High* **And** PIWPE=*High* **Then** ATTACK=*High*

If AFTP=*High* **And** AFTO=*High* **And** PIWPE=*High* **Then** ATTACK=*High*

If EPE=*High* **And** FEAR=*High* **Then** ATTACK=*Low*

If EPE=*High* **And** AFTP=*Low* **And** ADTA=*High* **Then** ATTACK=*Low*

If EPE=*High* **And** AFTA=*Low* **And** ADTA=*High* **And** PIWPE=*Low* **And** ADTO=*High* **Then** ATTACK=Low

If EPE=*High* **And** AFTO=*Low* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ATTACK=*Low*

If AFTA=*Low* **And** AFTP=*Low* **And** AFTO=*Low* **And** EPE=*High* **Then** ATTACK=*Low*

The same ATTACK rule-base in FBDL format

rulebase “**ATTACK**”

Rule *High* **when** “AFTA” is *Low* **and** “ADTA” is *Low* **and** “EPE” is *Low* **end**

Rule *High* **when** “AFTO” is *Low* **and** “ADTO” is *Low* **and** “EPE” is *Low* **end**

Rule *High* **when** “AFTP” is *Low* **and** “ADTA” is *Low* **and** “ADTO” is *Low* **and** “EPE” is *Low* **end**

Rule *High* **when** “FEAR” is *High* **and** “EPE” is *Low* **end**

Rule *High* **when** “AFTP” is *High* **and** “AFTA” is *High* **and** “PIWPE” is *High* **end**

Rule *High* **when** “AFTP” is *High* **and** “AFTO” is *High* **and** “PIWPE” is *High* **end**

Rule *Low* **when** “EPE” is *High* **and** “FEAR” is *High* **end**

Rule *Low* **when** “EPE” is *High* **and** “AFTP” is *Low* **and** “ADTA” is *High* **end**

Rule *Low* **when** “EPE” is *High* **and** “AFTA” is *Low* **and** “ADTA” is *High* **and** “PIWPE” is *Low* **and** “ADTO” is *High* **end**

Rule *Low* **when** “EPE” is *High* **and** “AFTO” is *Low* **and** “ADTO” is *High* **and** “PIWPE” is *Low* **end**

Rule *Low* **when** “AFTA” is *Low* **and** “AFTP” is *Low* **and** “AFTO” is *Low* **and** “EPE” is *High* **end**

end

The antecedent universes are AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR. The consequent universe is ATTACK, and *Low* and *High* are fuzzy linguistic terms in the corresponding universes.

In fuzzy rule-base format the ESCAPE Fuzzy Rule-base ($\boldsymbol{R}_{\text{ESCAPE}}$) is the following:

If EPE=*High* **And** FEAR=*High* **Then** ESCAPE=*High*

If EPE=*High* **And** AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** ESCAPE=*High*

If EPE=*High* **And** AFTA=*Low* **And** ADTA=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*

If EPE=*High* **And** AFTO=*Low* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*

If EPE=*High* **And** AFTP=*Low* **And** ADTA=*High* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*

If FEAR=*Low* **And** EPE=*Low* **Then** ESCAPE=*Low*

If FEAR=*Low* **And** PIWPE=*High* **Then** ESCAPE=*Low*

If AFTA=*High* **And** AFTO=*High* **And** AFTP=*High* **And** PIWPE=*High* **Then** ESCAPE=*Low*

If AFTA=*High* **And** ADTA=*High* **And** PIWPE=*High* **And** EPE=*Low* **Then** ESCAPE=*Low*

If AFTO=*High* **And** ADTO=*High* **And** PIWPE=*High* **And** EPE=*Low* **Then** ESCAPE=*Low*

The same ESCAPE rule-base in FBDL format

Rule base "**ESCAPE**"

Rule *High* **when** "EPE" is *High* **and** "FEAR" is *High* **end**

Rule *High* **when** "EPE" is *High* **and** "AFTP" is *Low* **and** "AFTA" is *Low* **and** "AFTO" is *Low* **end**

Rule *High* **when** "EPE" is *High* **and** "AFTA" is *Low* **and** "ADTA" is *High* **and** "PIWPE" is *Low* **end**

Rule *High* **when** "EPE" is *High* **and** "AFTO" is *Low* **and** "ADTO" is *High* **and** "PIWPE" is *Low* **end**

Rule *High* when "EPE" is *High* **and** "AFTP" is *Low* **and** "ADTA" is *High* **and** "ADTO" is *High* **and** "PIWPE" is *Low* **end**

Rule *Low* **when** "FEAR" is *Low* **and** "EPE" is *Low* **end**

Rule *Low* **when** "FEAR" is *Low* **and** "PIWPE" is *High* **end**

Rule *Low* **when** "AFTA" is *High* **and** "AFTO" is *High* **and** "AFTP" is *High* **and** "PIWPE" is *High* **end**

Rule *Low* **when** "AFTA" is *High* **and** "ADTA" is *High* **and** "PIWPE" is *High* **and** "EPE" is *Low* **end**

Rule *Low* **when** "AFTO" is *High* **and** "ADTO" is *High* **and** "PIWPE" is *High* **and** "EPE" is *Low* **end**

end

whereas AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR are the antecedent universes, ESCAPE is the consequent universe, *Low* and *High* are fuzzy linguistic terms in the corresponding universes

In fuzzy rule-base format the IMMOBILITY Fuzzy Rule-base ($\boldsymbol{R}_{\text{IMMOBILITY}}$) is the following:

If FEAR=*Low* **And** EPE=*Low* **Then** IMMOBILITY=*High*

If AFTA=*Low* **And** ADTA=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*

If AFTO=*Low* **And** ADTO=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*

If AFTP=*Low* **And** ADTA=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*

If AFTP=*Low* **And** AFTA=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*High*

If EPE=*High* **And** FEAR=*High* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*

If EPE=*High* **And** AFTA=*Low* **And** ADTA=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*

If EPE=*High* **And** AFTO=*Low* **And** ADTO=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*

The same IMMOBILITY rule-base in FBDL format

Rule base "**IMMOBILITY**"

Rule *High* **when** "FEAR" is *Low* **and** "EPE" is *Low* **end**

Rule *High* **when** "AFTA" is *Low* **and** "ADTA" is *High* **and** "EPE" is *Low* **end**

Rule *High* **when** "AFTO" is *Low* **and** "ADTO" is *High* **and** "EPE" is *Low* **end**

Rule *High* **when** "AFTP" is *Low* **and** "ADTA" is *High* **and** "EPE" is *Low* **end**

Rule *High* **when** "AFTP" is *Low* **and** "AFTA" is *Low* **and** "PIWPE" is *Low* **end**

Rule *Low* **when** "EPE" is *High* and "FEAR" is *High* **and** "PIWPE" is *Low* **end**

Rule *Low* **when** "EPE" is *High* **and** "AFTA" is *Low* **and** "ADTA" is *Low* **and** "PIWPE" is *Low* **end**

Rule *Low* **when** "EPE" is *High* **and** "AFTO" is *Low* **and** "ADTO" is *Low* **and** "PIWPE" is *Low* **end**

end

The antecedent universes are AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR, and the consequent universe is IMMOBILITY, the fuzzy linguistic terms are *Low* and *High* in the corresponding universes.

Table 1 presents a structured mapping between key ethological observations derived from Archer's aggression and fear model and their corresponding fuzzy logic rules within the proposed behavioural framework. Each rule is linked to specific contextual variables (e.g., FEAR, AFTA, EPE) and justified based on biologically observed survival responses such as Escape, Attack, or Immobility, thereby ensuring the fuzzy system retains behavioural plausibility and interpretability grounded in ethological theory.

Ethological Observation (Archer's Model)	Fuzzy Input Variables	Derived Fuzzy Rule (Example)	Justification
Discrepancy between expected and actual behaviour leads to increased arousal and potential attack	FEAR (High) Escape Path Exists (Low)	If FEAR is High AND EPE is Low THEN ATTACK is High	When the robot experiences high fear but no escape path is available, aggressive behaviour becomes a likely outcome, aligning with fight
Encounter with unfamiliar animal in unfamiliar environment triggers fear and retreat	AFTA (Low) AFTP (Low) ADTA (Low) EPE (High)	If AFTA is Low AND AFTP is Low AND ADTA is Low AND EPE is High THEN ESCAPE is High	Unfamiliarity and close proximity elevate threat perception; a clear escape route triggers flight behaviour, simulating natural fear-driven avoidance.
Familiar animal in familiar environment with low perceived threat does not provoke aggressive response	AFTA (High) AFTP (High) FEAR (Low)	If AFTA is High AND AFTP is High AND FEAR is Low THEN IMMOBILITY is High	Indicates no immediate threat; immobility as passive behaviour aligns with low arousal and situational comfort.
Prior positive experience with a similar agent or situation increases likelihood of aggression	PIWPE (High) AFTA (Low) ADTA (Low)	If PIWPE is High AND AFTA is Low AND ADTA is Low THEN ATTACK is High	Negative memory combined with current threat cues encourages preemptive aggression.
Proximity to a novel object in an unfamiliar environment triggers uncertainty and freeze response	AFTO (Low) AFTP (Low) ADTO (Low) EPE (Low)	If AFTO is Low AND AFTP is Low AND ADTO is Low AND EPE is Low THEN IMMOBILITY is High	Freezing is a common response when an animal cannot determine a safe action under ambiguous stimuli.
Presence of escape route reduces aggression even under high fear	FEAR (High) EPE (High)	If FEAR is High AND EPE is High THEN ESCAPE is High	High fear redirects behaviour toward safe avoidance rather than confrontation, aligning with adaptive strategies.
No escape route in threatening condition raises aggression probability	FEAR (High) EPE (Low) AFTA (Low)	If FEAR is High AND EPE is Low AND AFTA is Low THEN ATTACK is High	A blocked escape path combined with low familiarity and high fear justifies offensive action as a last resort.

Table 1. Mapping of Ethological Observations to Fuzzy Rules

Animal behaviours such as Fear, Escape, Attack, and Immobility are influenced by a variety of factors that determine how an animal responds to a given situation. These influences can be broadly categorized into *internal characteristics* and *behavioural outcome* variables. Internal characteristics refer to the mechanisms by which an animal interprets and reacts to external stimuli. A primary factor is the discrepancy between expectations and observations. When there is a significant mismatch such as an unexpected movement or the presence of an unfamiliar entity the animal often perceives it as a threat, triggering defensive responses like fear or escape. Conversely, if the observed stimulus closely matches the animal’s expectations, particularly in familiar environments, it may elicit assertive behaviours such as attack. Another critical internal factor is positive motivation shaped by prior experience. Animals reinforced for aggressive responses in the past are more inclined to attack rather than avoid similar situations in the future, illustrating how learned behaviour influences future responses. Additionally, experiential factors including early-life experiences, socialization history, or long-term isolation can substantially impact an animal’s perception of threat and its coping strategies. For instance, animals exposed to early social interactions may exhibit more cautious or avoidant behaviour [Aaqib1], while those with limited social exposure may escalate more quickly to aggression. Collectively, these internal variables underscore the role of memory, learning, and emotional regulation in shaping behavioural outcomes.

In parallel, behavioural outcome variables also significantly influence the response selection process. One such variable is the physical characteristics of the perceived target, including its size, mobility, and proximity. Larger or more mobile targets often provoke heightened vigilance or hesitation, whereas smaller or immobile targets may be approached with greater assertiveness. Another influential factor is the animal’s predisposition toward passive or active coping strategies. Some animals are naturally inclined either biologically or behaviourally to freeze or remain still in the face of danger, while others instinctively engage in active escape. These tendencies are shaped by both genetic predispositions and environmental conditioning and can also be affected by sensory discrepancies such as sudden movements or unusual sounds, which heighten arousal and vigilance. Finally, the perceived feasibility of escape is a crucial determinant of behaviour. When an escape route is available, animals typically choose flight over fight; however, when escape is obstructed such as in confined spaces aggression may be triggered as a last-resort defensive mechanism. These outcome-based factors interact fluidly with internal characteristics, forming a flexible, context-sensitive decision-making system. Together, they highlight the multifactorial, situational nature of animal aggression and defense, providing a robust framework for modeling such responses in fuzzy rule-based robotic systems.

Figure 5(a)-5(d) illustrates how changes in behaviour components Fear, Attack, Escape, and Immobility are modulated by varying observations within the fuzzy model of aggressive behaviour [Aaqib2]. The analysis decomposes each behaviour into its dynamic components, demonstrating how environmental and internal factors interact to shape an animal’s overall response. The graphs were generated using computational evaluations from the Fuzzy Behaviour Description Language (FBDL) [4], implemented through publicly available FBDL functions [37] [38]. In our example, two key input variables ADTA (Animal Distance Towards Another Animal) and EPE (Escape Path Exists) are varied (vary from Low to High). All other variables are held constant, with the animal assumed to be highly familiar with the environment (AFTP = High) and the conspecific (AFTA = High), but less familiar with an object (AFTO = Low) and its proximity (ADTO = Low), and with minimal positive influence from previous experiences (PIWPE = Low). In all plot graphs, red denotes a High response, and blue denotes a Low response.

The *Figure 5(a)* graph shows changes in Fear based on ADTA and EPE [Aaqib2]. Fear levels are High when no escape path exists (EPE=Low), and the approaching animal is unfamiliar (AFTA=Low). Conversely, Fear levels are Low when the animal is familiar with its surroundings (AFTA=High, AFTP=High, AFTO=High). *Figure 5(b):* Graph represents changes in Attack behaviour. Attack levels are High when the animal is unfamiliar with the approaching animal (AFTA=Low), the distance to the other animal is small (ADTA=Low), and no escape path exists (EPE=Low). Attack levels decrease to Low when an escape path is available (EPE=High).

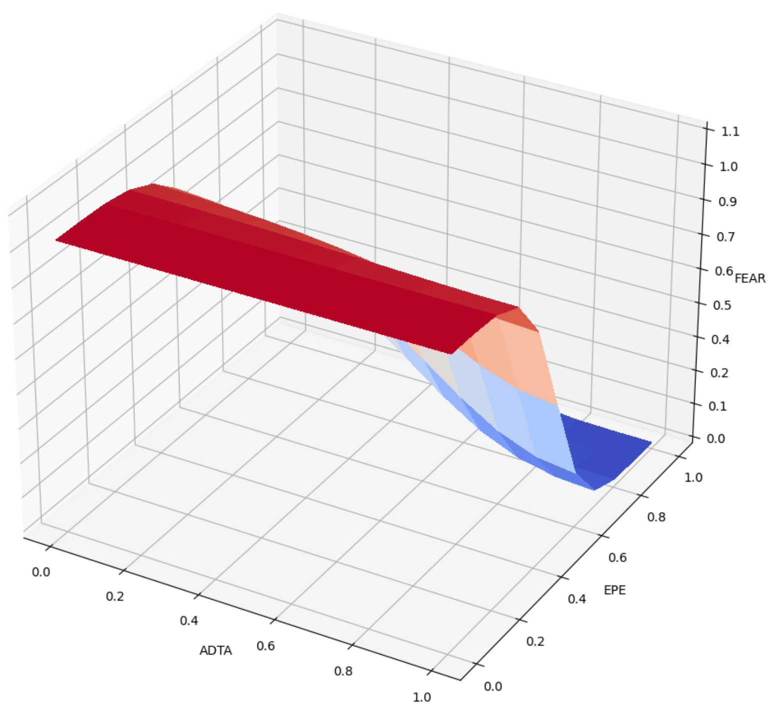

Figure 5 (a). Level of Fear Behaviour

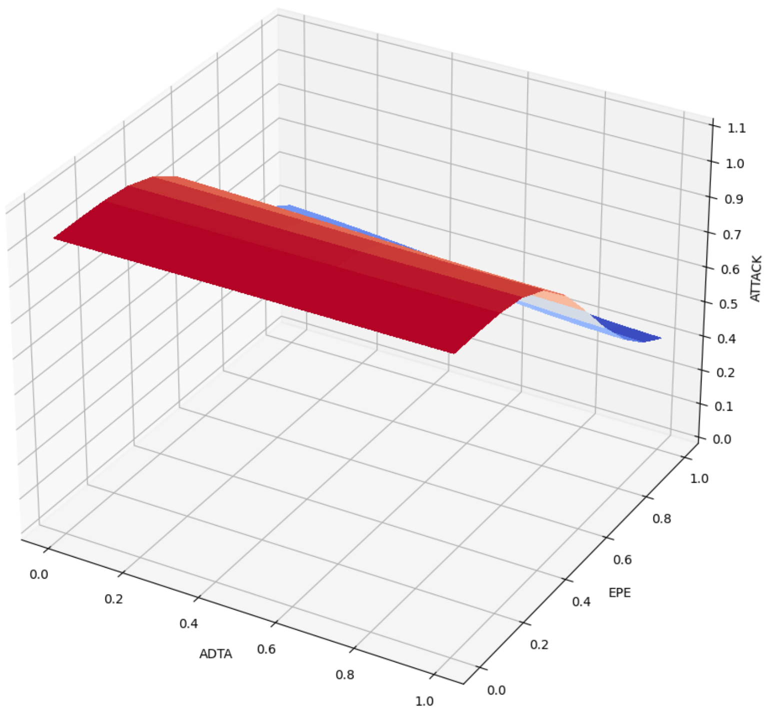

Figure 5 (b). Level of Attack Behaviour

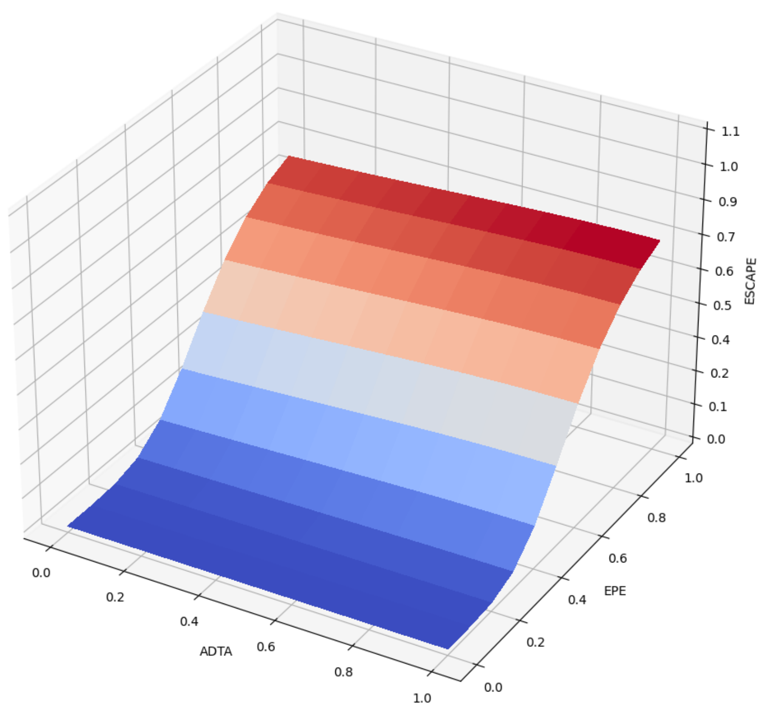

Figure 5 (c). Level of Escape Behaviour

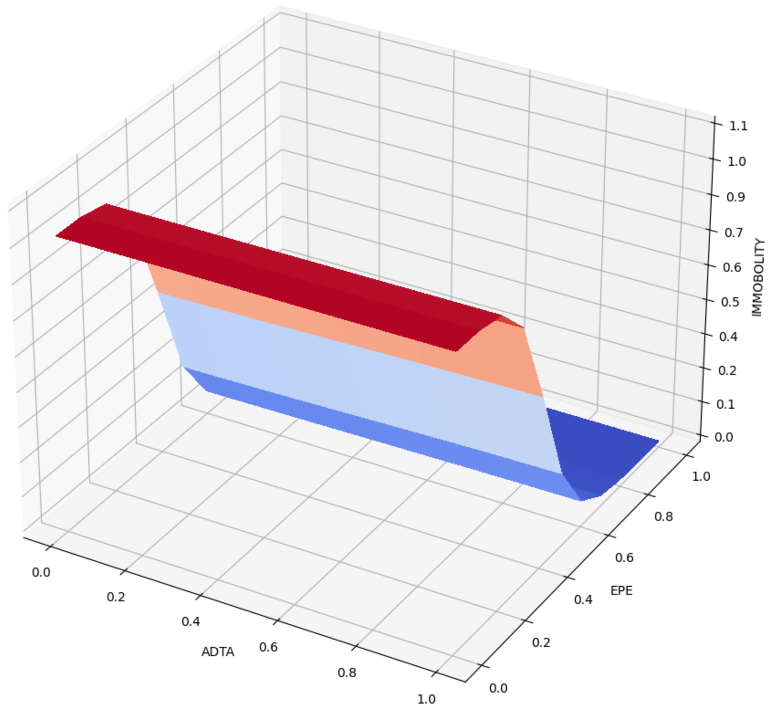

Figure 5 (d). Level of Immobility Behaviour

Figure 5 (a), (b), (c), (d). Graphical Representation of Behaviours

Figure 5(c) illustrates changes in Escape behaviour. Escape levels are High when the animal is unfamiliar with the approaching animal (AFTA=Low), unfamiliar with the place (AFTP=Low), and an escape path is available (EPE=High). Escape levels are Low when no escape path exists (EPE=Low). *Figure 5(d)* shows changes in Immobility behaviour. Immobility is High when the animal is unfamiliar with the approaching animal (AFTA=Low), the distance to the other animal is small (ADTA=Low), and no escape path exists (EPE=Low). Immobility decreases to Low when an escape path exists (EPE=High), and the distance to the other animal is large (ADTA=High).

These examples demonstrate how variations in input observations directly affect behavioural responses, highlighting the underlying complexity and sensitivity of the fuzzy aggression model. Table 1 presents of summary of behaviours and figures 5(a) through 5(d) illustrate how contextual factors modulate the likelihood of different behavioural outcomes Fear, Attack, Escape, and Immobility within an ethologically inspired fuzzy framework. Fear levels increase when the animal is in close proximity to an unfamiliar threat and lacks an escape route but diminish in familiar and controlled environments. Attack becomes more probable when the animal and the perceived threat are nearby, especially when escape options are unavailable. However, the availability of an escape path significantly reduces the tendency to attack. Escape behaviour is most likely when the animal is unfamiliar with both the intruder and the environment and perceives a viable escape route. In contrast, escape responses decline when no such path exists. Immobility, which often functions as a passive substitute for aggression, becomes prominent in scenarios involving immediate threat and restricted movement options. When the threat is distant and escape is possible, immobility is less likely to be exhibited. Overall, the model captures the nuanced interplay of environmental familiarity, proximity, and threat perception, offering a biologically grounded framework for modeling complex behaviour in both animals and autonomous systems.

Behaviour	High Behaviour Conditions	Low Behaviour Conditions	Key Influencing Factors
Fear	EPE = Low (No escape path) AFTA = Low (Unfamiliar with another animal)	AFTA = High AFTP = High AFTO = High i.e. High Familiar with animal, place and object	Escape path availability, Familiarity with animal, place and object
Attack	AFTA = Low ADTA = Low (Close distance) EPE = Low	EPE = High (Escape path exists)	Proximity and escape route
Escape	AFTA = Low AFTP = Low EPE = High	EPE = Low (No escape path)	Familiarity with environment and escape path
Immobility	AFTA = Low ADTA = Low (Close distance) EPE = Low	EPE = High (Escape path exists) ADTA = High (Greater distance)	Threat distance and mobility constraints

Table 2: Summary of Behavioural Responses Based on ADTA and EPE

3.2 Trajectories for simulating Aggressive Behaviour

This section investigates the implementation of ethologically inspired fuzzy control models through the simulation of robotic trajectories, focusing specifically on two fundamental behavioural responses observed in the animal kingdom: Escape and Attack. These responses are not only integral to the survival of biological organisms but are also critically relevant in the design of intelligent, adaptive robotic agents operating in unstructured and unpredictable environments. By modeling such interactions between two autonomous robots hereafter referred to as Robot_1 and Robot_2 the system aims to emulate real-time behavioural transitions governed by fuzzy logic, capturing the complexity of threat evaluation and decision-making.

The simulations integrate both internal motivational states (e.g., fear, familiarity) and external environmental cues (e.g., proximity, escape path availability) into a unified fuzzy control framework. Unlike traditional binary systems, fuzzy logic allows for gradated responses that reflect the ambiguity and contextual sensitivity of real animal behaviour. This results in the emergence of dynamic, continuous trajectories in which robots do not simply react, but rather adapt, negotiate, and learn from their environments and interactions with other agents. The following subsections detail the implementation and analysis of escape and attack behaviours, with associated visualizations (Figures 7 and 8) illustrating how these strategies unfold in both spatial and behavioural dimensions.

3.2.1 Escape Behaviour

Escape behaviour in animals is a rapid, adaptive response to immediate threats, often triggered by the perception of an approaching entity or an environmental anomaly. This simulation models such ethologically inspired escape dynamics using a fuzzy behaviour control system, with Robot_1 (R1) as the primary agent performing the escape response. Figure 6 depicts the interaction between Robot_1 (R1) and Robot_2 (R2), each following a trajectory influenced by its sensory and cognitive inputs. R1 starts at coordinates (0.5, 0.5), while R2 begins at (6, 6). Each robot is programmed to move towards near to the other's initial location, creating a deliberate encounter that escalates proximity and simulates a potential confrontation. The blue trajectory represents R1, and the green trajectory represents R2, both exhibiting complex patterns that resemble animal-like behaviour, with an emphasis on escape reactions to social stimuli.

R1 is initialized with low familiarity with both the environment and R2, resulting in a baseline fear state. In contrast, R2 is assumed to possess high familiarity, maintaining a neutral behavioural profile. As robots approach one another, R1 continuously assesses three factors using fuzzy inference: distance to the Robot_2 (ADTA), fear level (FEAR), and escape path existence (EPE). When the inter-robot distance drops below a predefined threshold, R1's internal fear metric increases. If an escape route is available (as determined by EPE), R1 initiates an evasive maneuver. This behavioural transition is visually encoded by a trajectory color shift from blue to red, signaling elevated arousal and active avoidance. The transition is not binary but reflects a gradual, context-sensitive modulation of behaviour. As R1 gains distance from R2 and re-establishes safety, its fear level declines, and the trajectory color gradually shifts back to blue representing a return to a calmer state.

This fear-response cycle anticipation, reaction, and recovery closely mirrors behavioural adaptations observed in prey species. Notably, the trajectories of R1 and R2 are interdependent, exhibiting behavioural synchronization that reflects real-world social modulation. R1's escape behaviour influences R2's spatial decisions, illustrating how one agent's actions can dynamically shape another's response. This emergent, bidirectional interaction highlights the strength of fuzzy control systems in capturing complex behavioural patterns. Such responsive coordination is particularly valuable in domains like robot swarms, multi-agent navigation, and socially adaptive robotics, where real-time context sensitivity and fluid behaviour modulation are essential for effective operation.

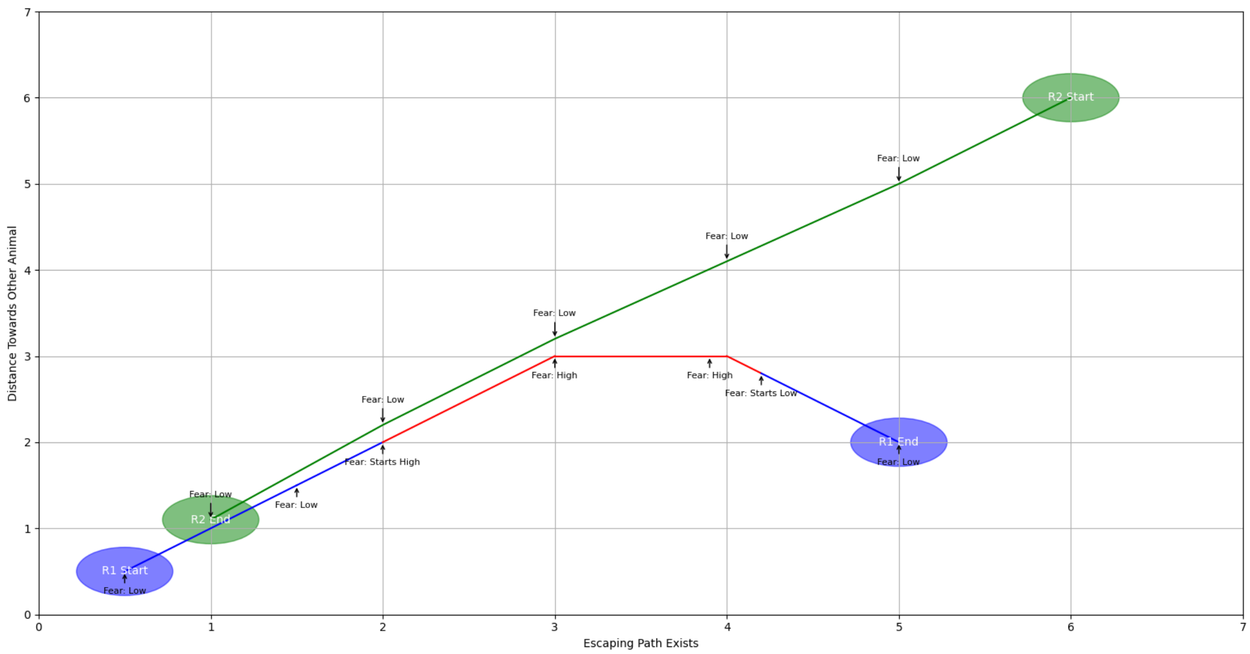

Figure 6. Trajectories for Escape Behaviour, where colours of the paths are representing the level of the "Fear" [Aaqib2]

Algorithm 1: Fuzzy Logic-Based Escape Behaviour for Robots
Input:
  Robot_1_Start ← (0.5, 0.5)
  Robot_2_Start ← (6, 6)
  Parameters ← {ADTA, FEAR, EPE}
  Threshold_Distance ← D (Critical distance for fear increase)
Initialize:
  Set Robot_1 fear_level ← LOW
  Set Robot_2 familiarity_level ← HIGH
  Move Robot_1 toward Robot_2_Start
  Move Robot_2 toward Robot_1_Start
While Robot_1 and Robot_2 are moving:
  CD ← ComputeDistance(Robot_1.position, Robot_2.position)
  FEAR ← EvaluateFuzzyLogic(ADTA, FEAR, CD)

```
    If CD ≤ Threshold_Distance:
        Increase Robot_1 fear_level
        If EPE exists:
            TriggerEscape(Robot_1)
        Else:
            ContinueMovement(Robot_1)
    SynchronizeBehaviour(Robot_1, Robot_2)
    If CD increases:
        Decrease Robot_1 fear_level
        SetTrajectoryColor(Robot_1, BLUE)
EndCondition:
    If Robot_2 reaches near Robot_1_Start location and Robot_1 escaped successfully:
        StopSimulation()
        LogBehaviourData()
Output:
    - Robot_1 trajectory: BLUE → RED → BLUE
    - Adaptive escape response recorded
    - Simulated natural escape behaviour in robotics
```

3.2.2 Attack Behaviour

While escape behaviour centers on evasion and retreat, attack behaviour involves assertive confrontation, often emerging from motives such as territorial defense, dominance assertion, or perceived superiority. Figure 7 illustrates the attack trajectories of Robot_1 (R1) and Robot_2 (R2), modeled through a fuzzy behaviour control system that simulates aggression dynamics inspired by animal interactions. This fuzzy rule-based framework captures the inherent uncertainty and complexity of aggressive behaviour in multi-agent systems. Each robot’s movement is visualized through color-coded trajectories that trace their spatiotemporal interactions. These visual patterns mirror behavioural phenomena commonly observed in animal encounters within shared spaces.

R1 begins at coordinates (1, 1), initially exhibiting low aggression, as denoted by its blue trajectory. R1's objective is to approach R2, assert dominance, and potentially escalate into an aggressive display. In contrast, R2 begins at (5.5, 5.5) with a green trajectory, representing a calm, non-threatening posture. As R1 advances, figure 7 captures its behavioural escalation from neutral to aggressive triggered by increasing proximity to R2. The behaviour of R1 and R2 are governed by fuzzy logic rules that evaluate multiple input variables: distance to another animal (ADTA), fear level (FEAR), familiarity with place (AFTP), and familiarity with another animal (AFTA). When R1 detects a specific pattern close proximity, low fear, and low familiarity the system triggers a transition to an aggressive state, visually marked by a shift from blue to red. This color transition represents the onset of assertive behaviour, akin to territorial charging or dominance displays in animals.

Simultaneously, R2 interprets R1’s behavioural shift as a threat. In response, its trajectory color changes from green to orange, signaling rising fear and a defensive posture. The system dynamically prompts R2 to retreat, reorient, or otherwise attempt de-escalation mimicking natural avoidance strategies observed in animal populations. This bidirectional modulation creates a feedback loop where both agents continuously adapt their actions based on the other’s behaviour and internal emotional states. As the proximity diminishes whether through movement or mutual de-escalation R1’s aggression subsides, and its trajectory returns to blue. Similarly, R2’s fear dissipates, reverting its trajectory to green. These changes reflect the system’s ability to simulate temporary, context-dependent emotional states and fluid behavioural transitions, grounded in environmental and social stimuli.

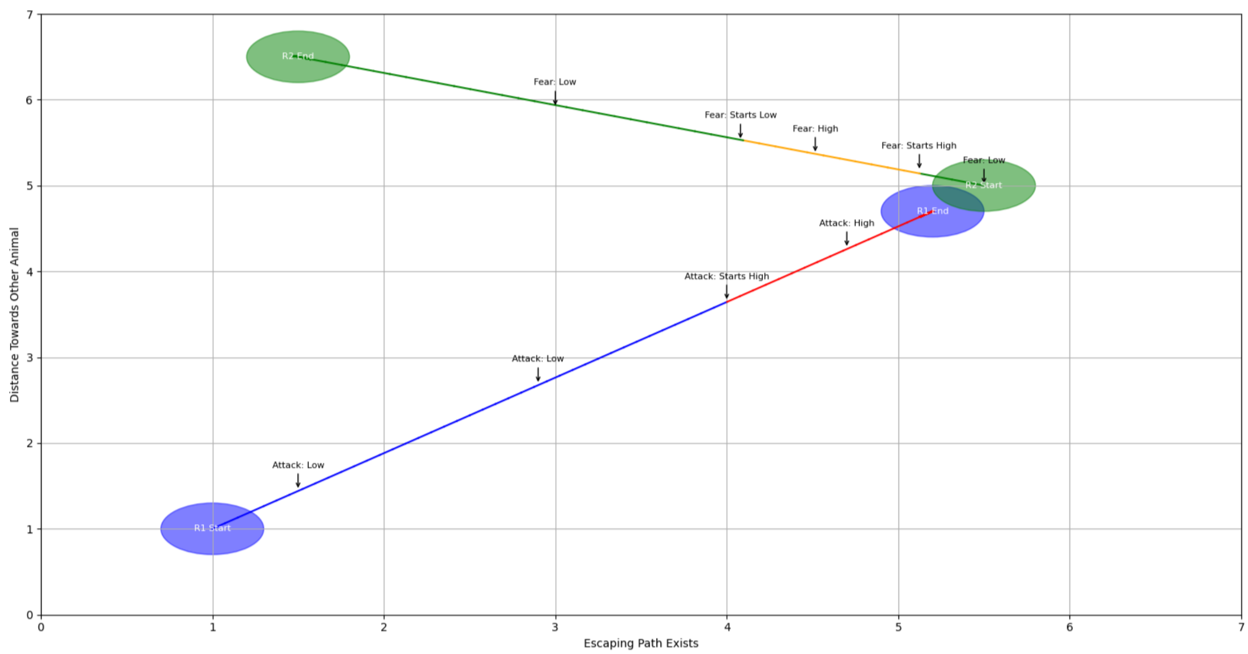

Figure 7. Trajectories for Attack Behaviour, where colours of the paths are representing the level of the “Attack” [Aaqib2]

The interaction patterns between R1 and R2 underscore the expressive power of fuzzy systems in modeling lifelike behaviours. By capturing aggression, fear, and adaptive responses in real-time, this framework offers a robust approach for simulating animal-inspired behaviour in autonomous robots. It also provides a foundation for applications in robot training environments, multi-agent conflict resolution, and even behavioural modeling in social psychology. More broadly, the model contributes to cross-disciplinary insights linking robotics, behavioural ecology, and cognitive systems. It supports the development of intelligent agents capable of naturalistic interactions, adaptive decision-making, and emergent behaviour in complex, uncertain environments.

Algorithm 2: Fuzzy Logic-Based Attack Behaviour for Robots

```
Input:
   Robot_1_Start ← (1, 1)
   Robot_2_Start ← (5.5, 5.5)
   Parameters ← {ADTA, FEAR, AFTP, AFTA}
   Threshold_Distance ← D (Critical distance for aggression increase)
Initialize:
   Set Robot_1 aggression_level ← LOW (BLUE)
   Set Robot_2 fear_level ← NONE (GREEN)
   Move Robot_1 toward near Robot_2_Start
   Keep Robot_2 stationary initially
While Robot_1 is moving:
   CD ← ComputeDistance(Robot_1.position, Robot_2.position)
   FuzzyParams ← EvaluateFuzzyLogic(ADTA, AFTP, AFTA, FEAR, CD)
   If CD ≤ Threshold_Distance:
      Increase Robot_1 aggression_level
      SetTrajectoryColor(Robot_1, RED)
      Increase Robot_2 fear_level
      SetTrajectoryColor(Robot_2, ORANGE)
      Robot_2 evades position to avoid damage
   If CD increases again:
      Decrease Robot_1 aggression_level
      SetTrajectoryColor(Robot_1, BLUE)
      Decrease Robot_2 fear_level
      SetTrajectoryColor(Robot_2, GREEN)
EndCondition:
   If Robot_1 presents Aggression successfully:
      StopSimulation()
      LogBehaviourData()
Output:
   - Robot_1 trajectory: BLUE → RED
   - Robot_2 trajectory: GREEN → ORANGE → GREEN
   - Adaptive attack behaviour recorded
   - Simulated animal-like attack behaviour in robotics
```

The simulated trajectories of both escape and attack behaviours provide robust validation for the capacity of fuzzy logic to emulate ethologically grounded behavioural patterns in autonomous robotic systems. Rather than functioning as rigid, pre-programmed reflexes, these behaviours emerge from a continuous and dynamic inference process, shaped by real-time sensory input and internal motivational states. The resulting behavioural expressions ranging from evasive maneuvers to assertive confrontations demonstrate a level of flexibility and nuance that closely parallels the situational adaptiveness observed in animal behaviour.

Furthermore, these simulations highlight the effectiveness of fuzzy behaviour-based systems in enabling robots to engage in complex social dynamics, including multi-agent coordination, emotional modulation, and contextual learning. The seamless behavioural transitions between states such as fear, aggression, avoidance, and calmness reveal an underlying architecture capable of mimicking emotional and cognitive fluidity, a characteristic essential for real-world applications where responsiveness to both environmental and social cues is paramount. These capabilities position fuzzy logic systems as not only a tool for behaviour modeling but also as a foundational approach for building emotionally intelligent, ethically aware, and socially interactive robots. As such, this work represents a meaningful step toward bridging the disciplinary gap between biological ethology and artificial intelligence, paving the way for next-generation robotic agents capable of operating autonomously, adaptively, and intuitively in dynamic human and non-human environments.

3.3 Conclusion

This research introduces a novel fuzzy behaviour model, developed in the FBDL language, to simulate aggressive behaviours in animals based on Archer's ethological framework of aggression and fear in vertebrates. Through a fuzzy rule-based system, the study effectively models complex behavioural responses ranging from evasion to confrontation in robotic agents, with visualized escape and attack trajectories that parallel adaptive patterns observed in nature. These simulations demonstrate the system's ability to support nuanced transitions between behavioural states such as fear, aggression, avoidance, and calmness, reflecting an underlying architecture capable of emotional modulation and context-sensitive decision-making. By integrating ethological principles with fuzzy logic, the model extends beyond technical functionality to support emotionally intelligent, socially interactive, and ethically aware robotic systems. Such behaviour-rich agents are equipped to handle real-world uncertainty with animal-like judgment and responsiveness, especially in dynamic multi-agent environments. The ultimate goal is to implement these ethology-inspired behaviours in both virtual simulations, such as TurtleBot, and physical mobile robots, marking a significant advancement in applying biological behaviour models to robotics. This work offers a foundation for developing intelligent, adaptive systems with the capacity to engage naturally within complex environments, paving the way for future innovations in robotics, autonomous systems, and bio-inspired artificial intelligence

3.4 Thesis I.

This thesis proposes a novel framework that translates Archer's ethological model of aggression and fear in vertebrates into a computationally interpretable and machine-executable architecture using the "Fuzzy Behaviour Description Language" [Aaqib1, Aaqib2].

3.4.1 Scientific Foundations

Unlike rigid binary control systems such as finite state machines (FSMs), FBDL supports continuous, graded behavioural transitions in ambiguous or multi-modal sensory environments. This work builds upon:

Archer's Model of Aggression: A theory grounded in vertebrate ethology, Archer's model conceptualizes behaviour as the outcome of internal motivational conflicts (e.g., fear vs. aggression), dynamically modulated by external environmental cues such as familiarity, proximity, and threat level.

Zadeh's Fuzzy Set Theory: Introduced by Lotfi Zadeh, fuzzy set theory allows input variables to belong partially to multiple linguistic categories (e.g., "Low", "Medium", "High") with degrees of membership. This enables graded reasoning and nuanced decision-making in ambiguous or noisy environments.

Fuzzy Rule Interpolation (FRI) with FIVE: The primary inference mechanism in this work, implemented in FBDL, enabling reasoning with sparse or incomplete rule bases. For baseline comparisons in dense rule sets, a Mamdani Type-1 FIS is used.

3.4.2 Mathematical Formalism

The proposed ethologically inspired fuzzy behaviour-based control architecture enables robots to make emotion-aware decisions by interpreting both internal affective states and external environmental stimuli. This process is governed by a multi-step fuzzy inference mechanism consisting of fuzzification, rule evaluation via interpolation, defuzzification, and optionally probabilistic state transitions. This section formalises each component of the inference chain using standard mathematical notation to enhance transparency and reproducibility.

Behavioural Mapping Function: The robot's active behaviour B_i (equation 1) is determined by a function f that maps internal emotional variables F_j and external context cues C_k to a behavioural decision:

$$B_i = f\,(F_j, C_k) \qquad (1)$$

Where: $F_j \in$ (FEAR, ATTACK etc.), and $C_k \in$ (ADTA, AFTA, AFTP, EPE etc.).

This mapping is implemented through fuzzy logic, using a set of predefined linguistic rules derived from Archer's Aggression Ethological Model.

Membership Function Definitions: Each crisp input variable $X_k \in R$ is mapped into the fuzzy linguistic terms $Lx_k \in$ *{Low, Medium, High}* via membership functions:

$$\mu_{Lxk}(x_k): R \rightarrow [0,1] \qquad (2)$$

Two commonly used membership functions in this framework are Triangular and Trapezoidal (equation 3 and 4), these functions are configured based on expert knowledge and empirical trials.

Triangular Membership Function (used for smooth variables like proximity):

$$\mu_{Tri}(x; a, b, c) = \begin{cases} 0 & if\ x \leq a\ or\ x \geq c \\ \frac{x-a}{b-a} & if\ a < x \leq b \\ \frac{c-x}{c-b} & if\ b < x < c \end{cases} \qquad (3)$$

Trapezoidal Membership Function (used for thresholds like EPE or familiarity):

$$\mu_{Trap}(x; a, b, c, d) = \begin{cases} 0 & if\ x \leq a\ or\ x \geq d \\ \frac{x-a}{b-a} & if\ a < x \leq b \\ 1 & if\ b < x \leq c \\ \frac{d-x}{d-c} & if\ c < x < d \end{cases} \qquad (4)$$

Fuzzy Rule Evaluation (Inference Engine): Behavioural decisions are made using fuzzy IF-THEN rules and are governed by ethologically grounded fuzzy rules derived from Archer’s aggression model, Example:

Fear Rule-Base: Rule Fear is High When AFTA is *Low* AND EPE is *Low*

Inference follows Fuzzy Rule Interpolation (FIVE), as implemented in FBDL:

Similarity & activation: For each rule R_k, compute the similarity between each input x_j and its antecedent fuzzy set $A_{k,j}$ combining them into an activation weight w_k.

Interpolation ratio: Determine how the input vector x lies between the closest rules in the antecedent space.

Consequent interpolation: Interpolate the consequent fuzzy sets B_k according to activation weights w_k and the interpolation ratio to produce a single inferred consequent $B^*(x)$, even when no rule matches exactly.

Defuzzification: If a crisp output is required, apply a standard method such as the centroid to $B^*(x)$.

This process ensures robust reasoning in sparse rule bases while preserving interpretability. Mamdani max-min composition is used only in baseline comparisons for dense rule bases. For example, for a behaviour Bi, the fuzzy output is (equation 5):

$$\mu_B(x) = \max_i (\min_j \mu_{Lxj}(x_j)) \qquad (5)$$

Whereas $\mu_{Lxj}(x_j)$ is the membership degree of input X_j to label L_{xj}, $\min_j$ represents the logical AND across antecedents, and $\max_i$ aggregates rules affecting the same behaviour.

Behaviour Arbitration and Defuzzification: When multiple behaviours are activated simultaneously, behaviour arbitration ensures that the robotic system selects the most contextually appropriate response. Following fuzzy inference, the system generates output membership functions for each candidate behaviour B_i. These fuzzy outputs are then aggregated across all rules to represent the total contribution for each behaviour. To convert these aggregated fuzzy sets into actionable decisions, the system applies the Centroid (Center of Gravity, equation 6) method for defuzzification. This method computes the crisp output value B_{crisp}, representing the weighted average location of the fuzzy output distribution:

$$B_{crisp} = \frac{\int_a^b \mu B(x) \cdot x \, dx}{\int_a^b \mu B(x) \, dx} \qquad (6)$$

Where $\mu B(x)$ is the aggregated membership function for behaviour B_i , x is the output domain variable (e.g., behavioural intensity or activation level), [a,b] defines the support range of the fuzzy set. The behaviour associated with the highest B_{crisp} value is selected as the dominant behaviour for execution. The centroid method is preferred for its smooth and continuous output transitions, which are essential for emotionally nuanced systems. Unlike binary or max-based methods, it reflects the full distribution of belief across fuzzy outputs, enabling realistic and adaptive modeling of graded emotional states like fear or aggression. This enhances context-sensitive behaviour and control stability in dynamic environments.
State Transition Dynamics: In the proposed fuzzy behaviour based system, behaviours are managed using a Fuzzy State Machine (FSM), allowing smooth transitions between states instead of abrupt switches. Transitions from one behaviour B_i to another B_j are governed by fuzzy activation levels based on sensor inputs x_k, such as distance to threat or escape possibility. The transition likelihood is defined as:

$$P(Bj \mid Bi, xk) = \frac{\mu Bj(xk)}{\sum_n \mu Bn(xk)} \qquad (7)$$

Here, $\mu B_j(x_k)$ is the fuzzy membership value representing how strongly behaviour B_j is activated by input x_k. The denominator normalizes across all behaviours, yielding a probability-like score. This mechanism enables behaviour blending for instance, allowing partial commitment to both escape and obstacle avoidance rather than strict selection. It reflects natural behaviour where multiple instincts operate in parallel. Additionally, temporal smoothing or hysteresis can be applied to avoid rapid state switching, ensuring coherent and biologically realistic behaviour over time.

Rule Derivation Based on Archer's Ethology: As an example, the following rule

Attack Rule-base: Rule ATTACK is High when FEAR is High AND EPE is Low

is derived directly from Archer's observation that high fear, when escape routes are limited, leads to defensive aggression rather than avoidance. This is mathematically translated as:

$$\mu_{\text{ATTACK}} = \min\left(\mu_{\text{FEAR:High}}, \mu_{\text{EPE:Low}}\right) \qquad (8)$$

This highlights the interpretability of the system: each rule is not only mathematically grounded, but also biologically justified.

3.4.3 Simulation-Based Evidence

The proposed fuzzy behaviour architecture has been validated through a series of controlled simulations that demonstrate its capacity to generate context-sensitive, ethologically grounded responses. As depicted in Figures 5(a-d) and Table 1, specific combinations of internal affective states and environmental inputs produce consistent and biologically interpretable behaviours:

- Low familiarity (AFTA) and low escape possibility (EPE) result in elevated fear and immobility, reflecting risk-averse defensive responses.
- Close proximity to other agents (low ADTA), when paired with low EPE, reliably triggers aggressive behaviour, simulating defensive confrontation.
- When EPE is high, the agent engages in escape behaviour, particularly when internal fear levels are concurrently elevated.
- Under favourable conditions (e.g., high AFTA and high EPE), agents revert to goal-directed exploration or navigation, indicating behavioural normalization.

Figure 6 illustrates real-time behavioural modulation using colour-coded motion trajectories that reflect transitions between affective states such as fear, escape, and aggression. Figure 7 captures inter-agent emotional influence, showing how Robot_1's aggression induces fear, and triggers escape responses in Robot_2. Collectively, these empirical results support the system's: Internal coherence (rule consistency and integration), Biological plausibility (alignment with ethological theories), Reactive realism (adaptive responses to dynamic multi-agent scenarios).

3.4.4 Falsifiability and Testability

The proposed architecture has been explicitly designed to support empirical verification, repeatability, and comparative evaluation:

- The fuzzy rule base comprises a finite and enumerable set of ~36 rules, each of which can be unit-tested in isolation to confirm correct input-output behaviour mappings.

- Behavioural trajectories and decision outcomes can be systematically benchmarked against conventional finite state machine (FSM) models under identical simulation conditions, enabling quantitative comparison of flexibility, response time, and behavioural richness.
- Key behavioural metrics including trajectory dynamics, reaction latency, and state transition frequencies are tracked across variable settings of critical input parameters (EPE, AFTA, ADTA etc.) to ensure robustness and generalizability.

3.4.5 Novelty and Impact

This thesis offers multiple contributions to the fields of bio-inspired robotics, fuzzy logic control, and computational ethology:

- First known implementation of Archer's theory of aggression in a robot-executable fuzzy inference framework, demonstrating the feasibility of translating ethological models into actionable control systems.
- Introduction of Fuzzy Behaviour Description Language (FBDL) as a declarative emotional modelling language, enabling transparent, modular, and expressive behaviour programming across platforms including mobile robots, virtual agents, and animal simulators.
- Provides explainability and visual traceability for emotion-driven behaviours which is essential features for ethical and accountable AI in Human-Robot Interaction (HRI) contexts.
- Establishes a modular architecture that can be extended to more complex domains such as: Multi-agent social interaction, Collective behaviour modelling, Learning-driven evolution of rule bases in adaptive robotic systems.

3.4.6 Applications

The proposed fuzzy ethological control system enables robust, interpretable, and adaptive navigation across diverse robotic applications. In *search and rescue* scenarios, fear-driven escape behaviours help robots avoid hazardous areas, improving mission safety. In *human-robot interaction*, emotionally grounded responses such as hesitation or retreat enhance user trust and social compatibility. For *multi-agent systems*, biologically inspired coordination supports emergent group dynamics without centralized control. In *public or unstructured environments*, the system dynamically modulates obstacle avoidance based on emotional salience, improving maneuverability. Its modular, transparent architecture also suits behavioural simulations and affective computing, making it a versatile tool for *emotion-aware robotic intelligence*.

Chapter 4: Implementing Aggressive Behaviour in ROS robotic environment

4.1 Embedded Model Overview

The rapid advancement of robotics, driven by emerging technologies and a deepening integration with the natural world, has opened new avenues for behaviour-based modeling. This research focuses on embedding ethologically inspired aggressive behaviours specifically escape and attack into robotic systems using fuzzy behaviour-based systems (FBBS). By fusing the precision of robotics with the adaptability of fuzzy logic, the work moves beyond traditional binary models to replicate the nuanced dynamics of animal-like responses. The resulting systems exhibit lifelike, context-sensitive behaviour capable of real-time adaptation to environmental stimuli.

Building on the behaviour models developed in Chapter 3, the study employs the Robot Operating System (ROS) [39] [40] in combination with tools such as Gazebo and RViz to simulate biologically plausible behaviour. The system orchestrates perception, decision-making, and motor execution within a virtual environment. A core component of this framework is Light Detection and Ranging (LIDAR), which offers real-time, high-resolution environmental scanning essential for detecting moving objects, evaluating spatial configurations, and executing rapid escape maneuvers. LIDAR's ability to gather spatial data from multiple angles ensures accurate recognition and response, particularly in fast-paced scenarios.

Integrating these ethologically inspired behaviours into ROS represents a key step in bridging biological and synthetic systems. Animal behaviours such as escape and attack are adaptive survival mechanisms shaped by a combination of sensory input, internal state, and contextual awareness. Escape behaviour demands rapid situational assessment and decisive action, while attack involves complex evaluations of proximity, familiarity, and threat level. FBBS effectively captures this decision-making under uncertainty, enabling flexible responses to perceived threats. By translating these processes into computational models, the system replicates animal-like adaptability in autonomous robots.

Attack behaviour, by contrast, combines aggression with situational judgment. Its replication in robotics requires not only target identification but also appropriate action modulation. FBBS supports this by interpreting dynamic inputs and determining graded responses based on context, much like animals adjust aggression levels in real-time. The integration of such biologically grounded strategies contributes to the development of robots that are intelligent, versatile, and responsive. Though challenging to implement, these capabilities unlock transformative applications across domains that require real-time environmental interaction.

However, embedding aggressive behaviours also raises important ethical considerations. As robots gain autonomy and emotional expressiveness, concerns emerge regarding control, responsibility, and societal impact. This research emphasizes the importance of interdisciplinary collaboration across ethology, neuroscience, and artificial intelligence to ensure that behaviour modeling is both scientifically robust and ethically grounded. Applications include search and rescue, defense, and wildlife interaction, where intelligent, context-aware robotics may operate with minimal human supervision. Ultimately, this work pushes the boundaries of both robotics and our understanding of intelligent behaviour, synthetic or biological.

4.2 Methodologies for Biologically Inspired Behaviour Modeling in Robotics

This section presents two complementary methodologies aimed at developing context-sensitive, biologically inspired behaviours in autonomous robotic systems. Each method addresses unique aspects of behavioural modeling, focusing on adaptability, interaction with dynamic environments, and inspiration from ethological studies. The approaches described herein form the theoretical and experimental foundation for simulating animal-like escape and adaptive behaviours in robots.

4.2.1 Knowledge-Based Ethologically Inspired Behaviour Design

The knowledge-based ethological design framework integrates behavioural insights from the field of ethology specifically, the study of animal behaviour under natural conditions into robotic system development [Aaqib1]. This interdisciplinary methodology supports the creation of biologically plausible robot actions by translating observed animal responses into functional robotic behaviours. This approach serves not only to improve robotic adaptability and performance but also to offer new perspectives for ethological investigations. The procedure follows an iterative, data-driven model as illustrated in figure 8. It begins with a comprehensive review of relevant ethological literature to extract structured behavioural patterns, including action triggers, behavioural sequences, and decision-making heuristics observed in biological organisms. These extracted models are subsequently mapped onto the robot's sensorimotor architecture, ensuring compatibility between naturalistic behaviours and the robotic platform's physical and computational constraints [Aaqib3].

Following model integration, robotic experiments are conducted under controlled and variable environmental conditions [Aaqib2]. These experiments assess the robot's ability to replicate the targeted behaviour accurately and adaptively. Quantitative and qualitative data obtained from these trials are analyzed to evaluate behavioural fidelity and performance consistency. Discrepancies between observed and expected behaviours inform iterative refinement of the implemented model. A distinguishing feature of this methodology is its bidirectional feedback loop between robotic implementation and biological inquiry. Insights from robotic experimentation often illuminate gaps or ambiguities in the original biological data, prompting the formulation of new hypotheses or the design of supplementary ethological studies. For instance, robotic failure to emulate a behaviour may indicate the presence of unmodeled environmental variables or inter-agent dynamics in the biological reference system. This framework supports a synergistic relationship between biology and robotics, wherein robotic models validate, challenge, or extend ethological theories while gaining biologically grounded robustness. The approach has demonstrated utility in various domains, including autonomous navigation, predator-prey modeling, and bio-mimetic swarm coordination.

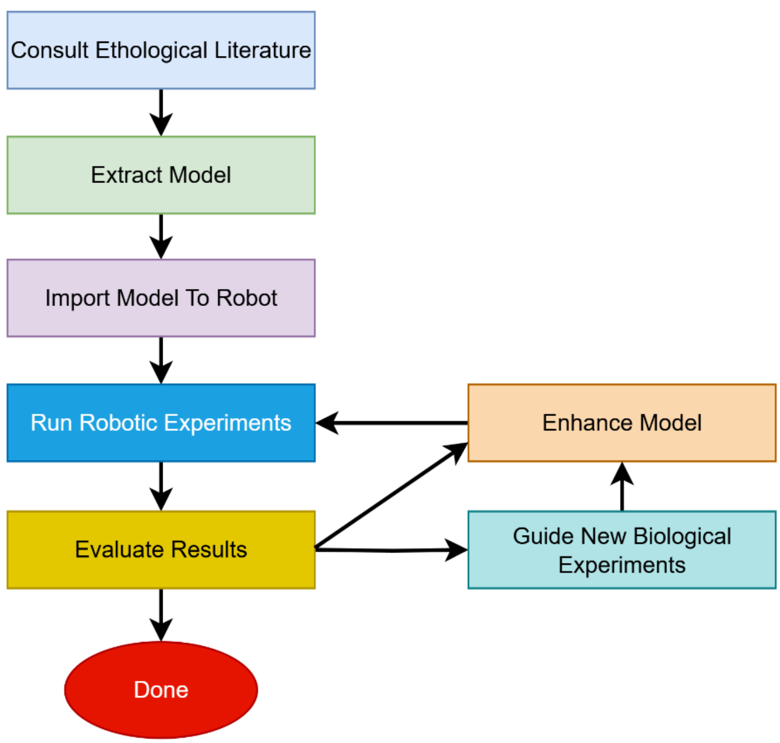

Figure 8. A Knowledge-Based Ethological Approach for Robot Behaviour Design.

4.2.2 Situated Action-Based Behaviour Design

Situated action-based behaviour design emphasizes the robot's capacity to interpret and respond to real-time environmental stimuli through context-dependent behaviours [Aaqib1] [Aaqib2] [Aaqib3]. In contrast to traditional rule-based systems that rely on pre-scripted decision trees, this methodology foregrounds situational awareness, behavioural fluidity, and environmental interaction as primary drivers of robotic action. This dynamic, stimulus-response framework is particularly suitable for deployment in unstructured and evolving operational domains. As outlined in figure 9, the design process initiates with an assessment of the robot's dynamic environment. This phase involves identifying potential environmental variables, challenges, and interaction zones that the robot may encounter. These environmental features are segmented into discrete, manageable "situations," each corresponding to a unique behavioural requirement. Contextual behavioural responses are then formulated for each identified situation. These responses are derived from empirical observations of animal behaviour or synthesized using domain-specific control strategies. Behavioural primitives are programmed into the robot, enabling it to select and transition between actions based on situational input received from onboard sensors (e.g., LIDAR) [Aaqib2].

Robotic trials are subsequently performed to evaluate behavioural effectiveness and adaptability. Feedback from these experiments is used to refine behavioural mappings, enhance decision robustness, and improve transition smoothness between contextual states. This iterative tuning process continues until the robot demonstrates consistent and reliable performance across a broad spectrum of environmental conditions [Aaqib3]. The situated action design model incorporates a hierarchical control structure that allows flexible switching between behavioural modules. This hierarchy improves reaction time, ensures decision prioritization, and enables concurrent management of multiple stimuli a critical requirement for robots operating in real-world scenarios.

The applications of this design strategy extend across a diverse range of domains that demand high levels of adaptability and real-time decision-making [Aaqib4]. In disaster response, autonomous robots are required to navigate debris-laden and unstable terrains, where environmental conditions change unpredictably, necessitating context-aware behavioural responses. In the field of social robotics, these methodology supports interactive capabilities that enable robots to engage in real-time human-robot interactions, particularly in caregiving settings or public service environments, where sensitivity to human behaviour and environmental cues is essential [Aaqib5]. In agricultural robotics, this approach facilitates operations in highly variable outdoor environments, such as uneven terrain, fluctuating weather conditions, and unpredictable biological elements, ensuring sustained performance and minimal human interv ention. Finally, in marine and environmental monitoring, the capacity for autonomous, context-sensitive behaviour allows robots to operate effectively within complex and dynamic ecological systems, such as underwater habitats or forested regions, where consistent data collection and adaptability to environmental changes are critical for success.

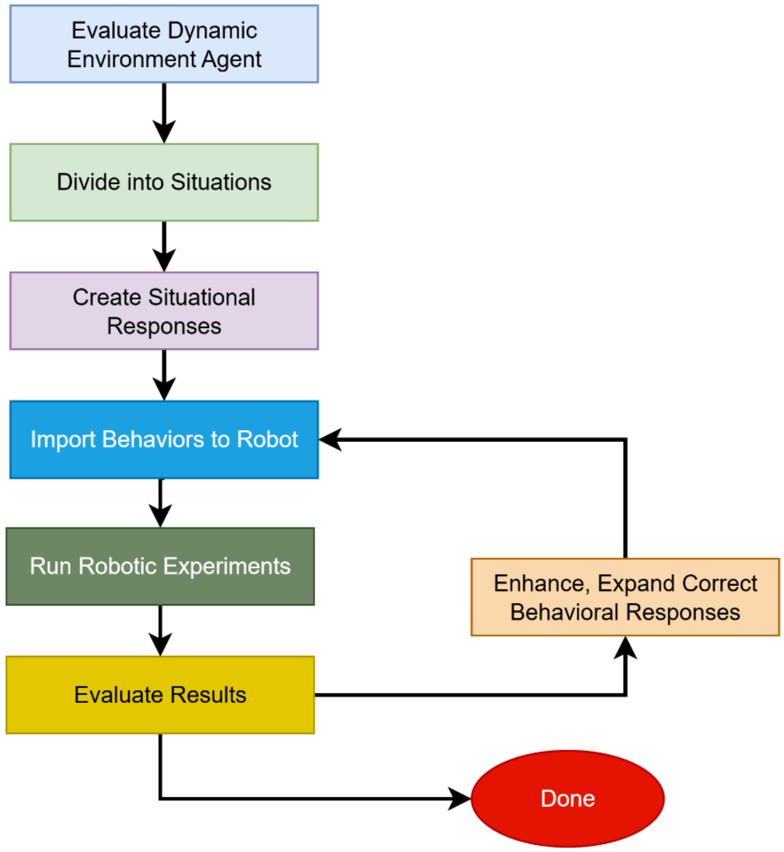

Figure 9. The Situated Action-Based Design.

In summary, situated action-based design facilitates the creation of robotic agents that exhibit high degrees of environmental responsiveness, behavioural plasticity, and operational autonomy. When coupled with bio-inspired strategies, this approach enhances the realism, efficacy, and robustness of robotic behaviour in dynamic and uncertain environments.

4.3 System Architecture and Implementation

To embed ethologically inspired behaviours such as escape and attack into robotic systems, a modular architecture was developed using the Robot Operating System (ROS) [40] as the foundational middleware. ROS offers a flexible and robust framework capable of integrating both high-level cognitive processes and low-level sensor-actuator loops. Its compatibility with advanced simulation and visualization tools such as Gazebo and RViz makes it well-suited for modeling complex animal-like behaviour in controlled yet realistic environments. Gazebo provides a physics-based 3D simulation platform, while RViz supports the real-time rendering of sensor feedback, navigation trajectories, and robot states.

The architecture is composed of several functional layers such as Perception, Behaviour Evaluation, Fuzzy Inference Engine, and Motion Execution each implemented as independent ROS nodes communicating via topics and services. This modular design promotes scalability, supports real-time operation, and facilitates the integration of diverse sensors and decision-making components. Each layer is engineered to handle a specific role, collectively enabling biologically inspired behaviour to emerge in dynamic and uncertain scenarios.

4.3.1 Perception Layer

The Perception Layer is responsible for real-time environmental sensing and situational interpretation. The core of this layer is a LIDAR-based mapping system, which generates high-resolution 2D or 3D spatial data of the surrounding environment. To enable situational awareness and spatial reasoning, the system employs Simultaneous Localization and Mapping (SLAM). SLAM allows the robot to construct a map of an unknown environment while simultaneously tracking its own position within that map. This capability is essential for context-aware behaviour, as it supports continuous localization even in environments with limited GPS or external positioning.

SLAM is implemented using ROS-compatible packages such as gmapping, hector_slam, depending on experimental requirements. The SLAM output is used to update the robot's occupancy grid and cost maps in real-time, which in turn inform behavioural decisions particularly in escape scenarios where spatial layout and obstacle proximity dictate viable paths.

In addition to LIDAR, the perception system incorporates cameras and RGB-D sensors (e.g., Intel RealSense or Kinect) to enhance object and agent recognition. These inputs are processed to extract behaviourally relevant variables:

ADTA / ADTO: Distance to other agents or objects,

EPE: Escape path availability based on free-space mapping,

PIWPE: Positive Impact With Previous Experience, modeling learned safety from past encounters,

AFTA / AFTO / AFTP: Familiarity metrics based on recognition of agents, objects, and places.

The integration of SLAM and multi-modal sensing enables the robot to maintain a persistent, high-fidelity understanding of its surroundings critical for nuanced and adaptive behavioural expression.

4.3.2 Behaviour Evaluation Layer

This layer transforms raw sensor data into fuzzy linguistic variables that can be processed by the inference engine. For example, a measured ADTA of 0.4 meters might be categorized as “Low,” while a PIWPE score may reflect a “Positive” prior outcome. This semantic transformation ensures that the robot can interpret complex, continuous data streams in terms of qualitative behavioural relevance.

The layer also computes historical metrics such as PIWPE, which serves to modulate threat perception based on previous encounters in similar environmental contexts. These fuzzy descriptors become the foundation for rule-based behavioural decisions in the subsequent cognitive layer.

4.3.3 Fuzzy Inference Engine

At the core of the decision architecture is a Fuzzy Inference Engine, implemented using the Fuzzy Behaviour Description Language (FBDL). This module evaluates a set of ethologically grounded fuzzy rules to infer the appropriate behavioural state. It supports:

Fuzzy Rule Interpolation (FRI) for reasoning with sparse or incomplete rulesets.

Multiple Rule Bases allowing parallel controllers for Escape, Attack, and Immobility.

Behavioural State Transition Management where supervisory logic governs switching between behaviours based on rule confidence and sensor inputs. For example:

If "EPE" is High and "FEAR" is High, Then "Escape" is High.

Such logic allows for graded behavioural output instead of binary choices, improving the realism and flexibility of the robot’s response to ambiguous stimuli.

4.3.4 Motion Execution Layer

Once a behavioural decision is made, the Motion Execution Layer translates it into a physical trajectory using ROS’s navigation stack. For escape behaviour, the robot selects paths that maximize distance from the identified threat, calculated using the SLAM-derived cost maps. For attack behaviour, the robot instead minimizes the distance to the target entity, adjusting its speed and trajectory based on proximity metrics.

Trajectory plans are visualized in RViz with color-coded indicators reflecting behaviour mode (e.g., red for Attack, blue for Escape). The robot’s controller uses these directives to generate velocity commands (/cmd_vel) which are executed through motor drivers in either simulation or real-world deployment.

4.3.5 System Synchronization and Communication

The architecture's modular layers communicate via ROS topics and services, orchestrated by a central controller node responsible for synchronization and behavioural arbitration. Key communication streams include:

/scan or /lidar_scan: Raw LIDAR input for SLAM and obstacle mapping

/map and /odom: SLAM outputs including the robot's estimated position and environment structure

/fuzzy_inputs: Processed fuzzy variables like FEAR, ADTA, and AFTA

/behaviour_state: Currently active behaviour (e.g., Escape, Attack)

/cmd_vel: Motor commands derived from the selected behaviour path

This decentralized communication model enables robust, scalable coordination, including multi-agent interaction, where multiple robots can synchronize aggression or escape in complex scenarios.

4.4 Motivation for Integration

Integrating aggressive animal behaviours into robotics through the fuzzy behaviour-based systems (FBBS) framework offers a novel pathway for enhancing robotic adaptability, decision-making, and situational awareness. Traditional robotic systems often operate on rigid, binary rules that limit their ability to respond effectively in unpredictable real-world environments. In contrast, animals have evolved complex survival strategies such as escape and aggression that are triggered by contextual factors and processed through flexible, experience-based reasoning. By emulating these behaviours, FBBS enables robots to interpret sensory inputs with varying degrees of uncertainty, leading to graded, context-sensitive reactions that mirror natural cognitive processes. This shift from deterministic logic to fuzzy inference significantly improves robotic flexibility and realism.

The practical applications of this integration are extensive. Robots with escape behaviours can improve navigation in hazardous settings, making them valuable in search and rescue operations. Similarly, environmental monitoring robots designed to behave unobtrusively can operate with minimal disturbance to wildlife. In defense and security contexts, aggression-capable robots could autonomously assess threats and respond in high-risk scenarios, reducing the need for human intervention. However, these advancements also raise important ethical concerns. As robots adopt increasingly autonomous and emotionally evocative behaviours, there is a growing need to assess their impact on human safety, ecological balance, and societal norms. This interdisciplinary research bridging ethology, neuroscience, artificial intelligence, and robotics not only drives technological innovation but also provides valuable insight into the cognitive mechanisms of animal behaviour, contributing to the development of intelligent, ethically aligned robotic systems.

4.5 Behaviour implementation

Implementing ethologically inspired behaviours such as escape, attack, and immobility into robotic systems is a critical step toward achieving autonomous agents that can exhibit biologically plausible and context-sensitive decision-making. This process involves enabling robots to perceive potential threats, assess situational cues, and select appropriate behavioural responses, such as retreating, confronting, or freezing in response to dynamic stimuli. Unlike conventional rule-based systems, this approach leverages models of natural behaviour observed in animals, particularly in predator-prey and threat-avoidance contexts, to inform robotic decision-making.

The implementation of such adaptive behaviours relies on the seamless integration of real-time sensor inputs, environmental mapping, and layered decision algorithms grounded in fuzzy logic systems. These systems introduced in detail in Chapters 2 and 3 comprise fundamental components such as fuzzy rule bases, behaviour arbitration mechanisms, and behaviour fusion modules. Together, these modules enable robots to evaluate multiple concurrent inputs (e.g., threat proximity, familiarity with agent or terrain, escape path availability) and execute actions that reflect biologically inspired priorities.

Figures 10 and 11 present high-level conceptual visualizations of escape and attack behaviours, highlighting the transition from an agent's initial path to a dynamically adjusted trajectory based on threat interaction. These diagrams emphasize the robot's capacity to change course in response to stimuli, mimicking naturalistic responses observed in ethological studies. In contrast, Figures 12 and 13 demonstrate the practical embedding of these behaviours within a ROS-based simulation environment, where real-time data streams and fuzzy logic modules collaboratively govern the robot's behaviour under controlled but dynamic conditions.

The successful embedding of such ethologically grounded behaviours holds significant importance for real-world applications, particularly in mission-critical domains such as search and rescue, exploration, and security operations. In these contexts, robots are often required to operate in unpredictable, hazardous, or unstructured environments, where the ability to adapt quickly and appropriately can directly affect mission success and system survivability. As shown in the referenced studies [17] [18] [Aaqib1] [Aaqib2] biologically inspired behaviour embedding improves both autonomy and resilience, positioning robotic systems as capable agents in complex, high-risk settings.

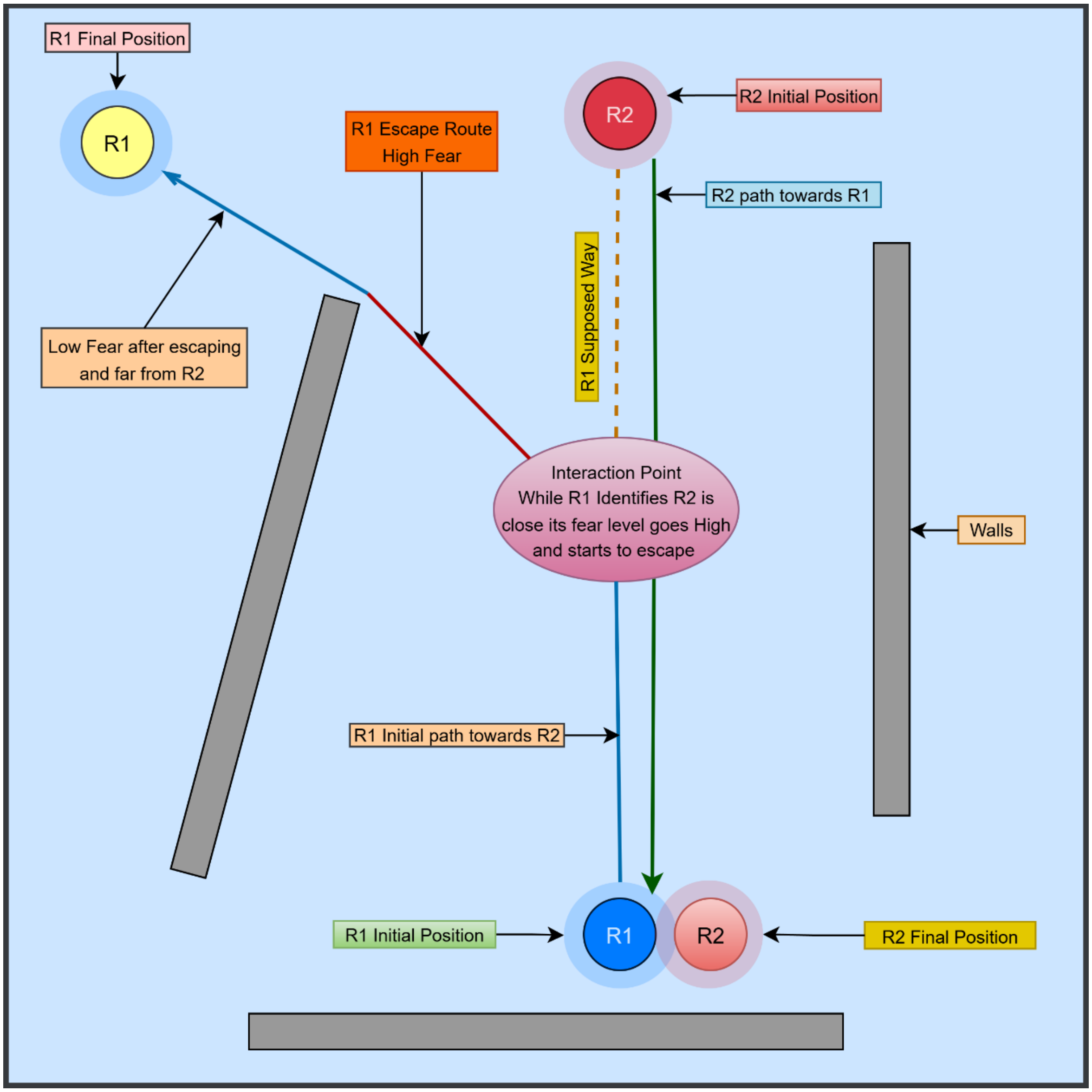

Figure 10. Basic Visualization of Escape Behaviour.

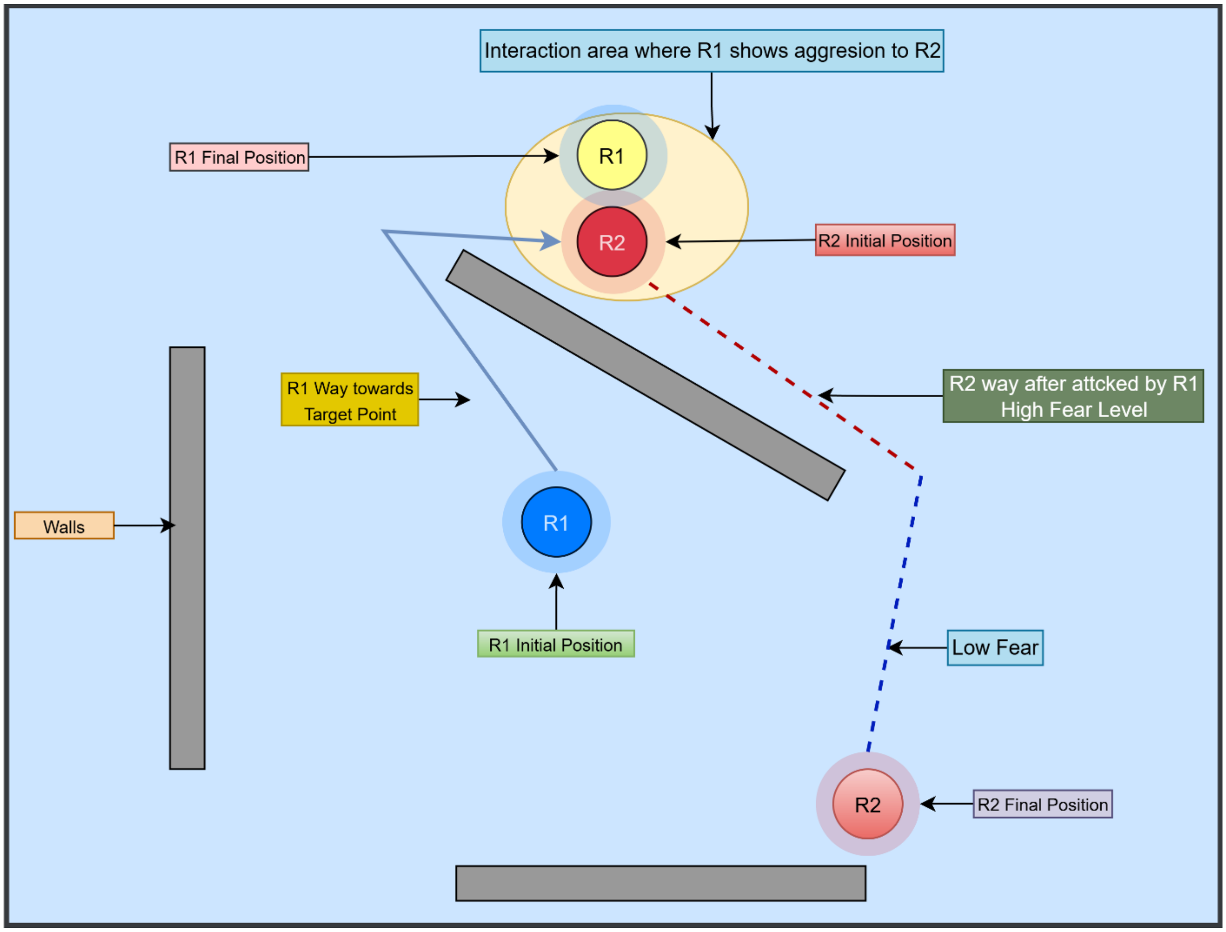

Figure 11. Basic Visualization of Attack Behaviour.

4.5.1 Implementing Escape Behaviour

The escape behaviour was tested using a ROS simulation involving two autonomous robots Robot_1 and Robot_2 within a bounded environment containing obstacles. This simulation, illustrated in Figure 12(a)-12(e), demonstrates how fuzzy behaviour-based control enables robots to adaptively avoid perceived threats. Robot_1, represented by blue trajectory points, starts near a central object, while Robot_2, depicted by red points, begins closer to a boundary wall. In this scenario, Robot_1 functions as the primary agent, with its behaviour serving as the focus for observation and analysis. Its decision-making is governed by fuzzy logic, sensor integration, and predefined escape rules modeled after animal-like reactions.

The simulation begins with both robots at rest, as shown in figure 12(a). As they begin to move towards one another, their trajectories evolve in accordance with their internal behavioural models, presented in figure 12(b). During this movement phase, Robot_1 employs LIDAR to continuously assess its proximity to Robot_2 and other environmental features. At this stage, behaviour fusion and coordination mechanisms come into play, integrating multiple behavioural signals such as trajectory analysis, object proximity, and direction of movement to shape Robot_1's adaptive responses.

Upon detecting Robot_2, Robot_1 evaluates the situation using its fuzzy rule-based system, shown in Figure 12(c). This assessment includes factors like familiarity with the other robot (AFTA), environmental knowledge (AFTP), relative distance (ADTA), and the availability of a viable escape path (EPE). When the calculated fear level exceeds a predefined threshold and an escape route is available, Robot_1 initiates an escape maneuver, demonstrated in figure 12(d). This transition is coordinated through the behaviour arbitration module, ensuring seamless control flow between perception and motor execution.

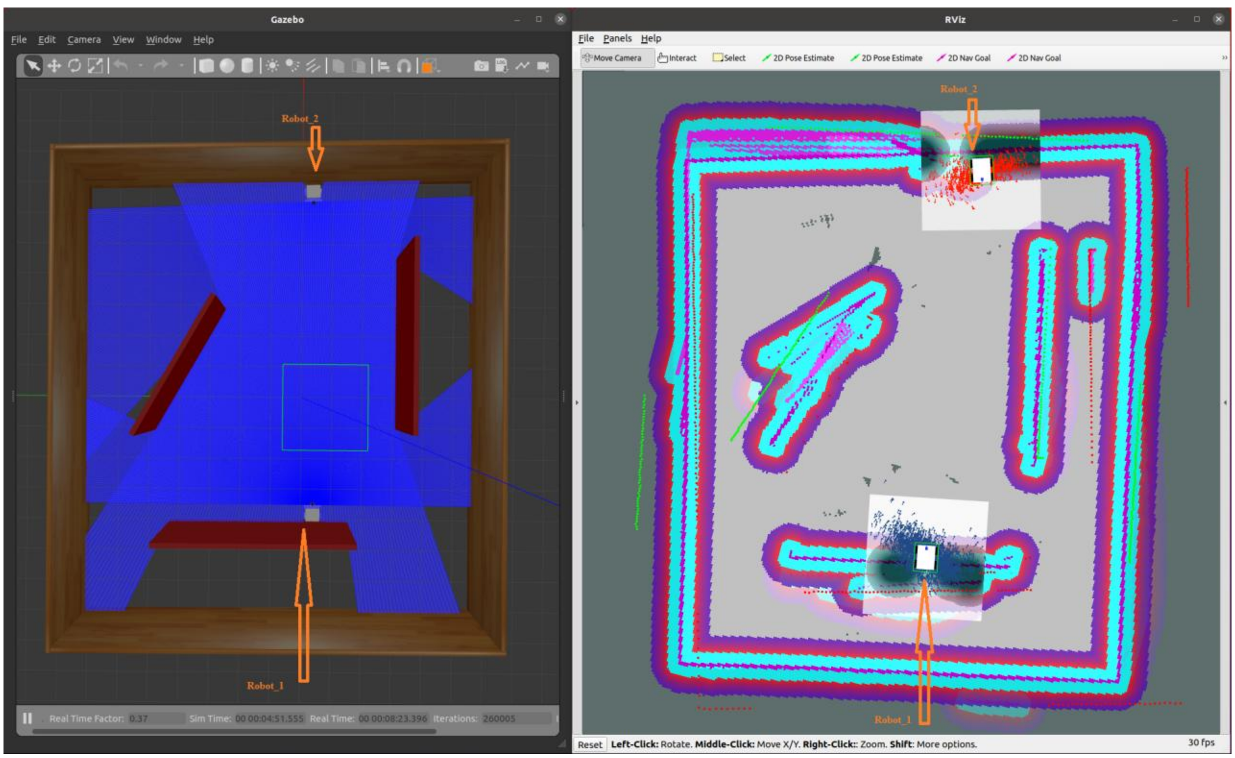

Figure 12(a). Initial Position of Robots: Both Robots Start at Designated Positions.

Finally, Figure 12(e) captures the outcome: Robot_1 successfully distances itself from Robot_2 and exits the threat zone. This result reflects the effective interaction of fuzzy logic, behaviour coordination, and fusion mechanisms. Robot_1's behaviour shows a realistic, adaptive escape response based on its internal states and sensory evaluations closely mirroring the situational adaptability found in biological organisms. The success of this simulation confirms the viability of using fuzzy behavioural models for embedding context-sensitive escape behaviours in autonomous robotics.

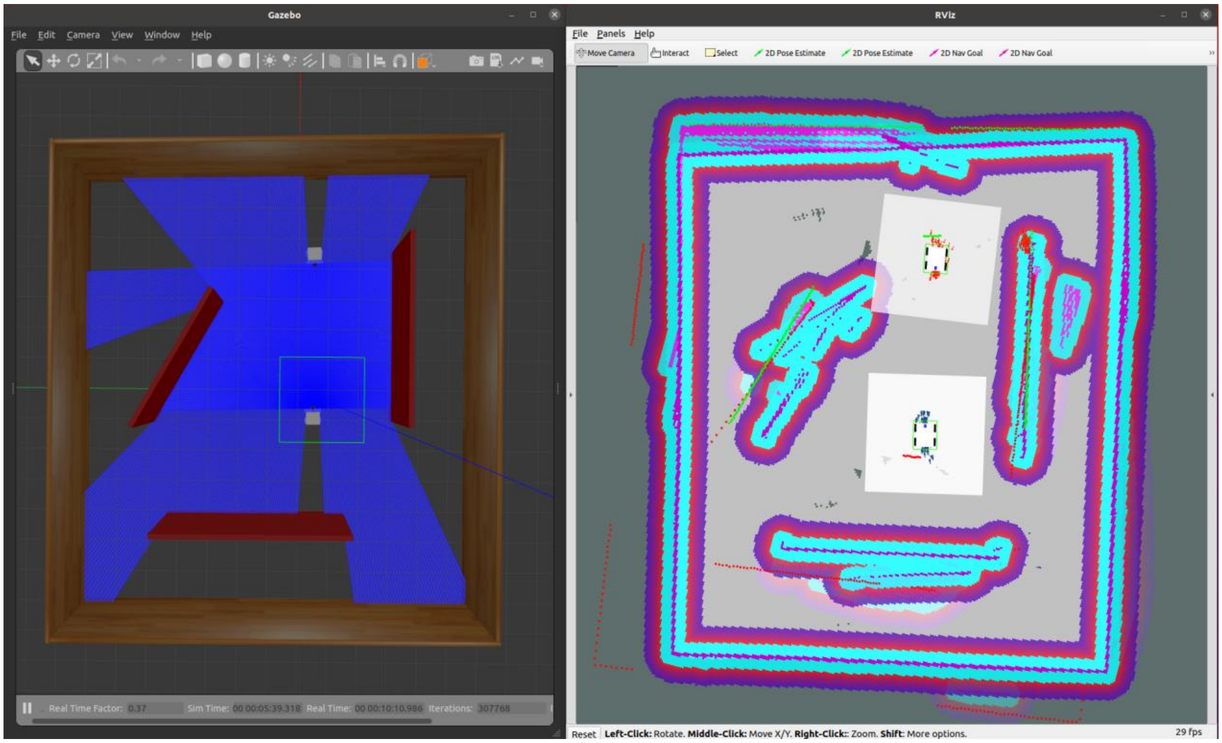

Figure 12(b). Movement Stage: Robots Start Moving.

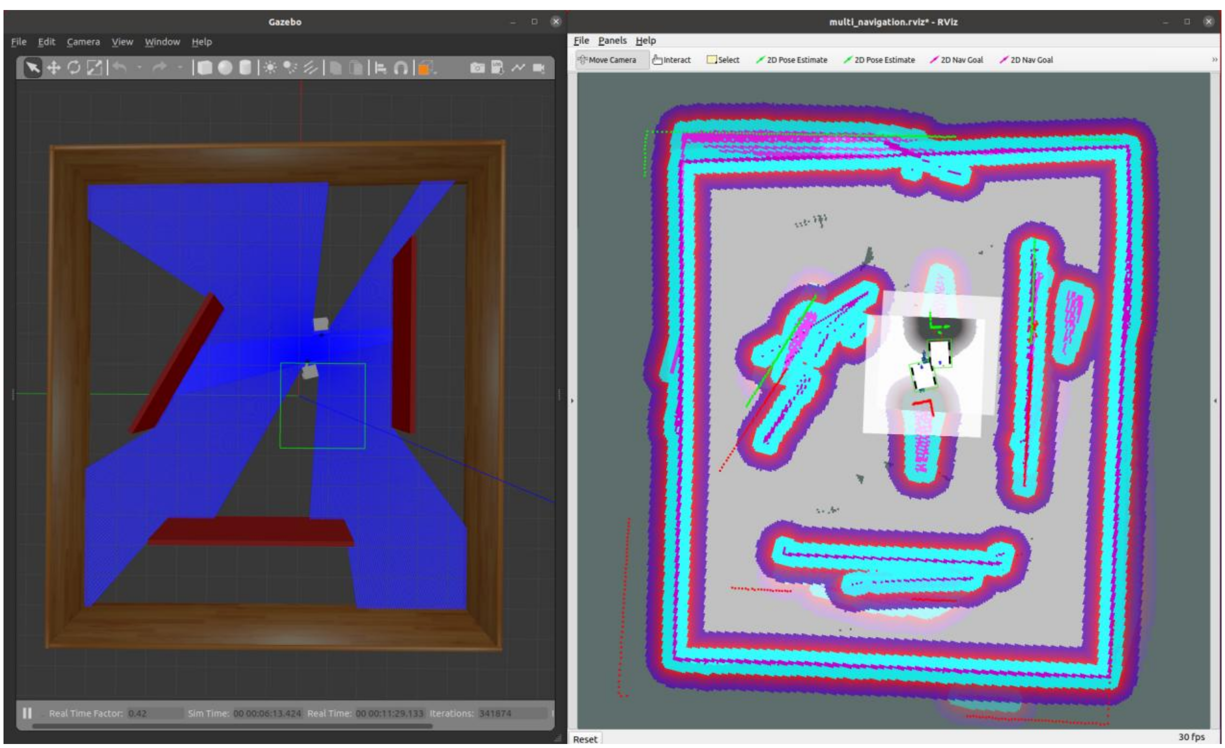

Figure 12(c). Detection and Fear Assessment: Robot_1 Detects Robot_2 and Assesses Fear Based on Proximity and Environment Unfamiliarity.

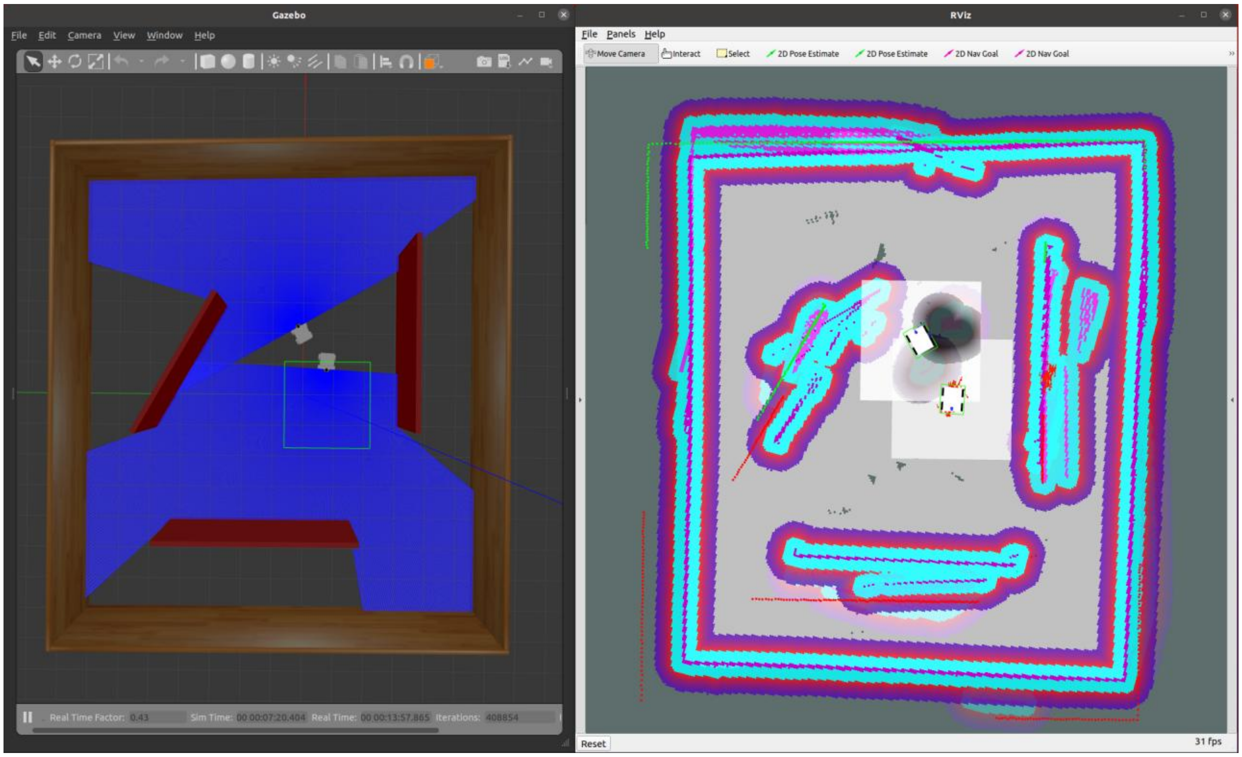

Figure 12(d). Robot_1 Escaping (Because of High fear and the Presence of an Escape Route)

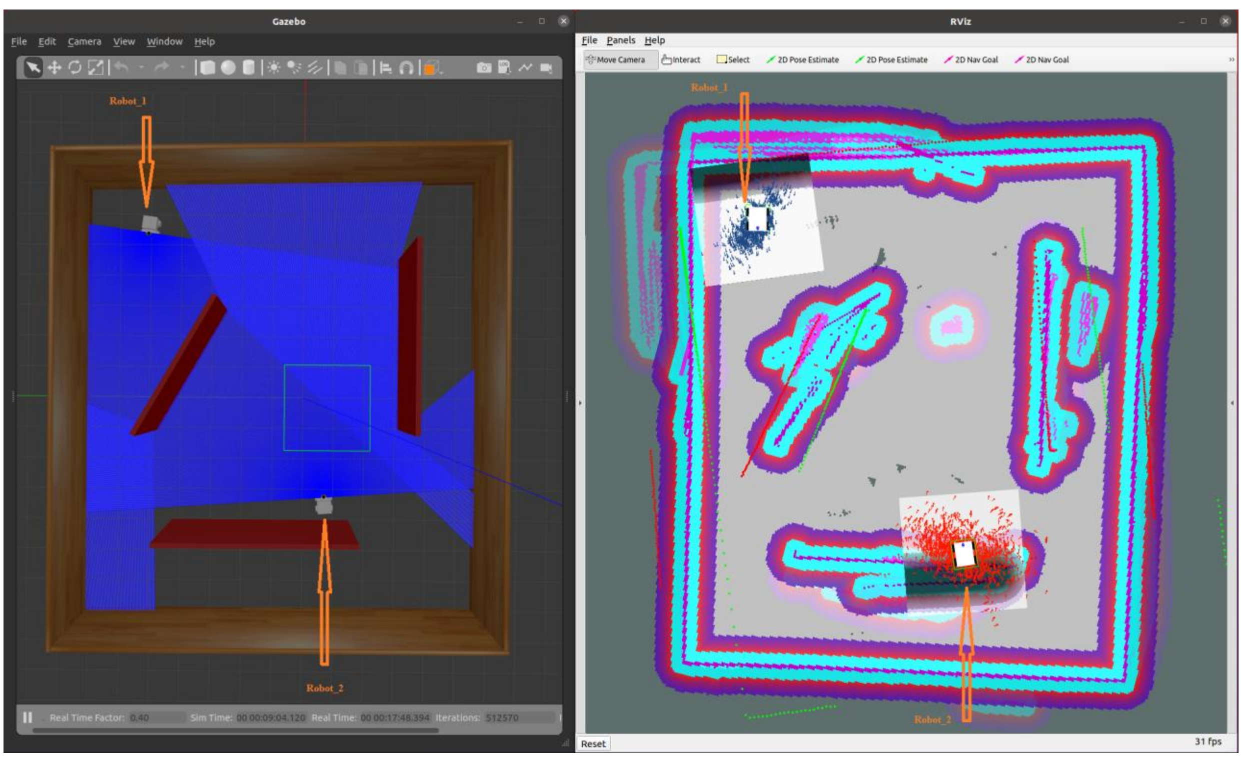

Figure 12(e). Robot_1 Successfully Presented Escape Behaviour

4.5.2 Implementing Attack Behaviour

The embedding of attack behaviour was simulated using two autonomous agents, Robot_1 and Robot_2, within a constrained indoor environment enclosed by obstacles and walls. As shown in Figures 13(a)-13(e) [Aaqib2], Robot_1, marked by blue trajectory dots, is initially placed at the center of the space, while Robot_2, represented by red dots, starts from a nearby peripheral location. The objective of this scenario is to simulate aggression by directing Robot_1 to approach Robot_2's initial position and initiate an attack response. As Robot_1 advances, Robot_2 evaluates the threat using its sensors and fuzzy logic-based fear assessment. A progressive increase in red dots around Robot_2 represents escalating fear intensity in response to Robot_1's approach.

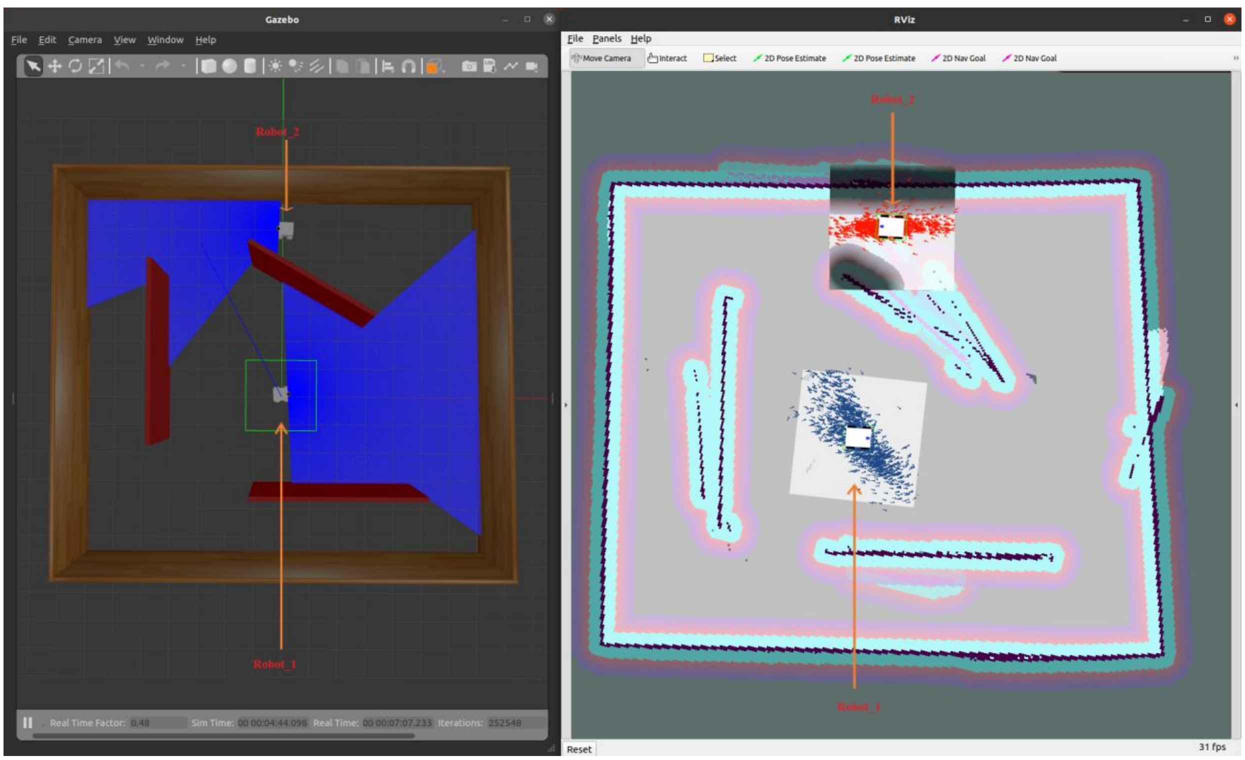

Figure 13(a). Initial Position of Robots

The simulation employs fuzzy component behaviour, behaviour fusion, and behaviour coordination to analyze the system's interactive performance. Robot_1's movement is driven by an aggression-triggering fuzzy rule set, while Robot_2 continuously evaluates its proximity to Robot_1, familiarity levels (AFTA), environmental awareness (AFTP), and the presence of viable escape paths (EPE). In figure 13(a), both robots are at their starting positions. As the simulation progresses, figure 13(b) shows Robot_1 initiating a goal-oriented trajectory toward Robot_2. In figure 13(c), Robot_2 detects the proximity of Robot_1 interpreted as a potential threat triggering a rise in its internal fear level based on fuzzy input evaluations.

Upon crossing a critical distance threshold and confirming the availability of an escape route, Robot_2 executes an evasive maneuver, depicted in figure 13(d). Concurrently, Robot_1 continues to pursue Robot_2's original position, enacting the attack behaviour encoded in its fuzzy logic rule base. Behaviour coordination synchronizes both agents' reactions: Robot_1's aggressive pursuit is dynamically linked to Robot_2's avoidance behaviour, reflecting ethologically inspired predator-prey dynamics. These synchronized responses result from behaviour fusion mechanisms, which resolve potential conflicts between overlapping behavioural priorities and ensure coherent interaction between multiple fuzzy controllers.

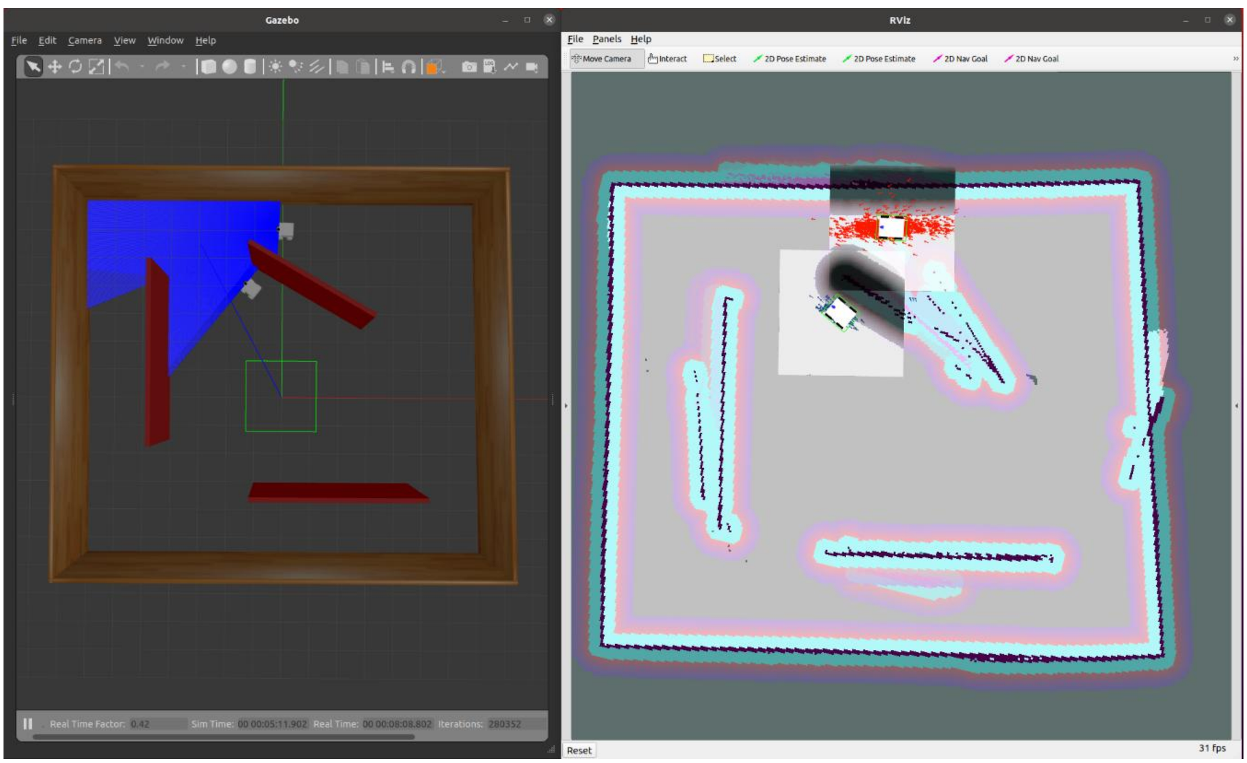

Figure 13(b). Robot_1 Starts Moving Towards its Goal Task

In the final stage, shown in figure 13(e), Robot_1 successfully reaches Robot_2's original location, signaling the completion of its attack task. This interaction validates the robustness of the fuzzy rule-based decision framework, highlighting the system's capacity to simulate lifelike aggressive interactions. By modeling combat-like behaviour through real-time sensory data, fuzzy inference, and spatial awareness, the system demonstrates high adaptability in unpredictable environments.

Beyond simulation fidelity, this scenario illustrates the broader potential of integrating fuzzy aggression modeling within robotic platforms. Technologies such as ROS, Gazebo, RViz, and LIDAR play a pivotal role in enabling this advanced behaviour embedding. The ability to simulate nuanced behaviours like attack and escape contributes to the development of emotionally responsive robotic agents. Moreover, this work has implications for human-robot interaction, where safety and ethical behaviour must be maintained. In multi-agent systems, such models can facilitate complex group dynamics in domains such as joint manufacturing, defense, autonomous surveillance, and coordinated search-and-rescue. By enabling robots to process ambiguous stimuli, adapt to context, and coordinate with peers, fuzzy behaviour embedding enhances decision-making under uncertainty advancing both autonomy and safety in intelligent robotic ecosystems.

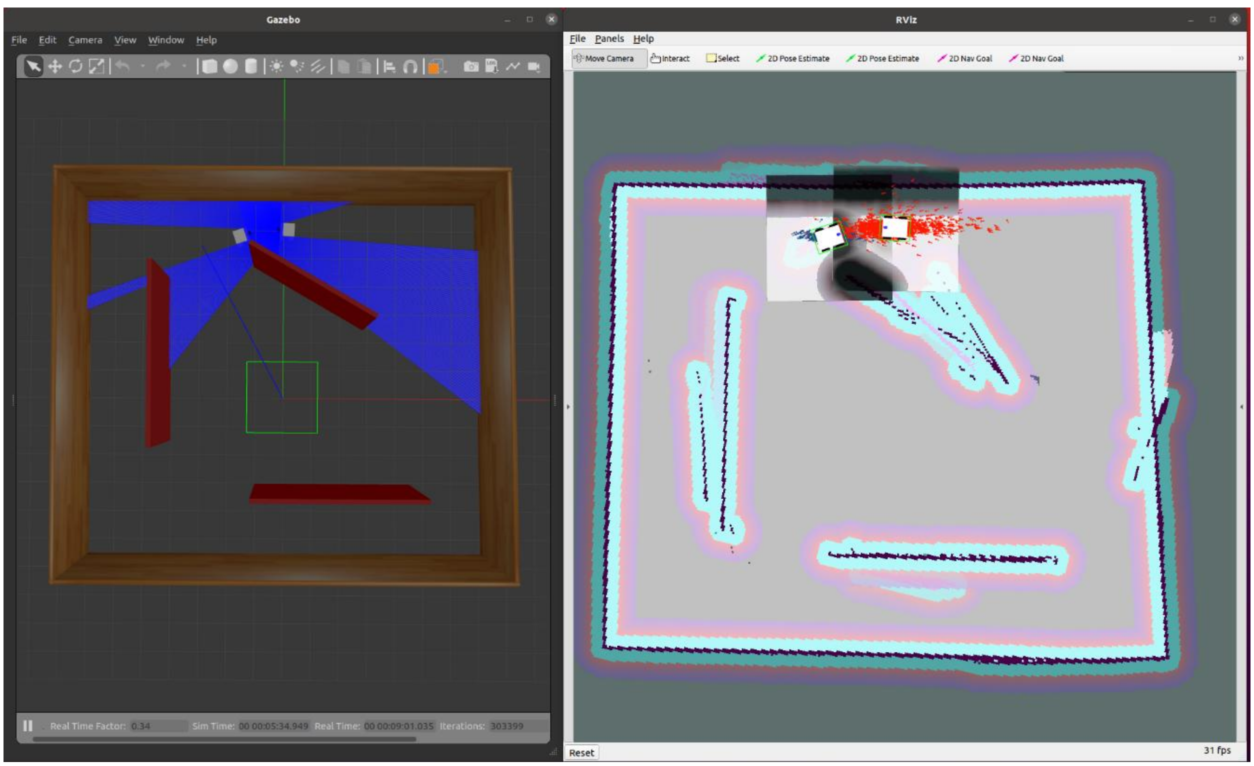

Figure 13(c). Robots are Getting Close to Each Other (Robot_2 Identifies an Unknown Animal Robot is Approaching).

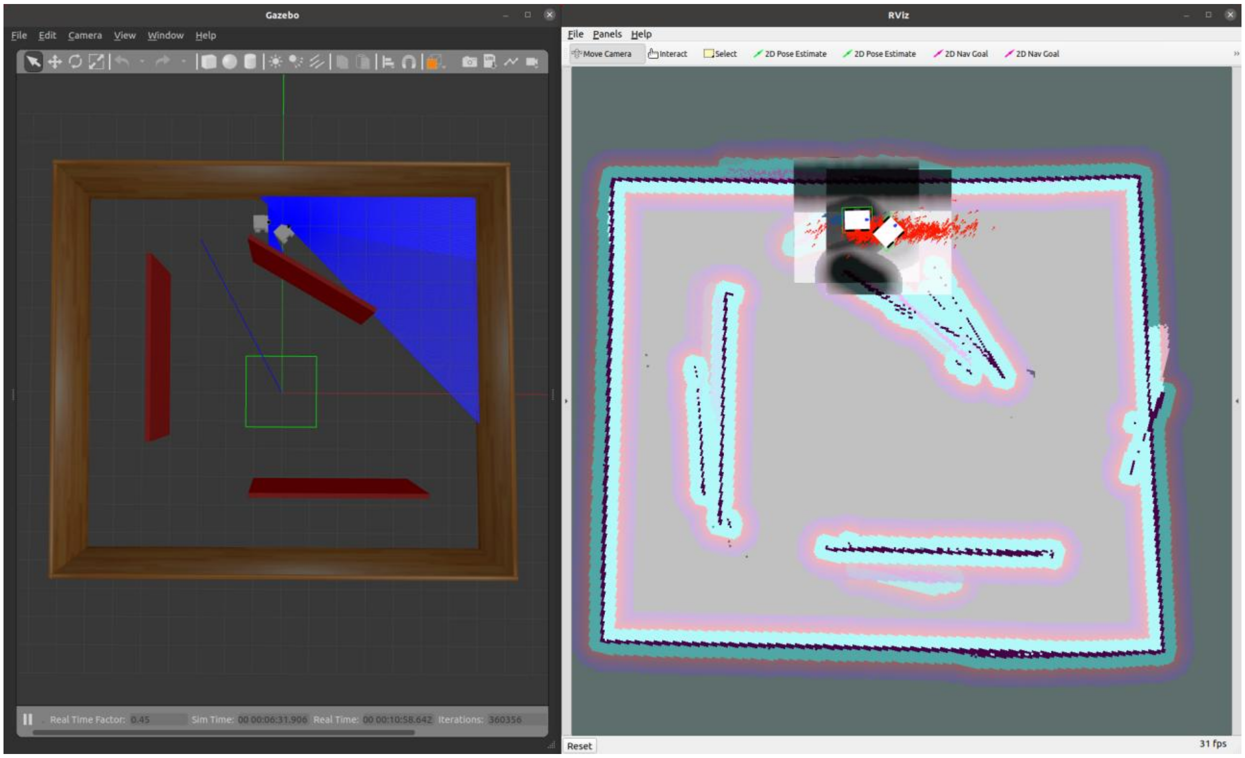

Figure 13(d). Robot_1 shows Aggression (Robot_2 Fear Level is Increasing and Starts to Leave) .

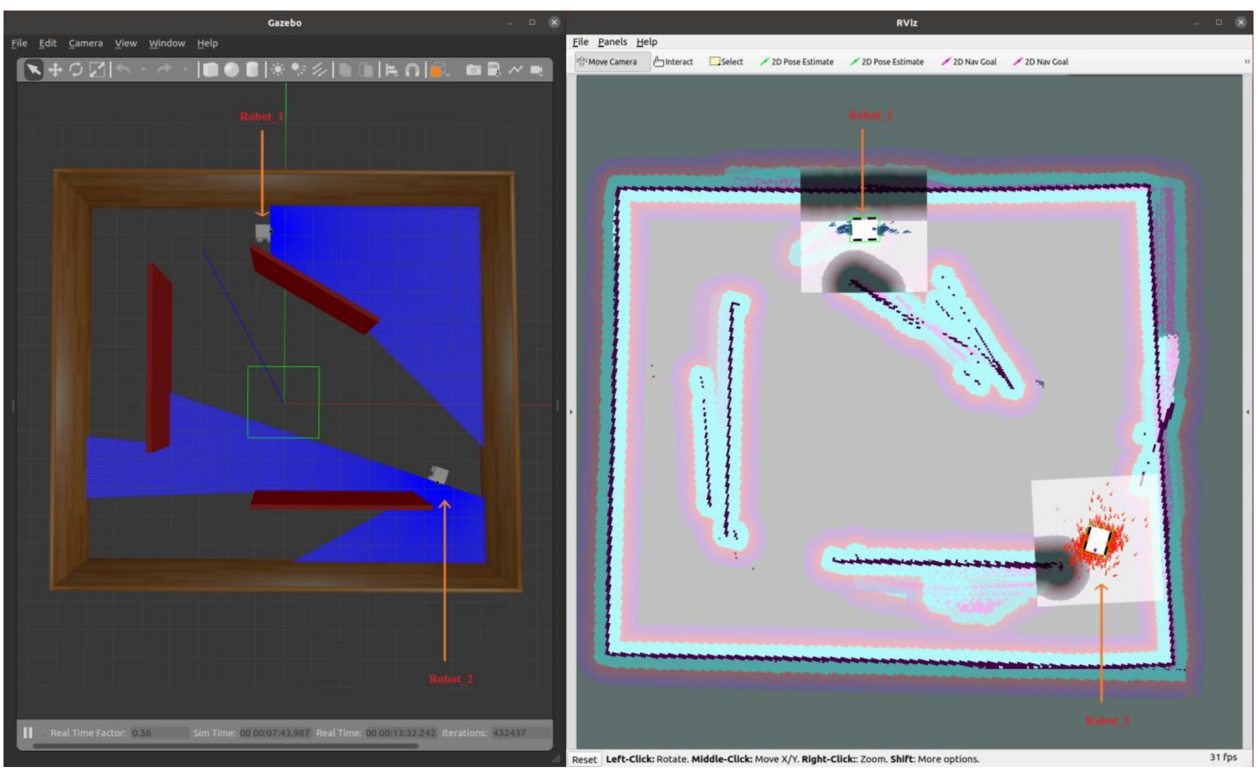

Figure 13(e). Robot_1 Successfully Presented Attack Behaviour (Robot_2 is far from Robot_1)

4.5.3 Classification Metrics and Empirical Benchmarking

Figures 14(a) and 14(b) present the classification performance of a fuzzy logic-based behavioural framework embedded in autonomous robotic agents. This evaluation assesses the model's ability to classify context-sensitive behaviours Escape and Attack under dynamic environmental conditions. Behaviour selection is governed by biologically inspired fuzzy rules. For example:

Escape behaviour is activated when: **Rule** *High* **when** "EPE" is *High* **and** "FEAR" is *High* **end**

Attack behaviour is triggered by: **Rule** *High* **when** "AFTA" is *Low* **and** "ADTA" is *Low* **and** "EPE" is *Low* **end**

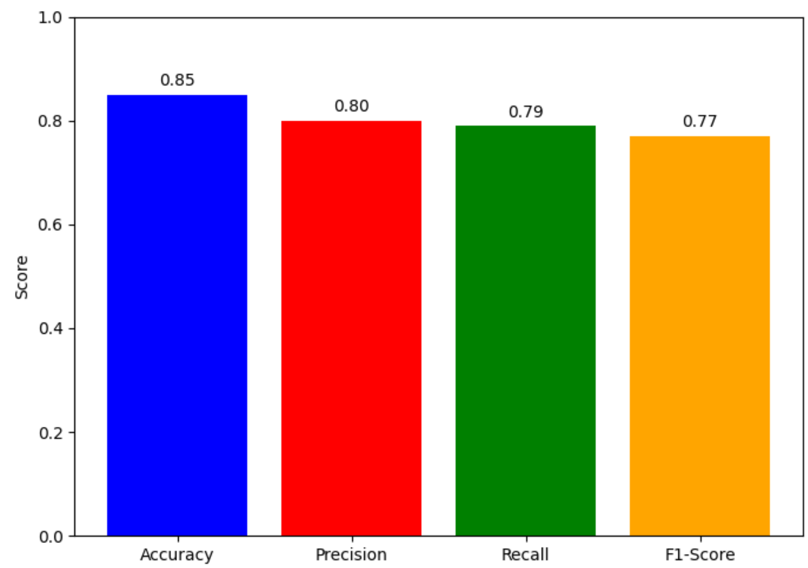

Figure 14 (a). Escape Behaviour Classification Metrics

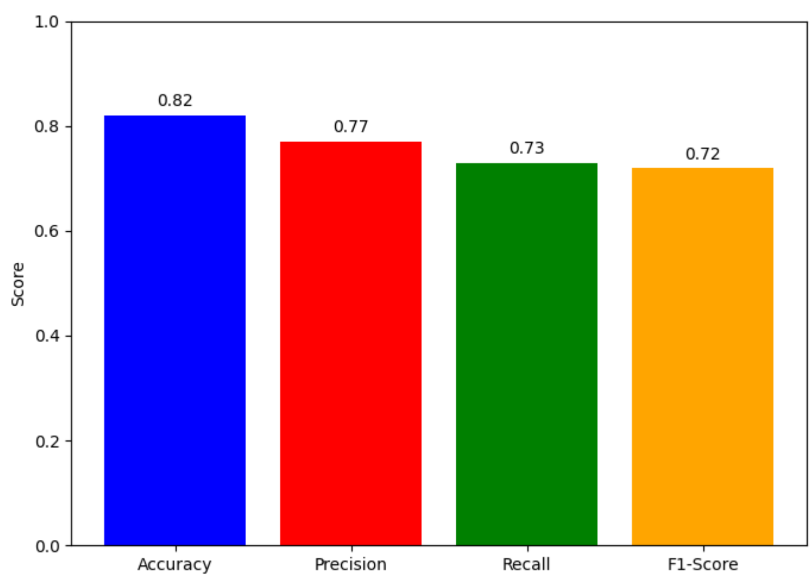

Figure 14 (b). Attack Behaviour Classification Metrics

To evaluate system performance, classification metrics including accuracy, precision, recall, and F1-score were computed from approximately 50 simulation trials conducted within the ROS environment. These trials covered a range of realistic scenarios using dynamic sensory inputs such as proximity, obstacle layout, robot speed, and environmental familiarity. To assess practical effectiveness, the fuzzy controller was benchmarked against a traditional reactive controller [22] [23] [30] [31]]32]. Key performance indicators included task completion time, number of collisions, behaviour-switching latency, and classification accuracy, summarized in Table 3 (more details in section 2.3). Additionally, Table 4 presents a conceptual comparison between the proposed fuzzy ethological architecture and traditional behaviour-based systems such as Subsumption Architecture, BDI Models, and Neuro-Fuzzy Systems (more details in section 2.3) [30] [31] [32] highlighting the unique integration of biological plausibility, emotional modeling, and interpretable decision-making in the proposed approach.

Metric	Fuzzy Behaviour Based System	Baseline System (Reactive)
Task Completion Time (sec)	49.6 ± 3.5	58.3 ± 5.7
Number of Collisions	2.5 ± 1.5	3.9 ± 1.1
Behaviour Switching Latency (ms)	390 ± 50	420 ± 52
Behaviour Classification Accuracy Escape Attack	 0.85 0.82	 0.75 0.75
F1-Score Escape Attack	 0.77 0.72	 0.70 0.70

Table 3. Fuzzy Behaviour Based Vs Baseline Controller

Aspect	Subsumption Architecture	BDI Models	Neuro-Fuzzy Systems	Proposed Fuzzy Ethological System
Behaviour Coordination	Layered suppression; limited adaptability	Symbolic reasoning for action selection	Adaptable rules via training; often opaque	Fuzzy rules enable blended, graded responses
Emotional Modeling	Not supported	Indirect and abstract	Implicit if trained; not interpretable	Direct representation of emotions (fear, aggression)
Environmental Reactivity	High but rigid (binary suppression)	Low in dynamic environments; high in planned domains	Reactive but can lack interpretability	High; real-time fuzzy inference based on sensor inputs

Real-Time Adaptability	Good, but fixed hierarchy	Poor due to high computational cost	Moderate; depends on training generalization	High; rule-based, interpretable, biologically grounded
Interpretability	Moderate	High (symbolic), but often abstract	Low ("black box")	High; rules are biologically and ethologically grounded
Training Data Needs	None	Not data-driven	Require large datasets	Rule-based; no training required

Table 4. Comparison of Traditional and Fuzzy Ethological Control Systems.

4.6 Conclusion

This work demonstrates the successful integration of ethologically inspired escape and attack behaviours into autonomous robotic systems through a fuzzy behaviour-based framework. Leveraging ROS, Gazebo, LIDAR, fuzzy inference, and SLAM, the system enables robots to perceive environmental stimuli, assess internal affective states, construct and maintain environmental maps, and execute adaptive, context-aware responses. Unlike rigid binary models, fuzzy logic supports graded, biologically realistic decision-making, yielding lifelike and interpretable behaviours. SLAM ensures continuous localization and spatial awareness, enhancing alignment between behaviour and environmental structure for real-time adaptation in dynamic scenarios. System performance was benchmarked against a traditional reactive controller and compared conceptually with Subsumption Architecture, BDI models, and Neuro-Fuzzy Systems, with results showing superior integration of biological plausibility, emotional modeling, and decision transparency. By grounding artificial behaviour in ethological principles, this approach advances robotic autonomy, resilience, and interpretability, with implications for multi-agent coordination, human-robot interaction, and real-world applications such as search and rescue, surveillance, and collaborative robotics.

4.7 Thesis II.

This thesis presents a novel implementation of Archer's ethological model of aggression and fear into autonomous robotic systems through a fuzzy state machine architecture. The work bridges animal behaviour science and robotics by enabling emotion-driven real-time behaviour switching based on both internal affective states and external stimuli [Aaqib1-Aaqib5].

4.7.1 Scientific Contribution

Robotic Instantiation of Ethological Behaviour: This research marks the first robotic realization of Archer's biological aggression model, enabling real-time behaviour transitions Escape, Attack, and Immobility governed by internal emotional states such as fear and prior experiential factors.

Fuzzy State Machine Design: A multi-state fuzzy behaviour system is developed using the Fuzzy Behaviour Description Language (FBDL), allowing interpretable, modular transitions between states. Each transition is dynamically modulated by real-time sensory context and affective history, reflecting biologically plausible decision-making.

Architectural Innovation: A multi-layered control system integrates ROS, Gazebo, RViz, and SLAM technologies, organized into distinct, testable modules: Perception→Fuzzy Behaviour Evaluation→ Inference Engine→Motion Execution, supporting both simulation and hardware deployment.

4.7.2 Mathematical and System Formalism

The robot's behavioural state S∈{Escape, Attack, Immobility}, is determined through a fuzzy inference process applied over perceptual and affective variables:

$$\mathrm{X} = \{\mathrm{ADTA}, \mathrm{AFTA}, \mathrm{AFTP}, \mathrm{EPE}, \mathrm{PIWPE}\}.$$

Inputs are fuzzified using trapezoidal membership functions into linguistic terms (e.g., Low, Medium, High). Fuzzy rules, defined in FBDL, are grounded in ethological behaviour models. For example:

Rule-base: Escape is *High* When FEAR is *High* AND EPE is *High*

Inference uses FRI (FIVE), consistent with the FBDL models. For submodules with a complete rule base, a Mamdani variant used as a baseline, but the deployed controller employs FRI (FIVE) to ensure reliable reasoning even with sparse rules. Behaviour fusion is then applied to combine module outputs.

$$S = \arg\max_i (\mu B_i) \qquad (9)$$

To avoid abrupt state changes, transitions between behaviours are governed by a Fuzzy State Machine (FSM), allowing partial activation through probabilistic blending:

$$P(Bj \mid Bi, xk) = \frac{\mu Bj(xk)}{\sum_{n} \mu Bn(xk)} \qquad (7)$$

Detailed membership equations, defuzzification, and full inference logic are presented in Chapter 2 mathematical formalism.

4.7.3 Empirical Validation & Simulation Based Evidence

To assess the effectiveness of the proposed fuzzy ethological behaviour architecture, approximately 50 simulation trials were conducted within the ROS environment. These trials spanned a range of realistic and dynamic conditions, including variations in obstacle layouts, proximity to agents, robot velocity, and environmental familiarity. The primary goal was to evaluate the controller's capacity for adaptive, context-sensitive behaviour selection in diverse operational scenarios.

Classification performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Figures 14(a) and 14(b) show the classification outcomes for "Escape" and "Attack" behaviours, respectively, confirming the architecture's robustness in interpreting perceptual and experiential variables. These results demonstrate the model's ability to capture nuanced, biologically inspired decision-making processes beyond conventional reactive logic.

A benchmarking study compared the fuzzy controller with a traditional reactive controller based on classical models. Performance indicators included task completion time, collision count, behaviour-switching latency, and behaviour classification accuracy, summarized in Table 3. Furthermore, Table 4 presents a conceptual comparison with control paradigms such as Subsumption Architecture, BDI Models, and Neuro-Fuzzy Systems, emphasizing the value of integrating emotional modeling, biological plausibility, and transparent decision-making.

4.7.4 Experimental Highlights

Several key experiments were designed to evaluate real-time behavioural responsiveness. In the *Escape* Behaviour scenario (Figures 10 and 12(a)-(e)), Robot_1 assesses inputs like AFTA, ADTA, and EPE. Upon detecting Robot_2 under threatening conditions, a high fear level is activated, prompting the robot to initiate escape. The robot's movement shows smooth and ethologically plausible trajectories, simulating fear-driven withdrawal. In the Coordinated *Attack* Simulation (Figures 11 and 13(a)-(e)), Robot_1 initiates an aggressive approach using fuzzy logic rules, while Robot_2 reacts by activating its escape behaviour. This dynamic interaction demonstrates emergent, lifelike decision-making and verifies the arbitration module's effectiveness in transitioning between attack and avoidance based on environmental context. Additionally, integration with SLAM (via the gmapping package) enables spatial awareness in GPS-denied environments. By continuously updating occupancy grids, the system ensures context-sensitive planning and behavioural transitions even in unknown or dynamic indoor spaces.

4.7.5 System-Level Testability and Reproducibility

The system's modular architecture enhances reproducibility and testability across both simulated and physical platforms. Each behaviour Escape and Attack is encapsulated within its own ROS node and linked via standard ROS messaging. The fuzzy rule base is implemented using FBDL, and each rule is traceable to specific ethological observations, ensuring interpretability and auditability. Simulation experiments in Gazebo were conducted using systematically varied environmental parameters (e.g., EPE, ADTA etc) to activate specific behaviour transitions. Behaviour states and fuzzy variable activations are visualized in real-time via RViz, providing a clear interface for analysis, debugging, and verification. Importantly, the system is hardware-compatible and can be deployable on physical robots such as TurtleBot platforms. ROS drivers and modular nodes allow seamless transition from simulation to real-world implementation.

4.7.6 Applications and Ethical Implications

The proposed fuzzy ethological behaviour model offers versatile applicability across several real-world domains. In *search and rescue operations,* robots equipped with fear-based reasoning can autonomously flee from hazardous environments or avoid structural collapses, improving safety and autonomy during mission-critical deployments. In *autonomous surveillance*, the system enables robots to assess potential threats and respond with appropriate aggression or withdrawal, offering adaptive situational awareness. For *human-robot interaction,* architecture supports emotionally expressive behaviour that goes beyond static scripting, enabling robots to react in socially intelligible ways without reliance on predefined dialogue trees. This emotional modeling fosters more intuitive and meaningful engagement between robots and humans.

However, embedding emotion-like behaviour in robots introduces important *ethical considerations*. It raises questions about intent interpretation, the transparency of decision-making, and accountability in autonomous systems. The proposed framework addresses these issues through biologically grounded and interpretable rule sets, implemented using fuzzy logic that makes internal states and decisions traceable. The system also supports behaviour-state reporting in real time, ensuring that robotic actions remain auditable and ethically defensible.

4.7.7 Novelty and Impact.

This work introduces a novel implementation of a fuzzy state machine grounded in ethological theory and deployed within a high-resolution, SLAM-integrated ROS environment. Unlike traditional controllers, the system models affective states such as fear and aggression using biologically inspired rules, enabling nuanced, context-sensitive behaviour.

By demonstrating that affective robotics can be driven by biological theory rather than heuristic or reinforcement-based logic, the system establishes a new paradigm for behaviour design in autonomous agents. Furthermore, the architecture is modular, reusable, and open-source, allowing easy adaptation to multi-agent setups and future emotion-aware robotic applications. It contributes a biologically principled, interpretable, and ethically aware foundation to the field of affective robotics.

Chapter 5: Fuzzy Behaviour-Based Control Framework with VFF

5.1 Introduction

The increasing integration of robots into human environments demands advanced navigation and obstacle avoidance systems that ensure both safety and efficiency in dynamic settings. This chapter presents a modular fuzzy behaviour-based control architecture tailored for adaptive robotic navigation in complex, cluttered, and dynamic environments. The system is composed of three modules:

Behaviour Coordination which uses fuzzy logic to evaluate environmental inputs and assign weights (or membership values) to available behaviours.

Component Behaviours which generate candidate navigational actions such as Goal Pursuit, Obstacle Avoidance, or Escape each suggesting a direction or response.

Behaviour Fusion (as a VFF here) where the outputs of the component behaviours are merged according to their assigned weights. The Virtual Force Field (VFF) method is used here as a fusion technique, calculating a net motion vector by combining attractive and repulsive forces in proportion to each behaviour's relevance.

The novel aspect of this architecture is the integration of Virtual Force Field (VFF) as a technique within the Behaviour Fusion module rather than as a standalone system. The integrated system draws from ethological models, particularly animal escape responses, to simulate internal affective states such as fear and adapt behaviour accordingly. Fuzzy logic maps sensor-derived observations (e.g., proximity to threats, familiarity with place or objects) to internal emotional activations, which then modulate the influence of each component behaviour during fusion.

This hybrid approach empowers robots with context-sensitive, lifelike decision-making, allowing them to continuously adapt their motion in response to environmental changes. The system simulation has been implemented using the Robot Operating System (ROS), validated in realistic environments through LIDAR sensing, SLAM-based localization, and dynamic simulation in Gazebo. By combining fuzzy reasoning with biologically inspired fusion, this architecture advances robotic autonomy and real-time decision-making in fields such as manufacturing, logistics, service robotics, and human-robot interaction.

5.2 Background

Robotics has evolved significantly from its early role in automated industrial systems to become a ubiquitous presence across sectors such as education, hospitality, and service industries. Once confined to high-tech laboratories and elite manufacturing, advancements in hardware and open-source platforms have democratized robotic technologies, enabling broader deployment in everyday contexts. This shift is further reflected in the growing emphasis on intelligent automation systems, including autonomous vehicles and service robots [41] [42].

Ethology, the scientific study of animal behaviour, offers valuable insights into adaptive motion, decision-making, and interaction strategies in natural environments. Ethologists employ methods such as direct observation, remote sensing, and motion tracking to analyze behaviours like pursuit, evasion, and foraging. These biologically inspired behaviours provide a rich foundation for designing adaptive control strategies in robotics [3] [8]. By embedding such strategies into robotic platforms, engineers can develop systems that exhibit flexible, ecologically valid responses suited to real-world environments.

Despite these advances, real-time robotic navigation remains a significant challenge particularly in unpredictable and densely populated environments. Robots must not only detect and recognize obstacles, including humans, other robots, and moving vehicles, but also respond with timely and context-appropriate actions to avoid collisions [43]. Mobile robots with cognitive capabilities are increasingly essential in critical domains such as warehouse automation, disaster response, patrolling, and search-and-rescue missions [44], where both spatial awareness and dynamic planning are required.

In response to these challenges, this study proposes a novel fuzzy behaviour-based control framework in which the Virtual Force Field (VFF) method is embedded as a behaviour fusion technique, rather than a standalone system. The architecture separates decision-making into distinct modules: Behaviour Coordination, which determines the relevance of each component behaviour using fuzzy inference; Component Behaviours, which generate direction vectors; and Behaviour Fusion, which merges these vectors based on coordination-assigned weights. Within this fusion process, the VFF method combines attractive and repulsive forces in proportion to each behaviour’s weight. By emulating adaptive animal strategies such as escape and threat avoidance, the system enables robots to navigate with increased intelligence, safety, and contextual awareness. The result is a biologically grounded, modular navigation architecture that unites engineering precision with naturalistic behaviour modelling.

5.3 Fuzzy Behaviour Fusion

In behaviour-based robotic control, behaviour fusion refers to the integration of outputs from multiple component behaviours into a single, coherent response that is sensitive to both context and environmental dynamics. This process is especially critical in systems where multiple objectives must be balanced such as navigation, obstacle avoidance, and threat escape and is widely applied in fields including robotics, artificial intelligence, and multi-agent systems [45]. At the core of this process lies the Behaviour Coordination module, which uses fuzzy inference to evaluate the robot's current situation and assign weights (or membership values) to each behaviour. These weights represent the degree to which a given behaviour is appropriate in the current context. Once weighted, the outputs of the component behaviours are passed to the Behaviour Fusion module, where they are combined into a unified action.

Fusion strategies can vary from rule-based mechanisms to more complex machine learning models. In this architecture, however, we apply a fuzzy behaviour fusion approach, which leverages fuzzy logic to handle conflicting or ambiguous behavioural recommendations. This is particularly advantageous in real-world robotic scenarios, where uncertainty and environmental variability are common. This design is inspired by mechanisms observed in animal behaviour. In nature, animals assess sensory inputs, internal states, and external threats to make fast survival decisions such as fleeing or freezing. These biological processes involve real-time coordination and fusion of multiple action tendencies a principle mirrored in this system.

In the proposed model, each component behaviour (e.g., Obstacle Avoidance, Target Following, Escape) generates a directional suggestion or response value. These outputs are not treated equally; instead, they are weighted based on coordination-derived fuzzy values that reflect behavioural suitability. The fusion process, guided by a Fuzzy Rule Base, then integrates these weighted contributions into a final action decision. This structure ensures that behaviours are not selected in isolation or based on binary logic but are blended proportionally using fuzzy inference rules. The result is a robot capable of nuanced, lifelike responses, capable of adjusting to rapidly changing environments while maintaining coherent goal-oriented navigation [46] [47] [48].

Figure 15 illustrates this process: the component modules (Escape Response, Target Following, Obstacle Avoidance) provide outputs that are routed into a Fuzzy Rule Base (Fusion). This base processes the weighted inputs, resolves conflicts, and produces the Final Action Decision a command that is both situationally aware and context adaptive.

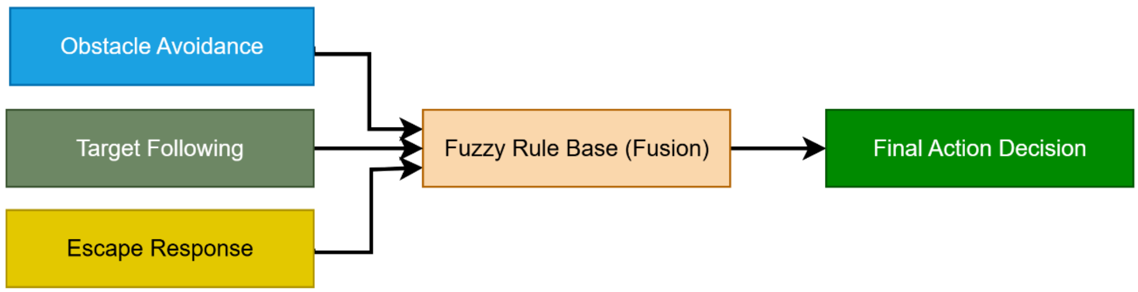

Figure 15. Fuzzy Behaviour Fusion Process

5.4 Virtual Force Field Navigation

Virtual Force Field (VFF) navigation is a widely utilized technique in mobile robotics and autonomous systems, particularly in tasks involving real-time obstacle avoidance and local path planning [49]. The core idea is to model the robot's operating environment as a field of virtual forces: attractive forces guide the robot toward its goal, while repulsive forces push it away from nearby obstacles. By continuously calculating the resultant force vector from these interactions, the robot can determine its movement direction and dynamically adjust its trajectory as the environment evolves. While VFF offers several benefits including algorithmic simplicity, intuitive control logic, and fast responsiveness it also suffers from well-known limitations such as susceptibility to local minima, oscillations in cluttered spaces, and difficulty in handling conflicting behavioural goals. Nonetheless, it remains an essential component of reactive navigation strategies in systems requiring rapid adaptation [50].

To overcome these limitations, this study introduced a novel approach that combines Fuzzy Behaviour-Based Control Framework with VFF Fusion. In this study VFF is not treated as a standalone navigation system but is instead embedded as the core mechanism within the Behaviour Fusion module of a fuzzy behaviour-based control architecture. The system's modular structure consists of three layers as described in the introduction section of this chapter. In this context, VFF operates as a fusion engine, using the weights produced by the coordination layer to scale the attractive and repulsive influences of each behaviour. For instance, in a threatening situation, escape behaviour might receive higher weight, resulting in stronger repulsive effects in the final motion vector. This hybrid approach overcomes VFF's limitations by introducing context-aware weighting and decision flexibility through fuzzy logic.

Figure 16 illustrates the fundamental concept of Virtual Force Field (VFF) navigation, where a robot is guided by virtual forces within its environment. An attractive force pulls the robot toward the target, while a repulsive force pushes it away from nearby obstacles. These opposing vectors combine to form a resultant force vector, which determines the robot's movement direction. This continuous vector calculation enables the robot to navigate toward its goal while dynamically avoiding obstacles, supporting real-time, adaptive path planning.

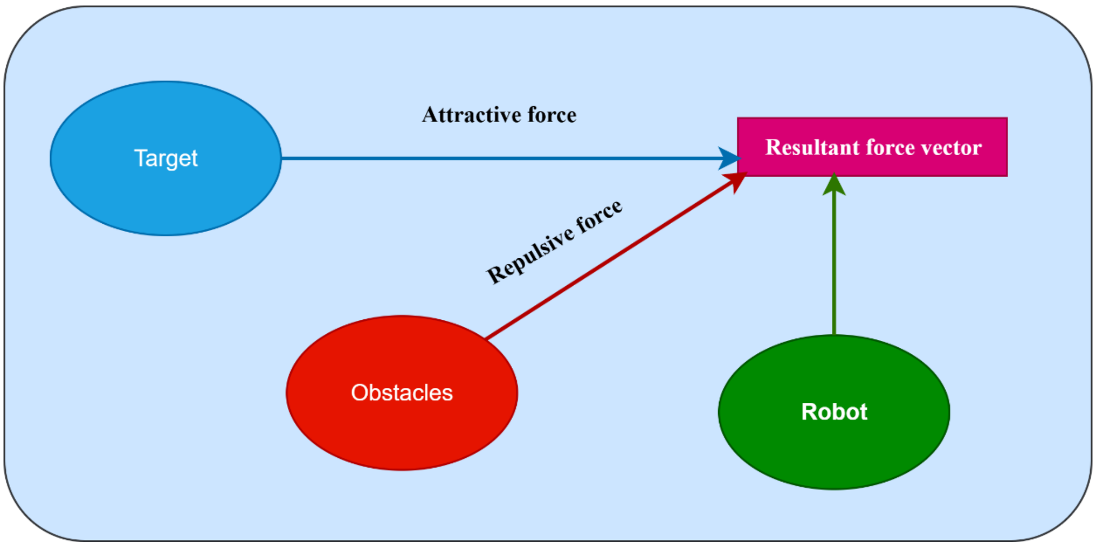

Figure 16. Virtual Force Field (VFF) Navigation

VFF is essential for a range of practical applications, including autonomous ground vehicles, unmanned aerial delivery systems, and mobile service robots. To quantify the influence of repulsive forces on the robot's motion, the system applies the mathematical model defined in Equation (10):

$$\mathrm{F}\,(i,j) = \frac{\mathrm{FcrC(i,j)}}{\mathrm{d2(i,j)}}\left[\frac{x_i - x_0}{\mathrm{d(i,j)}}\,\hat{x} + \frac{y_i - y_0}{\mathrm{d(i,j)}}\,\hat{y}\right] \tag{10}$$

where Fcr denotes the repelling force constant, d(i, j) represents the distance between the robot's current position and a given cell (i, j), and C(i, j) signifies the certainty level of that cell. The certainty level reflects the system's confidence in whether a particular cell contains an obstacle, influencing the robot's assessment of the repulsive force exerted by that cell. A high certainty level indicates a greater likelihood of an obstacle, leading to a stronger repulsive force, whereas a low certainty level suggests a lower probability of an obstacle, resulting in a weaker repulsive effect.

To determine the repulsive force F(i, j) from a given cell (i, j), equation (1) incorporates the repelling force constant Fcr, the distance d(i, j) between the cell's coordinates (x_i, y_i) and the robot's position (x_0, y_0), as well as the certainty level C(i, j). By summing the repulsive forces from all relevant cells, the system computes the total repulsive force Fr, shown in equation (11) which the robot utilizes to safely maneuver around obstacles.

$$Fr = \sum_{\mathrm{I,j}} F\,(i,\, j) \qquad (11)$$

This summation accounts for repulsive contributions from all relevant grid cells in the robot's sensory field. Combined with attractive forces toward the goal, the final resultant vector determines the robot's movement. By integrating this method within the fuzzy coordination and fusion framework, the VFF approach is enhanced with adaptive behaviour weighting, greater robustness, and biologically inspired flexibility. The result is a navigation system capable of intelligently responding to dynamic, cluttered, or ambiguous environments [51].

5.5 Implementation of Fuzzy Behaviour-Based Control Framework with VFF

The integration of a fuzzy behaviour-based control framework with the Virtual Force Field (VFF) method offers a biologically inspired and adaptive approach for real-time robotic decision-making in dynamic environments [Aaqib6, Aaqib7]. This hybrid model enhances flexibility in human-robot collaboration and enables context-aware navigation in uncertain, rapidly changing conditions. The system combines the strengths of its two key components: The *fuzzy control system*, which assigns relevance weights to multiple behaviours based on environmental inputs. The *VFF* technique, which serves as a behaviour fusion mechanism by combining these weighted behaviour outputs into a unified motion directive [52].

Specifically, VFF computes attractive and repulsive force vectors from sensor data, which are scaled proportionally to the behaviour weights derived through fuzzy inference. This produces a resultant force vector guiding the robot toward its goal while avoiding obstacles and responding to potential threats [53]. Importantly, VFF does not operate as a standalone system but functions as a fusion layer governed by fuzzy-assigned priorities.

The fuzzy behaviour coordination layer enhances adaptability by allowing dynamic reconfiguration of navigational responses based on real-time sensory input. This design improves operational safety, decision accuracy, and computational efficiency while supporting modular expansion. It is applicable to both physical and simulated environments, including autonomous vehicles, service robots, and assistive systems that require fast, biologically inspired, and context-sensitive navigation [54].

At its core, the system consists of three distinct modules:

Behaviour Coordination: This fuzzy inference module evaluates environmental context and assigns weights (membership values) to multiple component behaviours such as Obstacle Avoidance, Goal Pursuit, and Escape. The weights represent the relevance or urgency of each behaviour under the current situation, based on sensor data and contextual observations.

Component Behaviours: Each behaviour independently suggests a motion vector aligned with its objective. These vectors are not executed directly but are passed to the fusion layer for integration based on their assigned weights.

Behaviour Fusion (as a VFF here): The VFF method fuses the proposed motion vectors. It computes attractive forces (e.g., toward goals) and repulsive forces (e.g., from obstacles). Each force is scaled by its fuzzy-assigned weight. The resulting force vector determines the robot's final direction, allowing proportional contributions from each behaviour and ensuring safe, efficient navigation.

The fuzzy behaviour coordination serves as the central mechanism governing how various behaviours are combined and executed in response to environmental stimuli. The fuzzy rules of behaviour coordination consist of **If** *[conditions] and* **Then** *[actions]* statements that define relationships between input variables (e.g., environmental conditions) and output behaviours (e.g., movement adjustments, force modulation). These rules allow the system to make context-sensitive, adaptive decisions, mirroring the nuanced responses observed in biological organisms.

If AFTP=*Low* **And** AFTA=*Low* **And** ADTA=*Low* **And** EPE=*High* **Then** ESCAPE=*High*

Rule-base ESCAPE in FBDL:

Rule **ESCAPE** is *High* ***When*** AFTP is *Low* **And** AFTA is *Low* **And** ADTA is *Low* **And** EPE is *High*

Where the input (antecedent) variables include AFTP (Animal Familiarity Towards Place), AFTA (Animal Familiarity Towards Another), and ADTA (Animal Distance Towards Another Animal), EPE (Escape Path Exists). The output (consequent) variable is defined as ESCAPE. Further details on these notations and the corresponding aggression behaviour model can be found in [Aaqib2]. The rule (weight) does not cause an immediate escape but adjusts the influence of the Escape behaviour within the final vector generated by VFF.

After behaviour coordination assigns weights, each component behaviour (e.g., Escape, Goal Pursuit, Obstacle Avoidance) proposes a motion vector. These vectors are fused using the VFF method: Attractive forces are directed toward the goal; Repulsive forces are generated based on detected obstacles; The total force vector is the sum of all component vectors, each scaled by its fuzzy-derived weight. This process allows robots to: Escape from danger more strongly when fear is high; Pursue goals more assertively in safe conditions; Resolve conflicts dynamically between opposing behaviours. Thus, VFF serves as the computational substrate for behaviour fusion, driven by the weights from fuzzy coordination [Aaqib7].

To demonstrate this integration, the proposed study analyzes the "Escape" behaviour as modeled in the ethologically inspired aggression framework [Aaqib2], where the corresponding fuzzy rule bases are implemented using the Fuzzy Behaviour Description Language (FBDL) [4]. The system emphasizes the importance of identifying key internal state variables (e.g., "fear", "escape motivation") and external observations (e.g., familiarity with the environment, obstacle proximity, escape route availability). This hybrid approach enables the accurate modelling of ethologically inspired escape behaviour, with logic centered on critical state variables and contextual awareness, as discussed in Chapters 2 and 3.

***State Variables**:* These define the current condition of the system. The fuzzy escape behaviour model incorporates two state variables:

Escape: Represents actions aimed at distancing the animal from a perceived threat. Animals instinctively flee from danger by rapidly moving away.

Fear: A hidden state variable, meaning it does not directly correspond to a specific behaviour but influences other state variables. Fear is a complex reaction involving physiological, behavioural, and emotional responses to stimuli. When animals experience intense fear, they exhibit physical changes such as crouching, pulling back ears, widening eyes, and tucking their tails. Although fear cannot be observed directly, its effects on behaviour are evident.

Observations: These define the situations influencing state variables and contribute to an animal’s decision-making process:

Animal Familiarity Towards Place (AFTP): Represents how familiar an animal is with its surroundings. Unfamiliar environments often trigger fear responses.
Animal Familiarity Towards Another Animal (AFTA): Indicates the level of familiarity an animal has with another. Fear may increase if an unfamiliar animal enters its territory.
Animal Distance Towards Another Animal (ADTA): Refers to the proximity between two animals, affecting the likelihood of fear or aggression.
Animal Familiarity Towards Object (AFTO): Describes the degree to which an animal recognizes a specific object. Unfamiliar objects within a known space may provoke fear, aggression, or escape behaviours.
Animal Distance Towards Object (ADTO): The distance between an animal and an object, with unfamiliar objects potentially eliciting fear or defensive behaviour.
Escape Path Exists (EPE): Determines whether an escape route is available. If the escape path is blocked, the animal may react aggressively, even if it is fearful.

Understanding how animals respond to their environments and social interactions is essential for designing adaptive, intelligent robotic systems [Aaqib1] [Aaqib2] [Aaqib3]. In this context, the integration of Virtual Force Field (VFF) navigation with fuzzy logic offers a biologically grounded framework for replicating animal-like escape responses. While VFF governs motion through the computation of attractive and repulsive forces, fuzzy logic introduces real-time adaptability by evaluating contextual sensory inputs and modulating behavioural priorities accordingly.

This combined approach allows robots to define and pursue specific behavioural goals such as avoiding threats, seeking targets, or escaping confined areas based on environmental cues. Fuzzy rules are used to model these behaviours in a modular and interpretable manner [Aaqib6]. For instance, when an unfamiliar entity approaches, the fuzzy coordination module may increase the weight of the "Escape" behaviour, leading to stronger repulsive vector influence in the VFF fusion process. This rule-based modulation enables robots to respond dynamically to their surroundings in a way that mirrors natural animal strategies, such as evasion and threat avoidance.

Fuzzy Behaviour Descriptive Language (FBDL) [5] provides a structured framework to define input and state variables, including the terms used (e.g., "Low" or "High") and the rules that dictate behavioural responses. For example, when evaluating "Animal Familiarity with Another Animal" (AFTA) with possible values of "Low" or "High," FBDL might look like this:

```
universe: AFTA
description: How well the animal knows another animal
        Low   0 0
        High  1 1
end
```

A fuzzy rule might say:

Rule FEAR=*Low* **when** AFTP=*High* **and** AFTA=*High* **and** AFTO=*High*

The fuzzy rule base and corresponding Fuzzy Behaviour Descriptive Language (FBDL) definitions are designed to address a wide range of behaviourally relevant scenarios [Aaqib4] [Aaqib5]. These include:

(i) The degree of familiarity an animal has with a particular location, object, or other animal.

(ii) Proximity of an approaching object or agent.

(iii) Appearance of a new object or animal within a familiar territory.

(iv) Animal entering an unfamiliar environment, often triggering a fear response.

(v) Presence of a familiar object in an unfamiliar setting.

These scenarios inform the construction of fuzzy rules that govern key behaviours such as "Fear" and "Escape", enabling the robotic system to respond in a manner consistent with ethologically inspired models. The fuzzy logic rules supporting these behaviours are outlined in the following sections.

In fuzzy rule-base format the fuzzy rules of FEAR are the following:

If AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** Fear=*High*.

If AFTA=*Low* **And** ADTA=*Low* **And** EPE=*Low* **Then** Fear=*High*.

If AFTO=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** FEAR=*High*

If AFTP=*High* **And** AFTA=*High* **And** ADTA=*High* **Then** Fear=*Low*.

If AFTP=*High* **And** AFTA=*High* **And** EPE=*High* **Then** Fear=*Low*.

where antecedent universes are AFTP, AFTA, ADTA, AFTO, ADTO, EPE , and FEAR is the consequent universe, Low and High are fuzzy linguistic terms of the corresponding universes.

In fuzzy rule-base format the fuzzy rules of Escape are the following:

If EPE=*High* **And** FEAR=*High* **Then** ESCAPE=*High*

If EPE=*High* **And** AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** ESCAPE=*High*

If FEAR=*Low* **And** EPE=*Low* **Then** ESCAPE=*Low*

If AFTA=*High* **And** AFTP=*High* **And** ADTA=*High* **And** AFTO=*High* **And** ADTO=*High* **Then** ESCAPE=*Low*.

Where AFTP, AFTA, ADTA, AFTO, ADTO, EPE, FEAR are the antecedent universes, ESCAPE is the consequent universe, Low and High are fuzzy linguistic terms of the corresponding universes.

The same ESCAPE rule-base in FBDL format presents as:

RuleBase "ESCAPE"

Rule *High* **when** EPE=*High* **and** FEAR=*High* end

Rule *High* **when** AFTA=*Low* **and** AFTP=*Low* **and** EPE=*High* **and** AFTO=*Low* end

Rule *Low* **when** FEAR=*Low* **and** EPE=*Low* end

Rule *Low* **when** AFTA=*High* **and** AFTP=*High* **and** ADTA=*High* **and** AFTO=*High* **and** ADTO=*High* end

end

5.6 Conceptual Framework of VFF with Fuzzy Behaviour Control

The conceptual framework of the proposed system which combines VFF navigation with fuzzy behaviour fusion to enable adaptive, context-aware robotic motion is illustrated in figure 17. This layered architecture processes real-time environmental data through fuzzy inference and transforms it into motion directives via force field computation. The process begins with:

Input Layer: which gathers real-time environmental data critical for navigation and decision-making. Key variables include Animal Distance Toward Another Animal (ADTA), Animal Distance Toward Object (ADTO), Animal Familiarity Toward Place (AFTP), Animal Familiarity Toward Object (AFTO), Escape Path Exists (EPE) These variables represent perceptual observations that inform the robot's understanding of its surroundings and potential threats or escape opportunities.

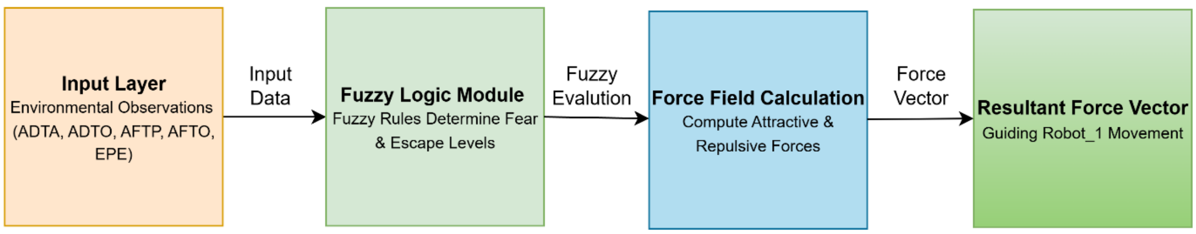

Figure 17. Conceptual Diagram of the Fuzzy Behaviour Control with VFF Navigation

Fuzzy Logic Module (Behaviour Coordination): Environmental inputs are processed by the Fuzzy Behaviour Coordination Module, which applies a set of fuzzy inference rules to derive internal states, particularly Fear and Escape. *Fear* an inferred emotional state representing threat intensity. *Escape* a behavioural tendency activated by high fear or unfamiliar stimuli. The fuzzy module functions as a state evaluator, transforming ambiguous or continuous environmental stimuli into discrete behavioural priorities using a rule-based system. This enables the robot to handle uncertainty and make graded decisions even in rapidly changing contexts.

Force Field Calculation Module (Behaviour Fusion): The output fuzzy states (e.g., high Escape, low Fear) are used to weight component behaviours such as obstacle avoidance and goal pursuit. These are then fused using the VFF method, where: Attractive Forces guide the robot toward its goal; Repulsive Forces steer the robot away from threats or obstacles. Each force vector is scaled according to its behaviour weight derived from fuzzy coordination. The system thus prioritizes behaviours in proportion to perceived environmental urgency and context.

Output Layer (Motion Execution): The final stage consolidates the weighted attractive and repulsive forces into a resultant motion vector that governs the robot's trajectory in real time. As environmental data updates continuously, the system recalculates and adjusts this vector dynamically, enabling fluid, adaptive navigation.

This integrated framework demonstrates how biologically inspired behavioural modeling (e.g., threat recognition, escape motivation) can be embedded within engineering systems to produce autonomous, intelligent, and ecologically valid robotic behaviour. The synergy between fuzzy logic and VFF navigation enhances decision granularity, environmental awareness, and response flexibility critical for high-stakes applications in dynamic and human-populated environments.

5.7 Trajectories of Fuzzy Behaviour Control with VFF

The Figure 18 illustrates a step-by-step simulation of ethologically inspired escape behaviour, implemented through the integration of Virtual Force Field (VFF) navigation and fuzzy behaviour control. This hybrid control architecture enables the robot to adapt its trajectory in real-time by combining fuzzy logic-based decision-making with force-based motion planning [Aaqib7]. The simulation involves two autonomous agents Robot_1 and Robot_2 alongside one static and one dynamic object. Robot_1 is the main actor tasked with reaching the target coordinates (5.5, 5.5). Its path is influenced by the dynamic behaviour of Robot_2, a potential threat, and a static obstacle, both of which test the robot's capacity for avoidance and path adaptation.

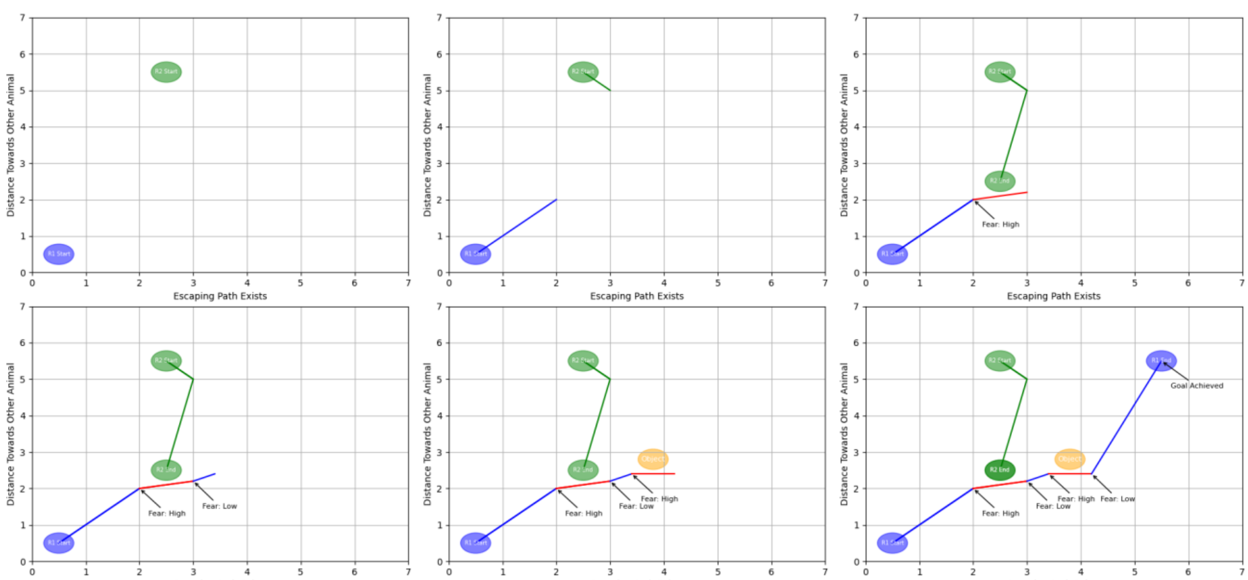

Figure 18. Trajectories of Escape Behaviour Through Fuzzy Behaviour-Based Control Framework with VFF [Aaqib7].

As Robot_1 progresses toward its target, it encounters two primary challenges: (i) the approach of Robot_2, which interferes with its direct path, and (ii) a physical object that obstructs its trajectory. Robot_1 navigates the environment; it continuously receives sensory input about its surroundings. The fuzzy behaviour coordination module interprets environmental observations such as AFTP, AFTA, ADTA, AFTO, ADTO, EPE. These variables are processed using a fuzzy inference engine to evaluate internal behavioural states

Fear and Escape. Based on a rule base derived from ethological observations [Aaqib2] (as described in Section 5.5 and section 3.1), the coordination module assigns weights to behavioural components like Goal Pursuit, Obstacle Avoidance, and Escape. For instance:

If ADTA = *Low* **AND** EPE = *High* **AND** AFTA = *Low*, **Then** ESCAPE = *High*.

The output of fuzzy coordination is a set of weighted behaviour suggestions. These weights are passed to the behaviour fusion module, which is realized through the VFF algorithm. In this stage: An attractive force pulls Robot_1 toward the goal and the Repulsive forces push it away from Robot_2 and the static obstacle. Each force is scaled by the corresponding fuzzy-derived behaviour weight. The resultant vector determines the robot's next movement step. This approach allows Robot_1 to: Prioritize Escape more strongly when threats are nearby, Shift toward Goal Pursuit when safe, Balance between multiple competing demands via weighted vector combination. The robot's trajectory dynamically evolves based on both contextual awareness and fuzzy behavioural reasoning. Figure 19 presents the flowchart of the hybrid control model. This structure supports intelligent and adaptive navigation, replicating biological decision-making in artificial agents and ensuring operational robustness in uncertain environments.

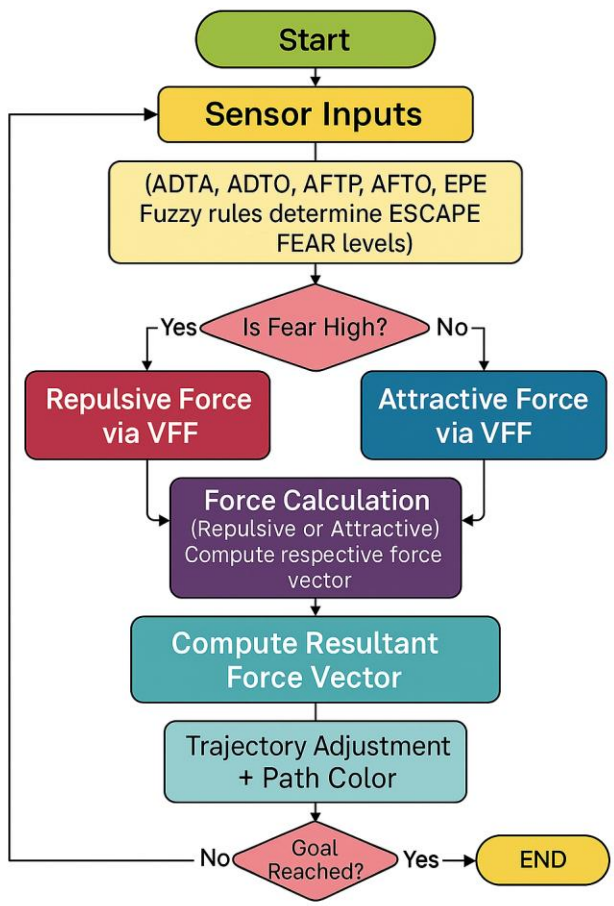

Figure 19. Flowchart of Fuzzy Behaviour-Based Control Framework with VFF.

The virtual force field utilizes equations (12) and (13) to measure the overall effect of repulsive forces, while equations (14) and (15) measure the attractive forces on the robot's motion.

$$X_{cr} = - F_{cr}\left(\frac{X_i - X_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_o)^2}}\right) \qquad (12)$$

$$Y_{cr} = - F_{cr}\left(\frac{Y_i - Y_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_o)^2}}\right) \qquad (13)$$

where X_{cr} is the x component repulsive force, Y_{cr} is the y component repulsive force, F_{cr} is the repelling force constant, (x_0, y_0) is the current coordinates of the robot_1, and (x_i, y_i) is the coordinates of the robot_2 or obstacle position.
Similarly, attractive forces are calculated using the same VFF to have an x and y component.

$$X_{ca} = F_a\left(\frac{H_x - X_0}{\sqrt{(H_x - X_0)^2 + \left(H_y - Y_0\right)^2}}\right) \qquad (14)$$

$$Y_{ca} = F_a\left(\frac{H_y - Y_0}{\sqrt{(H_x - X_0)^2 + \left(H_y - Y_0\right)^2}}\right) \qquad (15)$$

X_{ca} is x and Y_{ca} is the y component attractive force from goal location towards robot_1 (from robot_2 position and obstacle location). H_x is and H_y is the goal position at X and Y, and (x_0, y_0) is the current position of the robot_1, Fa is the Gain of attractive force.

Robot_1 initiates its journey from the origin point (0, 0) with low fear levels, represented by a blue trajectory. As it advances toward its goal (5.5, 5.5), it encounters Robot_2, which progressively obstructs its path. when Robot_2 approaches Robot_1, the proximity decreases (ADTA = Low), which combined with a valid escape path (EPE = High) and environmental unfamiliarity (AFTA = Low), leads to an increase in fear (color shift from blue to red in the trajectory) as evaluated by the fuzzy rule base. These conditions satisfy fuzzy logic rules such as: **If** AFTA = *Low* **AND** ADTA = *Low* AND EPE = *High*, T**hen** ESCAPE = *High*. This results in a high Escape state, prompting the fuzzy Behaviour Coordination module to assign stronger weight to Escape behaviour. In the VFF-based behaviour fusion layer, this increases the repulsive force vector, leading Robot_1 to retreat and initiate an evasive trajectory. This avoidance maneuver is reflected visually by a shift in the trajectory color from blue to red, denoting heightened fear and escape activation.

As Robot_1 distances itself from Robot_2, the proximity increases, and the system reevaluates the situation. The fear level decreases, and the weight of the Escape behaviour diminishes, causing the attractive force toward the goal to regain dominance. The trajectory color transitions back to blue, indicating low fear and the resumption of the original navigational objective. The behaviour coordination module thus dynamically adjusts the fusion strategy based on real-time contextual updates.

Further along its path, Robot_1 detects an unfamiliar object blocking its route. This triggers another rise in fear (the trajectory color changes from blue to red), as the fuzzy system evaluates: AFTO = Low (unfamiliar object), ADTO = Low (close distance), EPE = High (escape path exists). These inputs yield another High Escape condition, reinforcing the repulsive vector in the VFF module. Robot_1 performs another context-sensitive avoidance maneuver, reflected by a return to a red trajectory, and navigates around the object.

Once safely past the obstacle, the fuzzy coordination module reduces the Escape weight, and the robot's internal state returns to calm. The blue trajectory resumes, marking the final phase of its path toward the goal. The color-coded path captures Robot_1's internal behavioural modulation based on fuzzy inference and VFF vector dynamics: Blue: Calm, goal-seeking behaviour (low fear). Red: Escape-driven avoidance (high fear, high escape). Transitions: Real-time modulation of control priorities based on environmental interpretation.

This simulation clearly demonstrates the strength of the proposed fuzzy behaviour-based control framework, where: Fuzzy logic interprets context and assigns behaviour weights, VFF serves as the fusion method to compute the resultant force vector, The system mimics ethologically inspired escape strategies. By adhering to biologically grounded principles and incorporating graded behavioural priorities, the robot adapts continuously and intelligently to evolving threats. This affirms the viability of the proposed model in real-world, multi-agent navigation tasks, where environmental complexity and uncertainty are key challenges.

5.8 Simulation Environment and Evaluation in ROS

To evaluate the effectiveness of the proposed hybrid control framework, which integrates fuzzy behaviour coordination with VFF based behaviour fusion, a structured simulation experiment was developed in the Robot Operating System (ROS) environment [39] [40]. This framework allows mobile robots to perform context-sensitive, adaptive navigation by combining the real-time reactivity of force-based motion with the reasoning flexibility of fuzzy logic. The architecture and control flow are visualized in Figure 20, while ROS simulation outcomes showcasing the escape behaviour in action are depicted in figure 21.

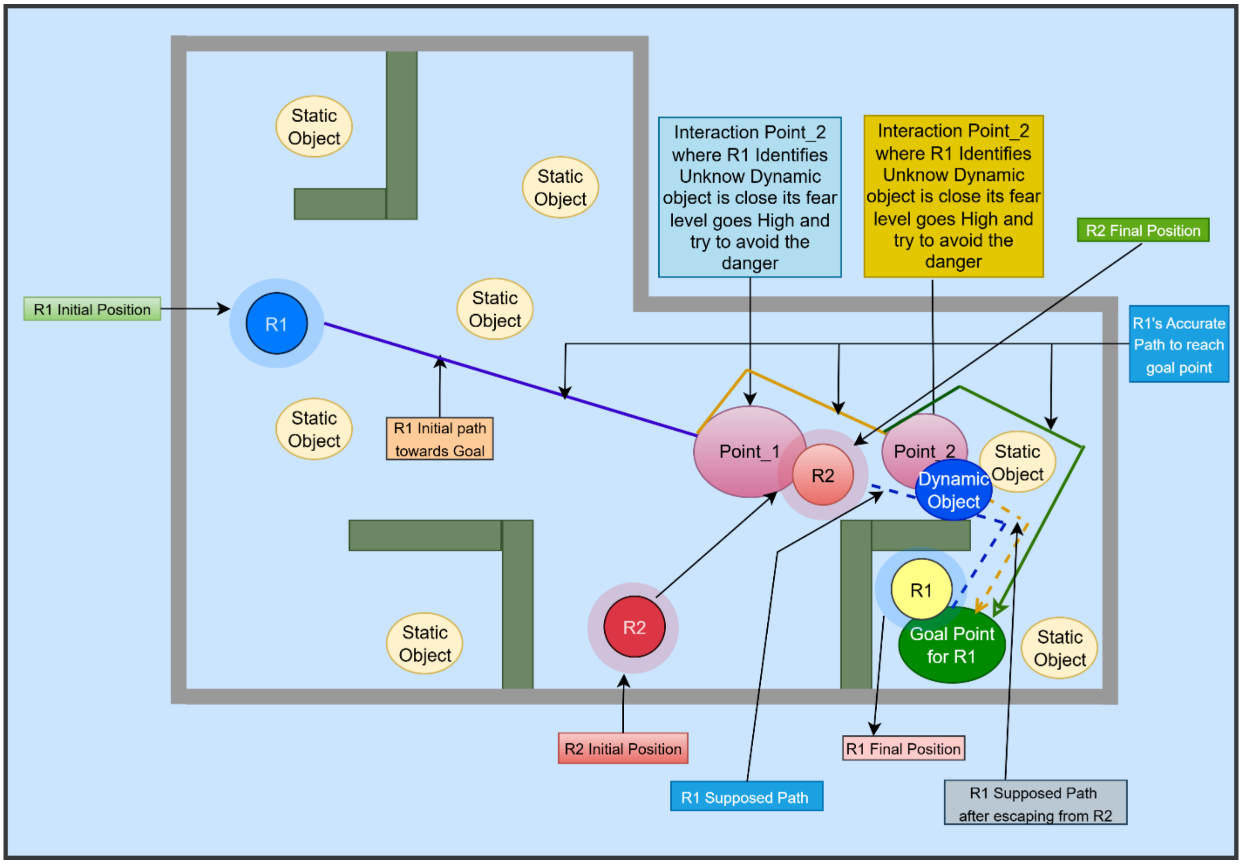

Figure 20. Visualization of Hybrid (Fuzzy Behaviour-Based Control Framework with VFF) Architecture

The simulation utilizes a range of ROS tools to ensure real-time behavioural visualization, environmental mapping, and performance monitoring: *Gazebo* provides a high-fidelity, physics-based 3D environment that models real-world constraints, including static obstacles, moving agents, and realistic robot dynamics. *RViz* serves as a visualization platform, enabling monitoring of trajectories, sensory input, and behaviour transitions in real-time. *LIDAR* sensing is integrated to offer detailed environmental scanning, forming the primary perception modality for obstacle detection and motion planning. SLAM enables the robot to construct and update an internal map of the environment while simultaneously localizing itself within that map. These maps provide the spatial foundation for both VFF force vector computation and fuzzy behavioural rule evaluation. In escape scenarios, SLAM data feeds both subsystems: The fuzzy behaviour coordination module evaluates real-time variables such as fear, threat proximity, and escape path availability. Simultaneously, the VFF module computes attractive and repulsive vectors based on mapped object locations and prioritizations set by fuzzy logic. This architecture enables Robot_1 to: Interpret the environment contextually (e.g., detect unfamiliar agents or objects), Update internal state variables (e.g., fear and escape levels), Compute motion trajectories that dynamically adjust to spatial changes, And respond with biologically inspired evasive behaviours in real-time. This tight coupling of SLAM with both behaviour coordination and vector-based navigation allows the robot to achieve fluid, autonomous adaptation, demonstrating the strength of this hybrid model in realistic, high-complexity tasks.

Figures 21(a)-(e) present a step-by-step visual sequence illustrating the robot's adaptive behaviour during a navigation task under dynamic environmental conditions. Each subfigure provides a synchronized view of both Gazebo (right pane) and RViz (left pane), offering simultaneous perspectives on the physical execution of behaviours and the sensor-based reasoning process that underpins them. This visualization approach highlights the transition of the robot from goal-directed behaviour to escape responses, governed by real-time fuzzy inference and force-based control.

The test scenario includes two mobile robotic agents Robot_1 and Robot_2 navigating within a bounded environment containing walls and static and dynamic objects. Robot_1 is assigned a navigation task from its starting position to a defined goal, while dynamically exhibiting escape behaviour in response to obstacles including Robot_2 and unexpected objects using fuzzy behaviour control with VFF.

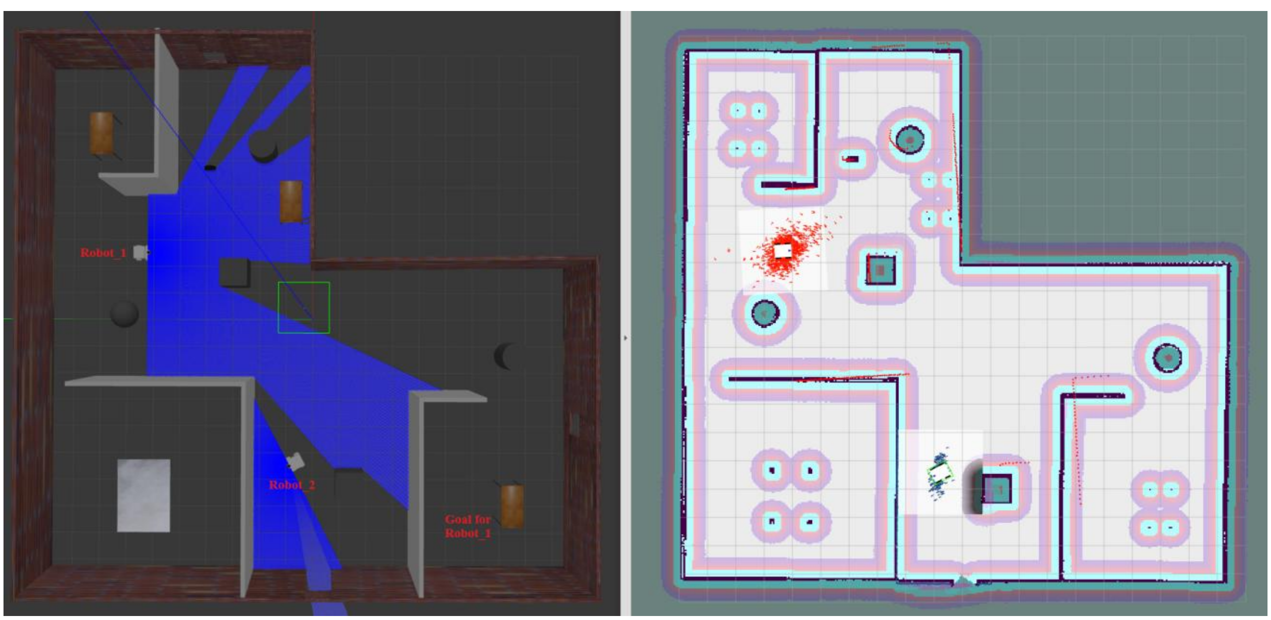

Figure 21(a). Initial Stage of Robots

Figure 21(a-b): Task Initialization and Early Navigation. *Figure 21(a)* both robots are initialized at defined starting positions. The goal location for Robot_1 is set at coordinate (5.5, 5.5). *Figure 21(b)* as Robot_1 begins its movement toward the target, Robot_2 starts to explore the environment, increasing the likelihood of an encounter and potential behavioural conflict.

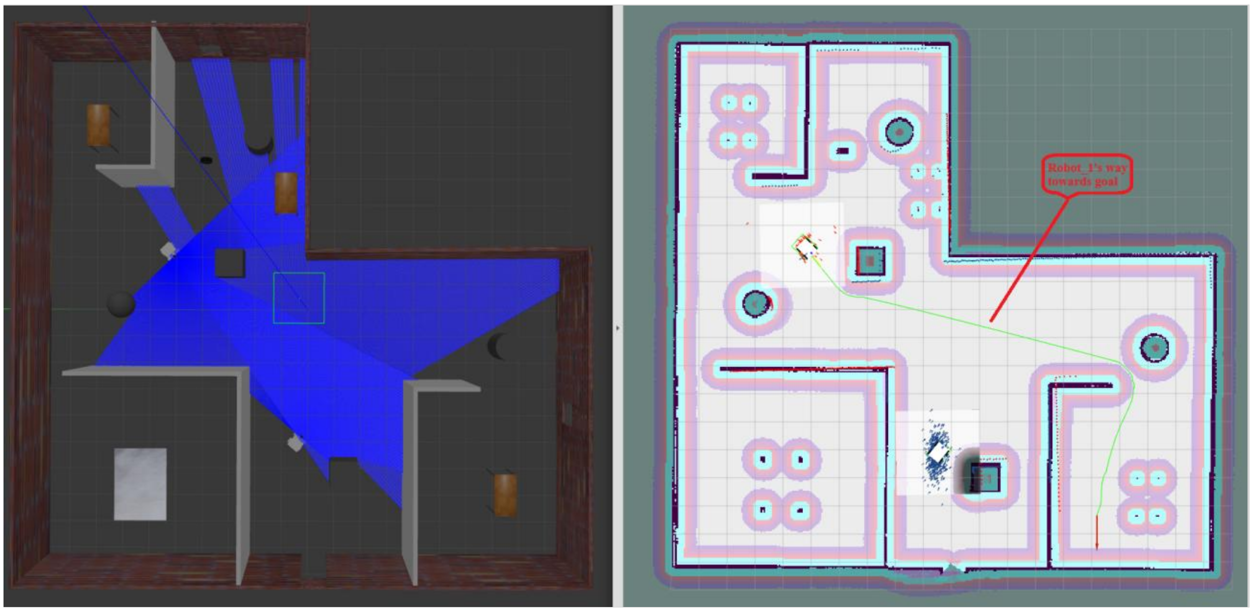

Figure 21(b). Robot_1 Starts to Move Towards its Goal.

Role of VFF and Fuzzy Coordination in Behaviour Generation: The VFF system forms the reactive motion backbone, It: Calculates attractive vectors toward the goal and computes repulsive vectors from obstacles (both static and dynamic). Continuously updates the net motion vector using real-time LIDAR data. Simultaneously, the fuzzy behaviour coordination module evaluates high-level contextual inputs such as: Fear level (derived from proximity, familiarity, etc.), Obstacle distances (e.g., ADTA, ADTO), Escape path availability (EPE). These variables trigger fuzzy rules that assign behaviour weights (e.g., increasing ESCAPE weight when danger is perceived), which are then passed to the behaviour fusion layer (VFF) to scale the attractive and repulsive vectors accordingly [Aaqib7].

As Robot_1 progresses, Robot_1 detects the approach of Robot_2 through LIDAR show in In figure 21(c). This detection, combined with unfamiliarity and decreasing distance, increases Robot_1's fear level. The fuzzy behaviour coordination system processes this input and classifies the escape level as high, meeting the triggering conditions for an escape maneuver: (i) high fear (ii) close proximity (ADTA = low) (iii) a clear escape path (EPE = high). Here, VFF supports the escape by intensifying the repulsive force vector, pushing Robot_1 away from Robot_2, while reducing the influence of the attractive force temporarily.

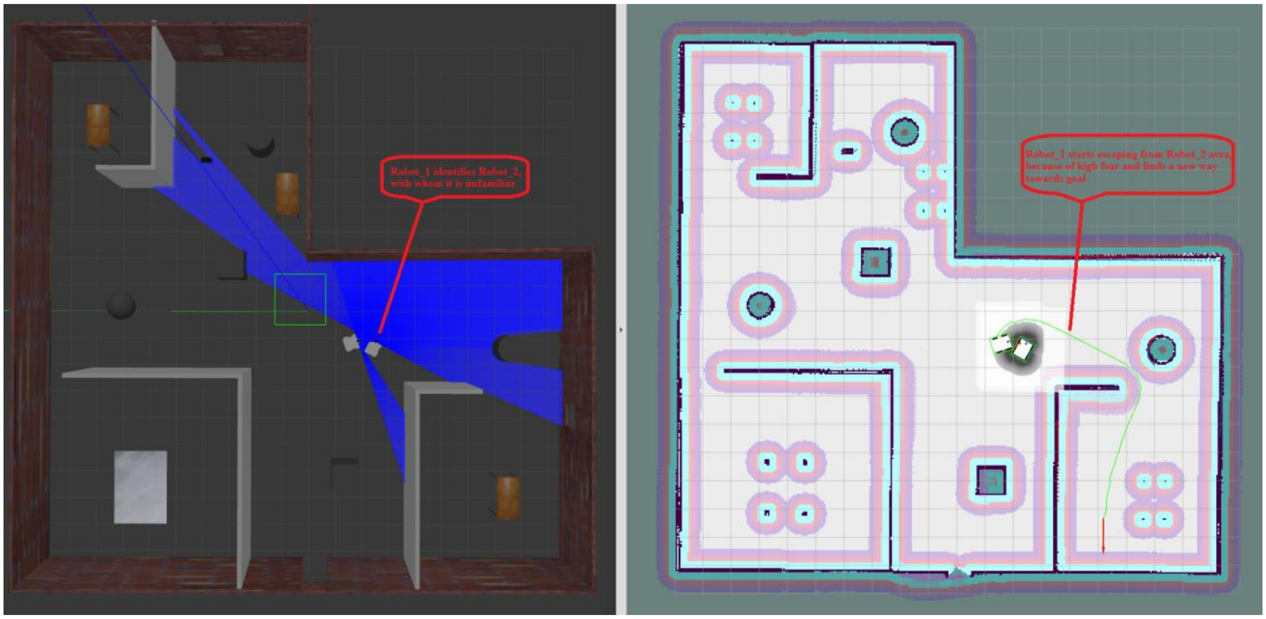

Figure 21(c). Robot_1 Detects Robot_2

The hybrid model operates in three coordinated stages: Behaviour Components, Behaviour Coordination, and Behaviour Fusion (as VFF) as described in the introduction and implementation section of this chapter. *Behaviour Components* are discrete actions Robot_1 can execute, such as escaping or goal pursuit, triggered based on real-time evaluations. Example When Robot_2 or an object is detected within close proximity, and an escape path exists, the ESCAPE behaviour is triggered.

Behaviour Coordination A fuzzy inference system assigns weights to each behaviour based on situational context. Inputs include fear level, environmental familiarity, and obstacle proximity. Example When fear level is high and escape path available is high, then the coordination system prioritizes ESCAPE behaviour with increased weight.

Behaviour Fusion (as VFF) the system merges the weighted behaviours into a single unified force vector. This involves integrating VFF outputs attractive forces toward the goal and repulsive forces from obstacles along with the fuzzy decision outcomes. This fusion ensures smooth transitions between behaviours and continuous adaptation to environmental stimuli.

As depicted in figure 21(d), after successfully evading Robot_2, Robot_1 encounters with a new unknow object. As it approaches, fear levels rise again due to reduced distance (ADTO = low), prompting another fuzzy-triggered escape. VFF adapts in real time by recalculating repulsive forces from the object and weakening the goal-attractive vector until the danger subsides. Once robot_1 escapes from object and distance between them increases the fuzzy controller redirects Robot_1 toward its goal by strengthening the attractive force vector.

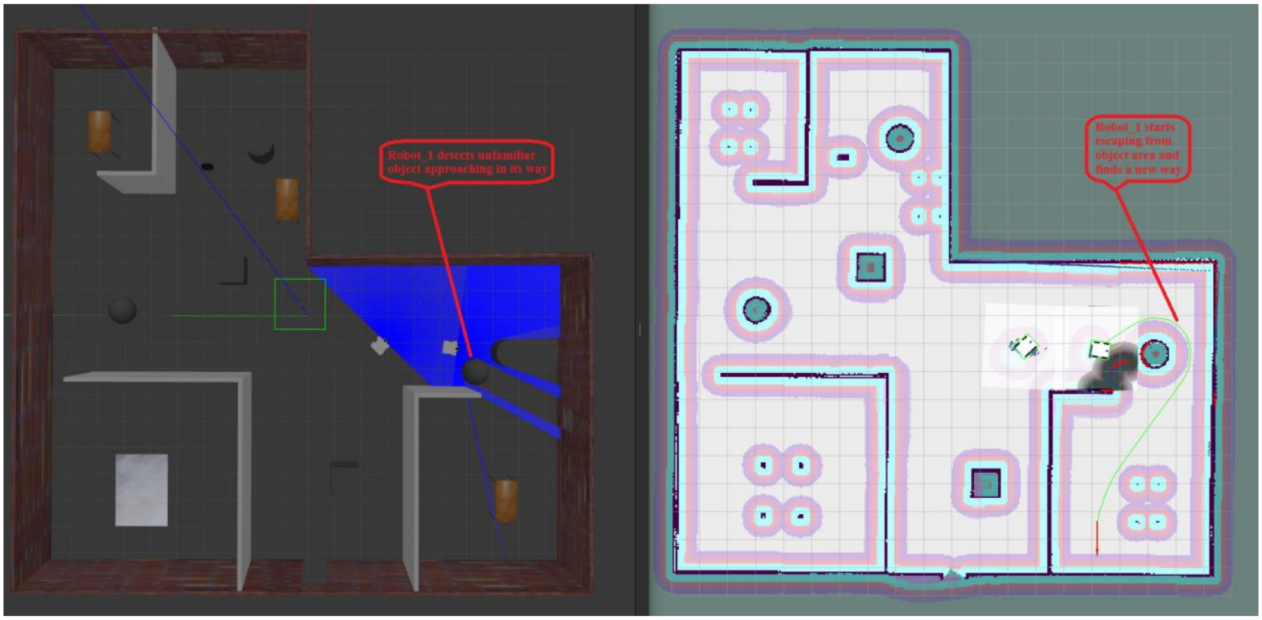

Figure 21(d). Robot_1 Object identification (the unfamiliar object that comes in its way).

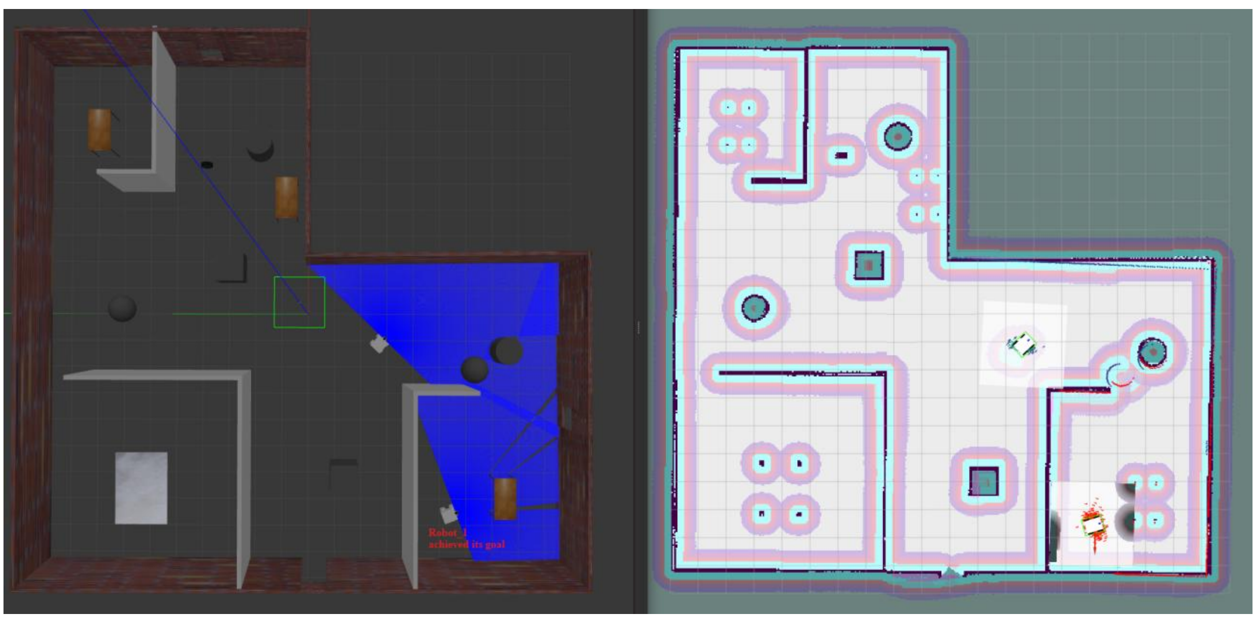

Figure 21(e). Robot_1 Successfully Achieved its Goal.

Figure 21(e) concludes the simulation by illustrating Robot_1's successful arrival at its target after dynamically avoiding both Robot_2 and an object. This outcome highlights the system's robustness in managing dynamic and unpredictable environments through a hybrid navigation model. The VFF provides continuous low-level control, generating real-time motion vectors from environmental inputs, while the fuzzy behaviour fusion system modulates these outputs based on internal states such as fear derived from sensor data. By embedding biological inspiration (fear, escape logic) into robotic control, the model demonstrates how naturalistic intelligence can be mimicked through algorithmic behaviour design.

5.9 Classification Metrics and Empirical Benchmarking

Figure 22 presents the classification performance of the proposed Fuzzy Behaviour-Based Control Framework integrated with Virtual Force Field (VFF) navigation. This hybrid architecture enhances robotic decision-making by fusing a biologically inspired fuzzy coordination layer responsible for dynamically weighting behaviours using real-time sensory inputs with the classic VFF algorithm that calculates motion vectors based on attractive (goal-directed) and repulsive (obstacle-avoidance) forces. The fuzzy-modulated behaviour scales these vectors, resulting in context-sensitive and emotionally grounded motion trajectories.

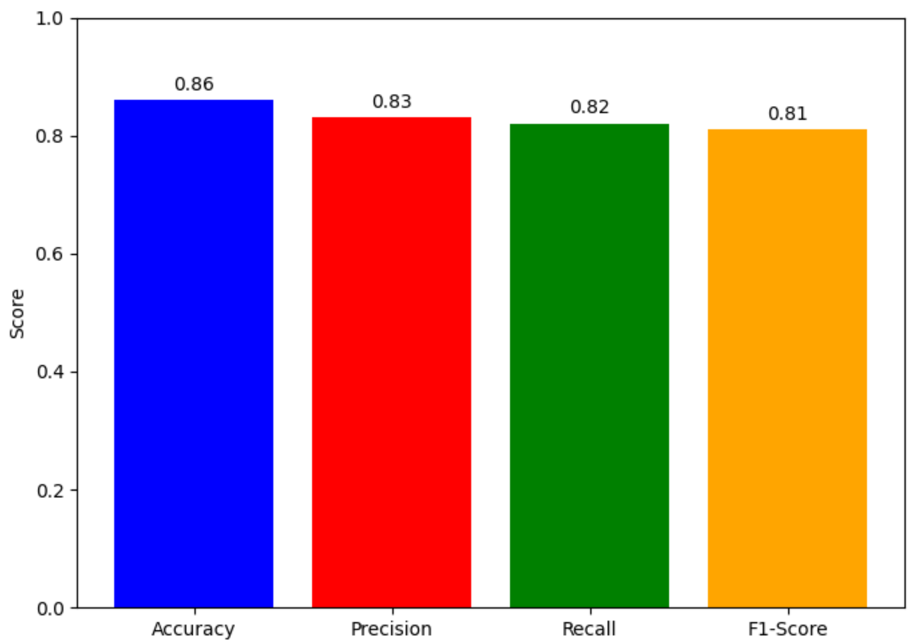

Figure 22. Classification Metrics of Hybrid Model

To rigorously assess behavioural classification performance, four key metrics accuracy, precision, recall, and F1-score were computed from 25 independent simulation trials conducted within the ROS. These trials simulated dynamic and unpredictable environments by varying obstacle layouts, robot speed, spatial proximity, and sensor inputs (e.g., AFTA, ADTA, AFTO). Behaviour selection was governed by fuzzy rules encoded in the FBDL. For example, Escape is triggered:

Rule *High* **when** “EPE” is *High* **and** “FEAR” is *High* **end**

This rule ensures that escape behaviour is triggered when high perceived threat and fear values are detected. The weighted outputs from such rules are fused with VFF vector fields to produce a single actionable motion directive. To quantify the practical benefits of the proposed system, a benchmarking study was conducted comparing the fuzzy-based framework against a traditional VFF controller, as described in canonical models [55] [56]. While classical VFF methods use fixed attractive and repulsive force equations, they often encounter issues such as local minima, trajectory oscillations, and limited adaptability in dynamic environments. Although enhancements such as behaviourally modulated VFF [49] improve responsiveness, they still lack emotional modeling, adaptive reasoning, and explainability. The comparative evaluation used key performance indicators, including task completion time, number of collisions, behaviour-switching latency, and classification accuracy for escape behaviours. As summarized in Table 5, the fuzzy-based system significantly outperformed the baseline across all metrics. To further position its contributions, Table 6 presents a conceptual comparison with three major paradigms: Subsumption Architecture, BDI Models, and Neuro-Fuzzy Systems [57] [58]. The proposed Fuzzy Ethological VFF architecture uniquely integrates biological plausibility, emotional dynamics, and real-time reactivity, bridging the gap between reactive and deliberative control strategies.

Metric	Fuzzy Behaviour-Based VFF	Baseline Reactive Controller
Task Completion Time (sec)	43.6 ± 3.5	50.3 ± 5.7
Number of Collisions	2.3 ± 1.5	3.2 ± 1.1
Behaviour Switching Latency(ms)	370 ± 35	400 ± 45
Escape Classification Accuracy	0.86	0.75

Table 5. Comparison of Fuzzy Behaviour-Based VFF with Traditional Reactive Controller

Aspect	Subsumption Architecture	BDI Models	Neuro-Fuzzy Systems	Proposed Fuzzy Ethological VFF
Behaviour Coordination	Hierarchical suppression	Symbolic reasoning	Learned rules, opaque	Fuzzy rule-based, emotion-weighted fusion
Emotional Modeling	Not supported	Indirect and abstract	Implicit, hard to trace	Directly modeled (e.g., fear, aggression)
Environmental Adaptability	Binary, high reactivity	Low in dynamic domains	Medium (data-dependent)	High (contextual and sensor-integrated)
Real-Time Adaptation	Moderate (fixed hierarchy)	Poor (high computational)	Moderate	High (interpretable and grounded)

Interpretability	Moderate	High but abstract	Low ("black box")	High (transparent fuzzy rules)
Training Data Requirements	None	Not required	Require large datasets	Not required
Obstacle Navigation Robustness	Prone to local minima	Planning-based	Sensitive to training bias	Emotionally weighted obstacle avoidance

Table 6. Comparison of Traditional vs Proposed Fuzzy Behaviour-Based VFF Navigation.

5.10 Conclusion

This study presents a hybrid navigation framework that integrates fuzzy behaviour coordination with the Virtual Force Field (VFF) method to enable adaptive and biologically inspired robotic navigation. The architecture consists of three stages: behaviour modules (e.g., Escape, Goal Pursuit), a fuzzy coordination layer that assigns contextual weights based on factors such as fear level, proximity, and environmental familiarity, and a VFF-based fusion layer that computes attractive forces toward goals and repulsive forces from obstacles. These forces, scaled by the fuzzy-assigned weights, generate a unified motion vector reflecting both environmental stimuli and internal state evaluations. Implemented in ROS with LIDAR and SLAM, the framework supports real-time, context-aware path planning in dynamic environments. Benchmarking against a traditional VFF controller showed that, unlike fixed-force methods prone to local minima, oscillations, and limited adaptability, the proposed system incorporates emotional modeling, adaptive reasoning, and explainability. A conceptual comparison with Subsumption Architecture, BDI models, and Neuro-Fuzzy Systems further confirmed its superior performance, demonstrating ethologically plausible escape behaviours, smooth action transitions, and robust decision-making under uncertainty. By combining biological plausibility with real-time reactivity, the framework bridges reactive and deliberative control, enabling scalable deployment in logistics, service robotics, and human-robot interaction.

5.11 Thesis III.

Thesis III.: This thesis proposes a novel hybrid control framework that integrates Virtual Force Field (VFF) navigation with fuzzy behaviour coordination to embed Archer's ethological model of aggression and fear into real-time robotic navigation. The approach enables mobile agents to exhibit biologically inspired, context-sensitive behaviours by modulating navigation in response to threat proximity, environmental familiarity, and escape path availability, [Aaqib1-Aaqib7].

5.11.1 Scientific Contribution

This research provides the first known integration of emotional modeling and geometric motion planning within a unified robotic control loop. Unlike traditional VFF systems with fixed force magnitudes, this framework dynamically scales repulsive vectors based on fuzzy-evaluated emotional states particularly fear. Environmental variables such as threat proximity, familiarity, and escape feasibility are processed by a fuzzy inference engine to produce affective activations. These modulate force intensities, converting binary obstacle avoidance into nuanced threat-response behaviours. The approach bridges the symbolic reasoning of fuzzy logic with the precision of vector-based motion planning, creating a biologically inspired control loop.

5.11.2 System Architecture and Mathematical Formalism

The hybrid control model comprises a dual-layered architecture integrating fuzzy emotional inference with VFF. The overall system determines the robot's behavioural response based on perceptual and affective cues and then translates that response into action using emotionally weighted motion vectors.

Fuzzy Emotional Coordination Module: This module interprets sensory and contextual inputs X={AFTA, AFTP, AFTO, EPE, ADTA} to generate behaviour activations such as Escape. These inputs are fuzzified using membership functions defined as:

Trapezoidal Membership Function (used for thresholds like EPE or familiarity):

$$\mu_{\text{Trap}}\ (x; a, b, c, d) = \begin{cases} 0 & if\ x \leq a\ or\ x \geq d \\ \frac{x-a}{b-a} & if\ a < x \leq b \\ 1 & if\ b < x \leq c \\ \frac{d-x}{d-c} & if\ c < x < d \end{cases} \qquad (4)$$

Triangular Membership Function (used for smooth variables like proximity):

$$\mu_{Tri}(x;a,b,c)=\begin{cases}0 & if\ x\ \le\ a\ or\ x\ \ge\ c\\ \frac{x-a}{b-a} & if\ a\ <\ x\ \le\ b\\ \frac{c-x}{c-b} & if\ b\ <\ x\ <\ c\end{cases} \qquad (3)$$

Rule Evaluation and Inference: Fuzzy rules are applied in the form

IF FEAR is High AND EPE is High THEN Escape is High.

The inference mechanism follows Fuzzy Rule Interpolation (FRI) using the FIVE method, suitable for sparse or incomplete rule bases. For baseline comparison in fully specified rule bases, the Mamdani max-min composition is applied. Detailed information is provided in Chapter 2-Mathematical Formalism.

$$\mu_{Bi}(x) = \max_i\ (\min_j\ \mu_{Lxj}(x_j)) \qquad (5)$$

Whereas μ_{Lxj} is the membership degree of input x_j to label L, B_i is the target behaviour (Escape)

Defuzzification Step (Centroid Method): After aggregation of multiple rule outputs, a crisp behaviour intensity *B*crisp is obtained using the centroid method:

$$B_{crisp} = \frac{\int_a^b \mu B(x)\ .\ x\ dx}{\int_a^b \mu B(x)\ dx} \qquad (6)$$

This value (e.g., Escape intensity) scales the reactive force in the VFF layer.

State Transition Dynamics: To allow graded transitions between behavioural states in a Fuzzy State Machine (FSM), state transitions are modeled probabilistically:

$$P(B_j \mid B_i, x_k) = \frac{\mu Bj(xk)}{\sum_n \mu Bn(xk)} \qquad (7)$$

This equation allows multiple behaviours to be partially activated (e.g., both escape and obstacle avoidance), enabling blended actions that reflect complex affective dynamics.

VFF Motion Control Layer: Once a behavioural decision is made, it informs the VFF motion planner. This triggers dynamic force computation:

The repulsive force from a perceived threat at (X_i, Y_i) is:

$$X_{cr} = -F_{cr}\left(\frac{X_i - X_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_o)^2}}\right) \qquad (12)$$

$$Y_{cr} = -F_{cr}\left(\frac{Y_i - Y_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_o)^2}}\right) \qquad (13)$$

The attractive force toward a goal at (H_X, H_Y) is:

$$\mathrm{X_{ca}} = \mathrm{F_a}\left(\frac{H_x - X_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}}\right) \qquad (14)$$

$$\mathrm{Y_{ca}} = \mathrm{F_a}\left(\frac{H_y - Y_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}}\right) \qquad (15)$$

The final motion vector becomes a weighted sum:

$$\vec{F}\text{result} = \vec{F}\text{attractive} + \vec{F}\text{repulsive} * \mu\text{FEAR} \qquad (16)$$

This formulation ensures that the robot's path changes not only due to geometric constraints but also due to fuzzy-evaluated emotional influence, resulting in trajectories that vary with context and intensity of perceived threat.

5.11.3 Empirical Validation and Simulation

The proposed framework was fully implemented in the ROS and evaluated using Gazebo for simulation and RViz for real-time visualization. The robot leveraged LIDAR and SLAM to autonomously map its environment and respond to dynamic threats.

Figure 22 illustrates the classification performance of the Fuzzy Behaviour-Based Control Framework integrated with VFF navigation. This hybrid model combines a biologically inspired fuzzy coordination layer responsible for dynamically assigning behaviour weights from real-time sensory inputs with the classical VFF algorithm, which computes motion vectors from attractive (goal-oriented) and repulsive (obstacle-avoidance) forces. The fuzzy-modulated weights scale these vectors, producing emotionally grounded and context-sensitive trajectories. To assess classification performance, 25 independent simulation trials in ROS. The trials covered diverse and dynamic scenarios, including variations in obstacle layout, robot velocity, spatial proximity, and sensory input (e.g., AFTA, ADTA, AFTO).

A benchmarking study compared the fuzzy-based framework to a traditional VFF reactive controller, using performance metrics such as task completion time, collision rate, behaviour-switching latency, and escape classification accuracy, see Table 5. Additionally, Table 6 presents a conceptual comparison of the proposed system with established paradigms such as Subsumption Architecture, BDI Models, and Neuro-Fuzzy Systems, highlighting the novel system's superior biological plausibility, emotional reasoning, and real-time adaptability. The Simulation (Figures 20 and 21(a)-(e)) show real-time behaviour modulation; Fearinduced repulsion steers the robot away from Robot_2 and unknown obstacles. Color-coded trajectories (blue = low fear, red = high fear) visualize internal emotional states derived from fuzzy inference. When the rule: "IF AFTA=Low AND ADTA=Low AND EPE=High THEN Escape=High" is triggered, the robot executes evasive maneuvers with increased repulsive force. All modules sensing, fuzzy logic evaluation, and motion computation are independently testable in ROS, facilitating unit-level validation and debugging.

5.11.4 Novelty and Impact

This thesis introduces a novel fuzzy-modulated force mechanism, enabling robots to adjust avoidance behaviour dynamically in response to computed fear intensity. Unlike conventional VFF systems with fixed repulsion, the proposed method scales repulsive forces through fuzzy logic inference, producing nonlinear, context-sensitive trajectories. This dynamic modulation is visually validated in Figure 20, where trajectory color shifts (blue to red) correlate with increasing fear levels and sharper evasive maneuvers.

A second key innovation lies in the direct integration of Archer's aggression-fear ethological model into the robotic control loop. By encoding emotional responses such as escape into fuzzy rule sets, the system simulates biologically grounded behaviours. These responses emerge naturally from situational inputs (e.g., threat proximity, environmental familiarity), eliminating reliance on rigid scripting.

Finally, the entire framework is fully implemented in the ROS incorporating: Fuzzy logic for emotional evaluation, VFF navigation for continuous motion control, and LIDAR sensing for obstacle detection, and SLAM for real-time localization and mapping. Simulations in Gazebo-RViz demonstrate robust, interpretable, and adaptive performance, confirming both the scientific merit and practical applicability of the approach for emotion-aware robotics.

5.11.5 Applications

The proposed hybrid control framework enables adaptive, emotionally responsive navigation in dynamic environments, with implications across various several domains:

Service Robotics: Robots dynamically adjust paths in response to perceived threats or discomfort, allowing safe and intuitive operation in crowded or unpredictable spaces.

Search and Rescue: Emotion-triggered behaviours (e.g., fear-based retreat) help agents avoid unstable or unfamiliar zones, enhancing resilience and mission success.

Human-Robot Interaction (HRI): Robots exhibit interpretable behaviours grounded in emotional models (e.g., hesitation, escape), improving social compatibility and user trust.

Swarm and Multi-Agent Systems: The system supports biologically inspired coordination among agents, applicable in cooperative drones, wildlife robotics, and group behaviour modeling.

Chapter 6: Conclusion and Future Work

6.1 Conclusion

This research has presented a comprehensive investigation into the embedding of ethologically inspired emotional behaviours specifically aggression, fear, escape, and immobility into autonomous robotic systems. Drawing from both biological models and computational intelligence, the work contributes a multi-layered framework for emotional robotics grounded in fuzzy logic, virtual force field navigation, and modular architecture. The findings are organized across three central thesis contributions:

6.1.1 Thesis I: Ethologically inspired Fuzzy Behaviour model of the Archer's "Aggression and fear in vertebrates" ethological model

This thesis proposes a novel framework that translates Archer's ethological model of aggression and fear in vertebrates into a computationally interpretable and machine-executable architecture using the "Fuzzy Behaviour Description Language".

The first contribution of this thesis establishes a novel computational framework that formalizes Archer's ethological model of aggression and fear in vertebrates using the Fuzzy Behaviour Description Language (FBDL). By translating complex behavioural triggers and responses into fuzzy linguistic variables and rule-based inference, this framework enables robotic agents to exhibit affect-like reactions that are both interpretable and dynamically modulated. The system operates in real-time, supports behavioural visualization, and is implementable on standard robotic platforms. It bridges a key gap between affective neuroscience and fuzzy control engineering, thereby contributing to the development of emotionally responsive and socially intelligent machines. The implications extend to domains such as affective computing, therapeutic robotics, and socially assistive systems, where biologically grounded emotional modeling is crucial.

6.1.2 Thesis II: Implementing Fuzzy State Machine for Behaviour control in robotic environment

This thesis presents a novel implementation of Archer's ethological model of aggression and fear into autonomous robotic systems through a fuzzy state machine architecture.

The second core contribution introduces a fuzzy state machine architecture that enables lifelike transitions between emotional states such as fear, escape, aggression, and immobility based on environmental stimuli and internal appraisal. Grounded in ethological principles and implemented in the ROS, this architecture allows robots to interpret real-time sensory inputs and dynamically select behaviour patterns appropriate to the situational context. A key component of this system is SLAM, which allows the robot to build a map of its environment while simultaneously tracking its position within it ensuring continuous localization essential for behaviour selection in dynamic settings. By leveraging modular behaviour coordination, the system supports scalable multi-agent interactions and robust behaviour arbitration. Moreover, it emphasizes transparency and ethical operability, essential for deployment in sensitive domains such as search and rescue, security surveillance, and human-robot interaction (HRI). The fuzzy state machine not only provides a technical mechanism for emotional behaviour modeling but also offers a foundation for ethical and socially aware robotic design.

6.1.3 Thesis III: Fuzzy Behaviour Based Control Framewok with Virtual Force Field Navigation

This thesis proposes a novel hybrid control framework that integrates Virtual Force Field (VFF) navigation with fuzzy behaviour coordination to embed Archer's ethological model of aggression and fear into real-time robotic navigation. The approach enables mobile agents to exhibit biologically inspired, context-sensitive behaviours by modulating navigation in response to threat proximity, environmental familiarity, and escape path availability.

The core innovation lies in how fuzzy coordination governs behaviour selection based on situational appraisals, while VFF serves as the fusion mechanism that translates weighted behaviours into motion directives. The fuzzy layer interprets emotional states particularly fear from sensor-derived inputs such as LIDAR, dynamically adjusting the influence of repulsive or attractive forces. As fear rises, repulsive forces are scaled, prompting avoidance maneuvers; as fear subsides, goal-directed motion resumes. Implemented in ROS, the system integrates SLAM for simultaneous localization and mapping, ensuring persistent environmental awareness even in dynamic, multi-agent settings. This architecture blends low-level geometric control with high-level behavioural reasoning, enabling robots to transition smoothly between goal pursuit and reactive escape. By embedding emotional logic into path planning, the model elevates robotic navigation from deterministic obstacle avoidance to intelligent, adaptive decision-making marking a significant advancement in affective robotics and human-robot interaction.

6.2 Future Work

The outcomes of this research open several promising avenues for further exploration, spanning both technical enhancements and theoretical advancements.

6.2.1 Investigating Human-Robot-Animal Behavioural Parallels

While the current work focused primarily on modeling fear and aggression based on animal ethology, future research could extend this paradigm to include other complex behaviours such as nurturing, social bonding, group coordination, dominance, and territoriality. These behaviours are central to both human and animal interactions, and their robotic analogs could significantly enrich empathetic and socially adaptive HRI systems. Studying behavioural parallels across species may also uncover deeper insights into shared cognitive-emotional frameworks, potentially leading to cross-disciplinary models of emotion that benefit both robotics and behavioural science.

6.2.2 Advancing Machine Learning Integration

Although fuzzy logic provides interpretable and controllable behaviour modeling, future work could benefit from the integration of machine learning approaches, including deep neural networks, reinforcement learning, and ensemble methods. These techniques would enable robotic agents to learn from historical experiences, improve behavioural generalization, and adapt to non-deterministic environments. Combining fuzzy systems with data-driven models could result in hybrid intelligence systems capable of both symbolic reasoning and experiential learning, thus broadening the applicability of emotional robotics in complex, real-world contexts.

6.2.3 Exploring Ethical and Societal Implications

As robotic agents begin to exhibit behaviours that simulate emotional states or responses, it becomes imperative to address the ethical, societal, and psychological dimensions of emotionally aware robotics. Future studies should examine issues such as emotional deception, user over-reliance, attribution of intent or morality, and boundaries of autonomy. Research in this direction could inform guidelines for emotionally ethical design, particularly in contexts where human safety, dignity, and agency are involved. The increasing realism of affective robots raises profound questions about trust, empathy, and responsibility, which must be carefully evaluated and regulated.

6.2.4 Expanding Sentiment and Behaviour Analysis Models

Further research is warranted in developing advanced models for sentiment detection, contextual emotion prediction, and multimodal behaviour interpretation. Incorporating data from audio, vision, tactile sensors, and environmental cues can improve the robot's ability to infer nuanced emotional states and respond appropriately. New computational frameworks that fuse these sensory channels with real-time behavioural assessment could support rich, adaptive interactions in domains ranging from caregiving and therapy to collaborative robotics and ambient intelligence. Enhanced behavioural inference would not only improve robot autonomy but also contribute to more natural and emotionally congruent human-robot relationships.

Author's Publications

Publications Related to Dissertation

Aaqib1. Lone Mohd Aaqib, Szilveszter Kovács. A Short Review on Ethological Behaviour Modelling Techniques. Multidiszciplináris Tudományok: A Miskolci Egyetem Közleménye, 15(1), 101–112, 2025, https://doi.org/10.35925/j.multi.2025.1.9

Aaqib2. Mohd Aaqib Lone, Owais Mujtaba Khanday, and Szilveszter Kovács, Implementation Guidelines for Ethologically Inspired Fuzzy Behaviour-Based Systems, Infocommunications Journal, Vol. XVI, No 3, September 2024, pp. 43-56., https://doi.org/10.36244/ICJ.2024.3.4 Q3

Aaqib3. Lone Mohd Aaqib, Owais Mujtaba Khanday, Aadil Ganie Gani. A Survey on Robot Behaviour and Distance Estimation in IndoorGML Maps Implementation. American Journal of Electronics & Communication, 1(3), 1–7, 2021. https://doi.org/10.15864/ajec.1301

Aaqib4. Lone Mohd Aaqib, Szilveszter Kovács. Implementation Guidelines for Ethologically Inspired Fuzzy Behaviour-Based Systems. In Péter Iványi (Ed.), Abstract Book for the 17th Miklós Iványi International PhD & DLA Symposium: Architectural, Engineering and Information Sciences (p. 92). Pécs, Hungary: Pollack Press, 2021.

Aaqib5. Lone Mohd Aaqib, Szilveszter Kovács. A Survey on Ethologically Oriented Fuzzy Behaviour-Based System Implementations. In Péter Iványi (Ed.), Abstract Book for the 16th Miklós Iványi International PhD & DLA Symposium (Paper 131). Pécs, Hungary: Pollack Press, 2020.

Aaqib6. Lone Mohd Aaqib, Owais Mujtaba Khanday, Aadil Ganie Gani. A Survey on Robot Behaviour and Distance Estimation in IndoorGML Maps Implementation. In Proceedings of the 18th International Conference on Emerging eLearning Technologies and Applications (ICETA 2020), ePoster Session, p. 57, 2020.

Aaqib7. Lone Mohd Aaqib, Szilveszter Kovács. Extending Virtual Force Field Navigation with Fuzzy Behaviour. International Journal of Intelligent Robotics and Applications. (*Under Review*), Q3.

Other Publications

O1. Lone Mohd Aaqib, Szilveszter Kovács. Ethologically Oriented Behaviour Modelling Methodologies. In Gabriella Vadászné Bognár, Imre Piller (Eds.), Doktoranduszok Fóruma: 2020. november 19-20. University of Miskolc.

O2. Lone Mohd Aaqib, Szilveszter Kovács. Fuzzy Rule-Based Implementation of an Ethologically Inspired Behaviour. In Gabriella Vadászné Bognár, Imre Piller (Eds.), Doktoranduszok Fóruma: 2021. november 18., University of Miskolc.

O3. Lone Mohd Aaqib, Owais Mujtaba Khanday, Aadil Ganie Gani. Survey on Indoor Navigation Solutions. Journal of Software Engineering and Intelligent Systems, 6(2), 2021.

O4. Lone Mohd Aaqib, Zsolt Tóth. Ontology Based Navigation Solutions. In Katalin Németh (Ed.), Tavaszi Szél 2019 Konferencia. Nemzetközi Multidiszciplináris Konferencia: Absztraktkötet (p. 437). Budapest, Hungary: Association of Hungarian PhD and DLA Students, 2019.

O5. Maen Alzubi, Mohammad Almseidin, Lone Mohd Aaqib, Szilveszter Kovács. Fuzzy Rule Interpolation Toolbox for the GNU Open-Source OCTAVE. In František Jakab (Ed.), Proceedings of the 17th International Conference on Emerging eLearning Technologies and Applications (ICETA 2019), pp. 16–22. Piscataway, NJ, USA: IEEE, 2019.

O6. Lone Mohd Aaqib, Zsolt Tóth. Distance Estimation in IndoorGML Maps. In Vanda Éva Molnár (Ed.), Az elmélet és a gyakorlat találkozása a térinformatikában X.: Theory Meets Practice in GIS (pp. 9–18). Debrecen, Hungary: Debreceni Egyetemi Kiadó, 2019.

O7. Owais Mujtaba Khanday, Samad Dadvandipour, Lone Mohd Aaqib. Effect of Filter Sizes on Image Classification in CNN: A Case Study on CIFAR-10 and Fashion-MNIST Datasets. IAES International Journal of Artificial Intelligence, 10(4), 872–878, 2021.

O8. Aadil Ganie Gani, Samad Dadvandipour, Lone Mohd Aaqib. Detection of Semantic Obsessive Text in Multimedia Using Machine and Deep Learning Techniques and Algorithms. Journal of Theoretical and Applied Information Technology, 99(11), 2567–2577, 2021.

O9. Aadil Ganie Gani, Samad Dadvandipour, Lone Mohd Aaqib, Owais Mujtaba Khanday. Covid-19 Situation in Hungary Using Time Series Analysis. In Proceedings of the International Conference on Advances in Communication Technology, Computing and Engineering (ICACTCE’21), pp. 1–4, 2021.

O10. Owais Mujtaba Khanday, Samad Dadvandipour, Lone Mohd Aaqib. Forecasting the Spread of COVID-19 in Hungary. Preprint, 2020.

References

1. Lehner, P.N., 1998. Handbook of ethological methods. Cambridge University Press.
2. McFarland, D., Bösser, T. and Bosser, T., 1993. Intelligent behaviour in animals and robots. Mit Press.
3. Miklósi Á, Korondi P, Matellán V and Gácsi M (2017) Ethorobotics: A New Approach to Human-Robot Relationship. Front. Psychol. 8:958. doi: 10.3389/fpsyg.2017.00958.
4. Piller, I., Kovács, Sz.: Fuzzy Behaviour Description Language: A Declarative Language for Interpolative Behaviour Modeling. In: ACTA POLYTECHNICA HUNGARICA 16:9, 2019, pp.47-72.
5. Archer, J. "The organisation of aggression and fear in vertebrates; in Perspeaives in Ethology" - Vol. 2 (eds P.P.G. Bateson and P. Klopfer), Plenum Press, New York, 1976. pp. 231-298.
6. Taylor, Charles, and Alva Noë. The explanation of behaviour. Routledge, 2021.
7. Michaud, François, and Monica Nicolescu. "Behaviour-based systems." Springer handbook of robotics (2016): 307-328.
8. Huntingford, F. ed., 2012. The study of animal behaviour. Springer Science & Business Media.
9. Bateson, Patrick, and Kevin N. Laland. "Tinbergen's four questions: an appreciation and an update." Trends in ecology & evolution 28.12 (2013): 712-718.
10. Abdai, Judit, and Ádám Miklósi, eds. An introduction to Ethorobotics: robotics and the study of animal behaviour. Taylor & Francis, 2024.
11. Vincze, Dávid, et al. "Ethologically inspired human-robot interaction interfaces." Proceedings of the 2012 Joint International Conference on Human-Centered Computer Environments. 2012.
12. Sugeno, M., 1985. An introductory survey of fuzzy control. Information sciences, 36(1-2), pp.59-83.
13. Maghzaoui, Ahlem, Emna Aridhi, and Abdelkader Mami. "Fuzzy Control of Mobile Robot Speed for Safe and Adaptive Navigation." 2023 IEEE Third International Conference on Signal, Control and Communication (SCC). IEEE, 2023.
14. Siciliano, Bruno, and Oussama Khatib, eds. Springer handbook of robotics. Springer, 2016.
15. Lei, Bin, and Wenfeng Li. "A fuzzy behaviours fusion algorithm for mobile robot real-time path planning in unknown environment." 2007 IEEE International Conference on Integration Technology. IEEE, 2007.
16. Nakhaeinia, Danial, et al. "A hybrid control architecture for autonomous mobile robot navigation in unknown dynamic environment." 2015 IEEE International Conference on Automation Science and Engineering (CASE). IEEE, 2015.

17. Towle, Bradford A., and Monica Nicolescu. "Real-world implementation of an Auction Behaviour-Based Robotic Architecture (ABBRA)." 2012 IEEE International Conference on Technologies for Practical Robot Applications (TePRA). IEEE, 2012.
18. Ronald C. Arkin. Behaviour-based robotics. MIT Press, 1998.
19. Vásconez, Juan Pablo, et al. "A Behaviour-Based Fuzzy Control System for Mobile Robot Navigation: Design and Assessment." International Conference on Advanced Research in Technologies, Information, Innovation and Sustainability. Cham: Springer Nature Switzerland, 2023.
20. Vincze, Dávid, et al. "A novel application of the 3d virca environment: Modeling a standard ethological test of dog-human interactions." Acta Polytechnica Hungarica 9.1 (2012): 107-120.
21. Mo, Hongwei, Qirong Tang, and Longlong Meng. "Behaviour-Based Fuzzy Control for Mobile Robot Navigation." Mathematical problems in engineering 2013.1 (2013): 561451.
22. Primova, H. A., D. T. Mukhamedieva, and L. Safarova. "Application of Algorithm of Fuzzy Rule Conclusions in Determination of Animal's Diseases." Journal of Physics: Conference Series. Vol. 2224. No. 1. IOP Publishing, 2022.
23. Sandeep, B. S., and P. Supriya. "Analysis of fuzzy rules for robot path planning." 2016 international conference on advances in computing, communications and informatics (ICACCI). IEEE, 2016.
24. Kovács, Szilveszter. "Interpolative fuzzy reasoning in behaviour-based control." Computational Intelligence, Theory and Applications: International Conference 8th Fuzzy Days in Dortmund, Germany, Sept. 29–Oct. 01, 2004 Proceedings. Springer Berlin Heidelberg, 2005.
25. Benbouabdallah, Karim, and Zhu Qi-dan. "A fuzzy logic behaviour architecture controller for a mobile robot path planning in multi-obstacles environment." Research Journal of Applied Sciences, Engineering and Technology 5.14 (2013): 3835-3842.
26. Chang, Hyunjin, and Taeseok Jin. "Command fusion based fuzzy controller design for moving obstacle avoidance of mobile robot." Future Information Communication Technology and Applications: ICFICE 2013 (2013): 905-913.
27. Oliveira, Leandro Daros, and Armando Alves Neto. "Comparative Analysis of Fuzzy Inference Systems Applications on Mobile Robot Navigation in Unknown Environments." 2023 Latin American Robotics Symposium (LARS), 2023 Brazilian Symposium on Robotics (SBR), and 2023 Workshop on Robotics in Education (WRE). IEEE, 2023.
28. Abduljabbar, Abduljabbar Khudhur, Yousif Al Mashhadany, and Sameer Algburi. "High-Performance of Mobile Robot Behaviour Based on Intelligent System." 2023 16th International Conference on Developments in eSystems Engineering (DeSE). IEEE, 2023.

29. Jeong, Youngwoo, et al. "The Design of Embedded Fuzzy Logic Controller for Autonomous Mobile Robots." 2023 20th International SoC Design Conference (ISOCC). IEEE, 2023.
30. Brooks, Rodney. "A robust layered control system for a mobile robot." IEEE journal on robotics and automation 2.1 (2003): 14-23.
31. Rao, Anand S., and Michael P. Georgeff. "BDI agents: From theory to practice." Icmas. Vol. 95. 1995.
32. Jang, Jyh-Shing Roger, Chuen-Tsai Sun, and Eiji Mizutani. "Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]." IEEE Transactions on automatic control 42.10 (1997): 1482-1484.
33. Izumi, Kiyotaka, Keigo Watanabe, and T. Miyazaki. "Fuzzy behaviour-based control for a miniature mobile robot." 1998 Second International Conference. Knowledge-Based Intelligent Electronic Systems. Proceedings KES'98 (Cat. No. 98EX111). Vol. 3. IEEE, 1998.
34. Vadakkepat, Prahlad, et al. "Fuzzy behaviour-based control of mobile robots." IEEE Transactions on Fuzzy Systems 12.4 (2004): 559-565
35. KOVÁCS, SZ, KÓCZY, L.T.: Approximate Fuzzy Reasoning Based on Interpolation in the Vague Environment of the Fuzzy Rule base as a Practical Alternative of the Classical CRI, Proceedings of the 7th International Fuzzy Systems Association World Congress, Prague, Czech Republic, (1997) 144-149.
36. Alzubi, Maen, et al. "Fuzzy rule interpolation toolbox for the GNU open-source OCTAVE." 2019 17th International Conference on Emerging eLearning Technologies and Applications (ICETA). IEEE, 2019.
37. Piller, I.: EXPRAIL: https://github.com/piller-imre/exprail-python
38. Piller, I.: FRIBE: https://github.com/piller-imre/fribe-python
39. Koubaa, Anis, ed. Robot Operating System (ROS). Vol. 1. Cham, Switzerland: Springer, 2017.
40. Macenski, Steven, et al. "Robot operating system 2: Design, architecture, and uses in the wild." Science robotics 7.66 (2022): eabm6074.
41. Gul, F., Rahiman, W. and Nazli Alhady, S.S., 2019. A comprehensive study for robot navigation techniques. Cogent Engineering, 6(1), p.1632046.
42. Pronobis and B. Caputo. "COLD: cosy localization database," The International Journal of Robotics Research, vol. 28, no. 5, pp. 588-594, May 2009.
43. Scovanner, P. and Tappen, M.F., 2009, September. Learning pedestrian dynamics from the real world. In 2009 IEEE 12th International Conference on Computer Vision (pp. 381-388). IEEE.
44. Drew, Daniel S. "Multi-agent systems for search and rescue applications." Current Robotics Reports 2 (2021): 189-200.

45. Skarmeta, Antonio Gómez, Humberto Martínez Barberá, and Manuel Sánchez Alonso. "Learning behaviour fusion in autonomous mobile robots." IX ESTYLF 99 (1999).
46. Gyawali, Pratik, and Praveen Kumar Agarwal. "Fuzzy behaviour based mobile robot navigation in static environment." 2018 IEEE Recent Advances in Intelligent Computational Systems (RAICS). IEEE, 2018.
47. Zadeh, Lotfi Asker. "Fuzzy sets as a basis for a theory of possibility." Fuzzy sets and systems 1.1 (1978): 3-28.
48. Hong, Tang Sai, Danial Nakhaeinia, and Babak Karasfi. "Application of fuzzy logic in mobile robot navigation." Fuzzy Logic-Controls, Concepts, Theories and Applications (2012): 21-36.
49. Nia, D. Nakhaei, et al. "Virtual force field algorithm for a behaviour-based autonomous robot in unknown environments." Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering 225.1 (2011): 51-62.
50. Jom J. Kandathil1, Robins Mathew1, and Somashekhar S. Hiremath Modified bug-1 algorithm-based strategy for obstacle avoidance in the multi-robot system.
51. K.-S. Tseng and C.-W. Tang, "Stream field based people searching and tracking conditioned on SLAM," IEEE International Conference on Robotics and Automation Workshop on People Detection and Tracking, May 2009.
52. VWang, Meng, and James NK Liu. "Fuzzy logic-based real-time robot navigation in unknown environment with dead ends." Robotics and autonomous systems 56.7 (2008): 625-643.
53. Sun, Q., Guo, Y., Fu, R., Wang, C. and Yuan, W., 2020. Human-Like Obstacle Avoidance Trajectory Planning and Tracking Model for Autonomous Vehicles That Considers the Driver's Operation Characteristics. Sensors, 20(17), p.4821.
54. J. Borenstein, Member, IEEE, and Y. Koren,' Real-time Obstacle Avoidance for Fast Mobile Robots, 1989 IEEE. Reprinted, with permission, from IEEE Transactions on Systems, Man, and Cybernetics, Vol. 19, No.5, Sept./Oct. 1989, pp. 1179-1187.
55. Khatib, Oussama. "Real-time obstacle avoidance for manipulators and mobile robots." The international journal of robotics research 5.1 (1986): 90-98.
56. Ge, Shuzhi Sam, and Yun J. Cui. "Dynamic motion planning for mobile robots using potential field method." Autonomous robots 13.3 (2002): 207-222.
57. Ni, Jianjun, et al. "An improved VFF approach for robot path planning in unknown and dynamic environments." Mathematical Problems in Engineering 2014.1 (2014): 461237.
58. Chong, Hui-Qing, Ah-Hwee Tan, and Gee-Wah Ng. "Integrated cognitive architectures: a survey." Artificial Intelligence Review 28.2 (2007): 103-130.