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ETHOLOGICALLY INSPIRED FUZZY BEHAVIOUR-BASED SYSTEMS

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Prepared by

Mohd Aaqib Lone

BACHELOR OF INFORMATION TECHNOLOGY

MASTER OF COMPUTER SCIENCE

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Head of Doctoral School

Prof. Dr. László Kovács

Full Professor

Scientific Supervisor

Prof. Dr. Szilveszter Kovacs,

Associate Professor

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List of Abbreviations and Symbols

FBDL	Fuzzy Behavior Description Language
FSM	Fuzzy State Machine
FLC	Fuzzy Logic Controller
FBBS	Fuzzy Behavior-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
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 behavior 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, behaviorally 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 behavior that is both functionally intelligent and socially interpretable. The central argument of this work is that embedding emotional constructs into machine behavior 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 behavioral execution, visual tracking of emotion-driven behavioral 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 behavior 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 behavioral 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 behavior 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 behavioral 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 behavior, the nuanced complexity of the ethological systems that inspired them.

Chapter 1: Introduction

1.1 Overview

In recent years, there has been a growing convergence between ethology the scientific study of animal behavior and the fields of robotics and artificial intelligence. This convergence reflects a compelling vision: designing machines that do not simply function mechanically, but behave adaptively and intelligently, inspired by nature's most refined evolutionary strategies. Ethology examines diverse behaviors such as communication, predation, defense, and aggression, both in wild habitats and under experimental conditions, providing an invaluable blueprint for navigating complex, unpredictable real-world environments [1].

At the heart of ethological modeling lies the empirical analysis of observable animal behavior, culminating in developing robust, behavior-based models [2]. These models, grounded in systematic naturalistic observation, have increasingly informed the design of intelligent robotic systems by enabling the decomposition of complex tasks into modular, behavior-oriented components. This interdisciplinary domain referred to as Ethorobotics [3] represents the convergence of ethology, robotics, and fuzzy logic. It provides the theoretical foundation for this research by translating biologically derived behavioral strategies into adaptive robotic control architectures, ultimately bridging the gap between natural intelligence and artificial autonomy.

This work introduces an innovative methodology known as the Fuzzy Behavior Description Language (FBDL) [4], to describe and analyze aggression models drawn from animal behavior research, particularly based on Archer's observation-based ethological framework [5]. FBDL leverages the power of fuzzy set theory and logic to capture the subtleties of aggression how it arises from internal values, external stimuli, and situational contexts. Before delving deeper, it is vital to understand that "behavior" in this research refers to the repertoire of actions and reactions that living organisms or artificial agents demonstrate in response to environmental stimuli [6].

By adopting a behavior-based architecture, intelligent robots acquire the capacity to manage complex tasks through the coordination of simple, purpose-driven behavioral components [7]. In the context of autonomous navigation, for instance, these components may include discrete modules such as path-following, obstacle avoidance, and goal-seeking, each functionally independent yet cohesively integrated within the control system. This modular design confers significant advantages in flexibility and adaptability, enabling robotic agents to operate effectively in dynamic, unpredictable environments while maintaining robust performance across a range of mission scenarios.

1.2 History

Ethology provides valuable insights into how species interact with their natural environments [8]. One of the key contributors to this field, Nikolaas Tinbergen, developed a comprehensive framework for analyzing animal behavior, structured around four fundamental questions [9]:

Function of Behavior: This aspect explores, "What purpose does the behavior serve for the animal?" It examines how specific behaviors enhance survival and reproductive success. Critical behaviors such as foraging, predator avoidance, and mating displays are analyzed to understand their adaptive significance. For instance, birds often use songs to attract mates, while fish may exhibit vibrant coloration during courtship. Understanding the function of behavior helps reveal how these actions contribute to an organism’s fitness within its ecological niche.

Mechanism Behind Behavior: This dimension addresses, "How does the behavior occur?" It investigates the underlying physiological and neurological processes, including brain activity, hormonal regulation, and sensory systems. Examples include studying hormonal changes during mating seasons in birds or the neural mechanisms governing social interaction in primates. This approach illuminates the biological systems that generate observable behaviors.

Evolutionary History of Behavior: This perspective asks, "How did the behavior evolve?" It examines the phylogenetic origins and historical development of behaviors across species, offering insights into evolutionary adaptations. For example, comparative studies of mating rituals in birds highlight how similar behaviors have diversified through evolutionary processes. This perspective sheds light on long-standing evolutionary pressures that shape behavioral repertoires.

Ontogeny of Behavior: This aspect focuses on, "How does behavior develop throughout an organism's lifetime?" It explores the interplay between genetic predispositions and environmental influences from infancy through adulthood. Research examples include how juvenile birds learn songs by imitating adult models or how young primates develop social skills through group interaction. Understanding ontogeny provides a detailed view of behavioral maturation processes.

Ethology serves as a foundational discipline for developing robotic behavior models that seek to emulate the efficiency and adaptability of biological systems [10]. Various domains within ethology such as aggression, defense strategies, and communication offer critical insights that guide the design of robotic behaviors. Applying these insights enables the creation of robotic systems that are both practical and ethically informed [11]. Understanding animal behavior is essential not only for advancing biological knowledge but also for ensuring that robots can address real-world challenges while adhering to ethical standards.

This research work applies fuzzy logic, fuzzy behavior modeling to simulate the aggressive behaviors observed in animals. Fuzzy logic is a computational paradigm adept at handling uncertainty and imprecision, assigns degrees of truth to inputs, enabling robots to respond flexibly rather than rigidly. Its applications span numerous fields, including automotive control systems and environmental management.

A prominent example of its application is the Fuzzy State Machine (FSM), which integrates fuzzy logic into robotic decision-making to manage uncertainties inherent in dynamic environments [12]. Unlike traditional finite state machines that rely on rigid state transitions, FSMs define transitions based on fuzzy rules, allowing for smooth, gradual behavioral shifts. This approach reduces the risks associated with abrupt behavioral changes and enhances resilience and adaptability [13].

Robotic behavior can be described using several control architectures, including deliberative, reactive, hybrid, and behavior-based methods [14]. Fuzzy logic, with its high accuracy in reasoning under uncertainty, has proven invaluable in managing robotic systems effectively. This research explores the implementation of fuzzy logic for simulating aggressive animal behaviors, aiming to enhance the realism and responsiveness of robotic models.

In deliberative control, robots determine their next actions by analyzing past experiences combined with current sensory data. Often referred to as "Think Then Act," this method requires the robot to gather environmental information, reason about possible outcomes, and formulate a plan before executing an action [14]. Symbolic world models are created internally, allowing the robot to reason abstractly about its surroundings. Although deliberative control allows for optimized and calculated decision-making, it typically involves longer processing times, which may limit responsiveness in highly dynamic environments.

Reactive control, by contrast, is based on a direct mapping between sensory inputs and motor outputs. Termed "Don't Think, Just Act," this approach does not involve complex reasoning or symbolic modeling. Instead, robots using reactive control rely on pre-programmed rules to produce immediate responses, making them particularly effective in unpredictable and rapidly changing environments [15]. The simplicity of reactive systems enables quick adaptation, though sometimes at the expense of long-term strategy or flexibility.

Hybrid control seeks to combine the strengths of both deliberative and reactive approaches [16]. This strategy, known as "Simultaneously Think and Act," enables robots to make rational decisions when time permits, while still allowing for instant reactions when immediate challenges arise, such as obstacle avoidance. Typically, hybrid systems involve a layered architecture where the deliberative layer plans long-term actions based on abstract representations, and the reactive layer deals with real-time interactions. Coordination between these layers ensures that robots can achieve cohesive and effective behavior, even when facing unforeseen events.

Another important control paradigm is the behavior-based control approach [17]. This method organizes robotic systems into multiple distributed modules, known as behaviors, that operate concurrently and interact dynamically. Following the principle "Think the Way You Act," robots develop adaptive responses through trial-and-error interactions with the environment. Each behavior module processes specific sensory inputs and produces outputs that influence other behaviors or directly control the robot's actuators. Behavior-based systems offer high flexibility and robustness, making them particularly suitable for complex, dynamic environments [18], [19].

Building upon these control frameworks, this study develops robotic behavior models that replicate animal aggression based on Archer's ethological model [5]. These models aim to accurately simulate aggression patterns observed in animals, including behaviors associated with fear, escape, attack, immobility, and the recognition of familiar versus unfamiliar individuals. Designing such models necessitates a thorough analysis of animal interactions, proximity responses, and the influence of past experiences.

For example, when encountering an unfamiliar animal, many species exhibit a pronounced fear response, often culminating to flee. Robotic systems can replicate these physiological and behavioral reactions, enabling realistic responses to perceived threats. Similarly, aggressive behaviors such as posturing, vocalizations, and physical attacks can be studied, encoded, and integrated into robotic control architectures to mimic animal-like attack responses.

Moreover, incorporating recognition algorithms is crucial for enabling robots to distinguish between known and unknown entities in their environment. When combined with mapping and navigation tools, these algorithms allow robots to navigate their surroundings intelligently, avoid obstacles, and adjust their behavior based on environmental familiarity. Collectively, these features ensure that the robotic models developed are not only functionally effective but also realistically emulate the complex dynamics of natural animal aggression across diverse operational scenarios.

1.3 Motivation

The motivation for "Implementing Ethologically Inspired Fuzzy Behaviour-Based Systems" comes from the desire to make robotic system behave more naturally, particularly 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 for dynamic, real-world conditions. In contrast, animals demonstrate a wide range of adaptive behaviors such as escaping, freezing, or displaying aggression that are context-sensitive and evolutionarily refined. These behaviors reflect not just mechanical reactions but emotional and situational assessments that contribute to survival. The aim is to create machines 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 design robots that can interpret and react to their environment in ways that mimic animal decision-making under stress. By integrating principles from ethology, fuzzy behavior-based control, and Virtual Force Field navigation, the system enables robots to make graded decisions based on continuous variables such as perceived threat levels, proximity, and environmental familiarity instead of rigid rules.

Beyond technical innovation, this work moves toward building emotionally aware, context-sensitive robotic systems. Such robots are well-suited for applications like search and rescue, where rapid, instinct-like responses are critical, or human-robot interaction, where socially intelligent behavior enhances safety and trust. By simulating emotional behavior computationally, the research also supports ethical progress, potentially reducing the need for animal-based behavioral experiments. Ultimately, this work aspires to create robotic systems that blend computational precision with the fluid adaptability of biological intelligence.

1.4 Methodology

To build an emotionally aware and behaviorally intelligent robotic system, this research integrates principles from animal behavior science, fuzzy behavior systems, and robotics [20]. The framework is primarily inspired by Archer's ethological model of aggression and fear [5], which forms the central conceptual foundation of this study. Additional behavioral insights are drawn from the dynamics observed in human-animal interactions [21], reinforcing the system's grounding in real-world behavioral contexts.

At the core of the system lies a fuzzy behavior-based control architecture, modeled on Archer's framework. This architecture processes multiple environmental factors including the distance to other agents, environmental familiarity, and the availability of escape routes using fuzzy logic to determine behavioral intensity. Rather than using binary commands, the system applies fuzzy rules to evaluate how strongly the robot should respond in a given situation, such as whether to escape, pause, or proceed toward a goal.

Behavioral decision-making is defined using the Fuzzy Behaviour Description Language (FBDL) [4], which provides a modular and human-readable method for encoding fuzzy rules. This allows real-time, flexible behavior modulation, replacing traditional rigid schemes with context-sensitive evaluations. The resulting behavioral outputs are passed to the Virtual Force Field (VFF) navigation module, which computes attractive and repulsive forces for motion control. A key innovation of this model is that the repulsive force vector is dynamically scaled based on internal emotional states like "fear," enabling adaptive avoidance behaviors that reflect the intensity of perceived threats.

The system is implemented within the Robot Operating System (ROS), simulated using Gazebo, and visualized in RViz. Environmental sensing is achieved through LIDAR and sonar, while Simultaneous Localization and Mapping (SLAM) enables the robot to build and update its internal map in real time. Together, these components empower the robot to interpret and respond to its surroundings with contextual awareness and emotional nuance, achieving a robust and biologically inspired model of autonomous navigation.

Chapter 2: Ethologically Inspired Fuzzy Behaviour Model

2.1 Ethology

Ethology, the scientific study of animal behavior, focuses on how animals interact with their environment and with one another [1]. Ethological models are critical for understanding and predicting behavior patterns and have become foundational elements for developing behavior-based robotic control systems. These models operate on the principle that natural selection favors behaviors 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 behavior systems. Pioneering ethologists such as Baerends, Tinbergen, and Lorenz developed foundational frameworks for describing animal behaviors, 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 behavioral theories through synthetic implementations.

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 behaviors, whereas robotics seeks to recreate and operationalize these behaviors 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 behavior models in both biological and synthetic systems [2].

2.2 Fuzzy Behavior-Based Systems

One effective approach to implementing ethologically inspired behavioral models in robotics is through Fuzzy Behavior-Based Systems [22]. 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 behaviors observed in animals such as avoidance, aggression, and exploration. Individual behavior units control these actions, and fuzzy rules integrate their outputs to ensure coherent system performance. A Fuzzy Behavior-

Based System is essentially constructed upon a framework of fuzzy rule-based systems, which are particularly effective for modeling animal behavior and designing autonomous systems that must adapt to evolving environments [23], [24].

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 behavioral 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 behavior transitions based on environmental conditions.

The architecture of a Fuzzy Behavior-based System [25] comprises several key modules, including Behavior Coordination (or Arbitration), Behavior Fusion, and individual Component Behaviors. Each module and its respective behaviors are implemented as fuzzy rule-based systems, also called Fuzzy Logic Controllers (FLCs), as depicted in Figure 1.

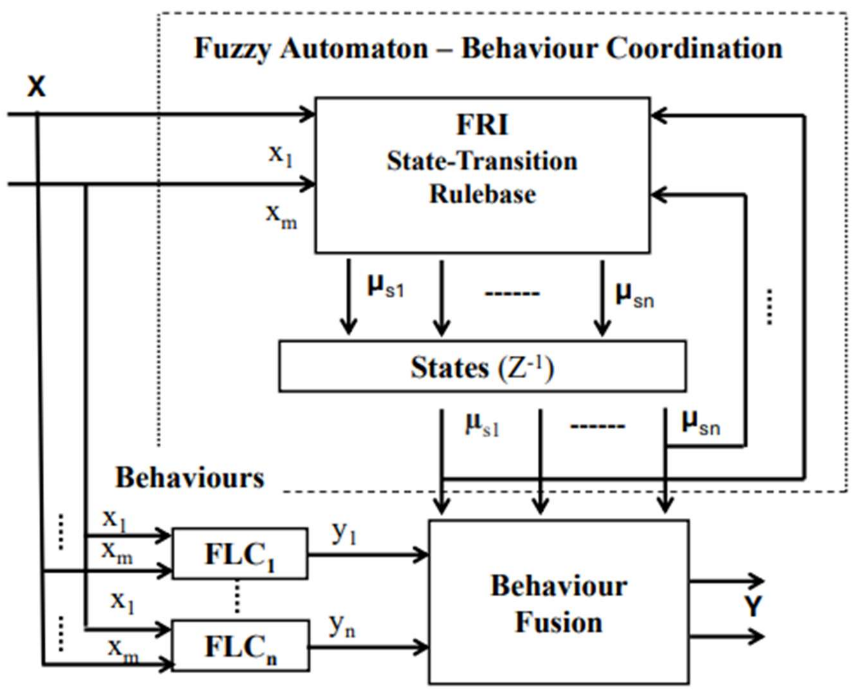

Figure 1. The applied Fuzzy Behaviour-based System [25]

Behavior Coordination plays a critical role in determining which behavior should control the robot's actions at any given time. This selection is based on the system's current objectives and external conditions. Also known as arbitration, this technique is widely used in autonomous system design, especially in robotics, to address conflicts arising from multiple active behaviors competing for resources or interfering with one another. Behavior coordination mechanisms resolve these conflicts by prioritizing tasks and allocating resources, ensuring smooth and efficient system operation.

Various methods exist for behavior coordination, each with distinct strengths and limitations. A commonly employed method is the hierarchical approach, where behaviors are arranged in a hierarchy, giving higher precedence to critical tasks. In this approach, the system overrides the lower-priority actions if lower-priority behaviors conflict with higher-priority ones. In some scenarios, multiple behaviors may operate simultaneously, requiring a context-sensitive blending of outputs. This is illustrated in Figure 2, where fuzzy behavior coordination integrates multiple behaviors such as target tracking and obstacle avoidance by dynamically adjusting decisions based on current conditions [26].

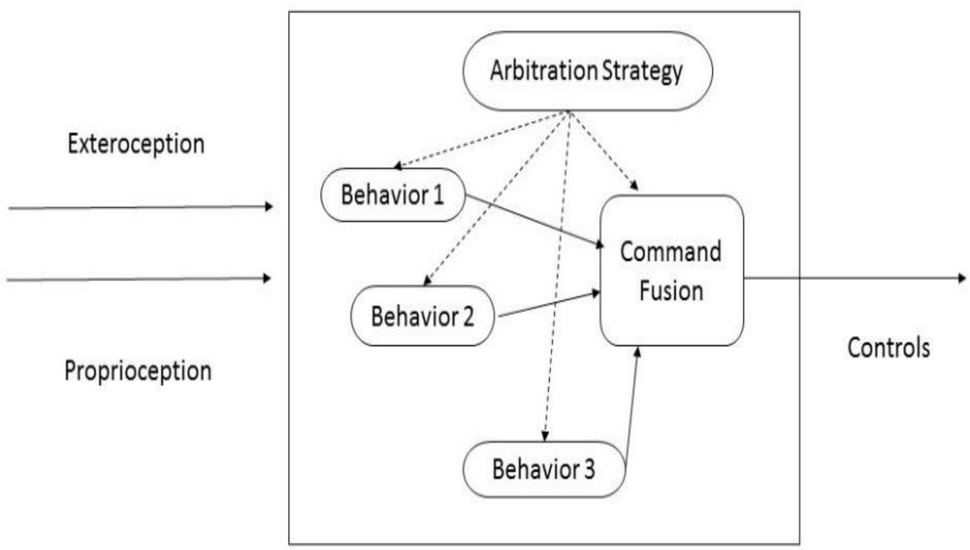

Figure 2. The architecture of behavior arbitration [26]

Behavior Fusion involves merging the outputs from behavior 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 behavior fusion alone cannot fully resolve conflicts between behaviors. A fuzzy rule-based system can evaluate competing conditions and determine which behavior to prioritize [27].

The Fuzzy behavior fusion is a behavior fusion built upon the elements of fuzzy systems. It has wide applications in fields such as robotics, autonomous vehicles, and healthcare [28] [29]. More broadly, fuzzy behavior fusion provides a versatile computational mechanism for synthesizing complex behavior components, facilitating precise and flexible decision-making.

A behavior-based system consists of interconnected modules, referred to as behaviors, that collectively define a robot's functionality and decision-making architecture. Each behavior models a specific action or interaction scenario, enabling the robot to operate adaptively and intuitively within complex environments [30]. In the context of social robots, which are designed to engage naturally with humans, behaviors 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 behavior 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 behaviors and translate them into robotic behavior models. This approach enables robots to exhibit socially intelligent behavior and engage with human users in a more natural and context-aware manner [11].

Developing ethologically inspired fuzzy behavior-based systems to replicate animal aggressive behaviors 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 behavior-based robotics. Archer's model is then translated into a fuzzy logic framework, where key behavioral components are linked to fuzzy rules capable of managing the variability and uncertainty inherent in aggressive behaviors.

A fuzzy inference system is constructed to process sensory inputs and generate appropriate behavioral outputs [20]. Integration of the Fuzzy Behavior Description Language (FBDL) enables seamless communication between the robot's sensory systems and control architecture, allowing adaptive behavior modulation. This research ultimately aims to develop a resilient and flexible robotic system capable of accurately simulating aggressive behaviors 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 behavioral models in robotics.

2.3 Implementing the "Aggression" Behavior

This research aims to develop a fuzzy behavior-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 behaviors 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 [31], the model can better represent the complexity and variability inherent in animal aggression.

The combination of Archer's ethological principles with fuzzy behavior-based system design enables the development of a more adaptable, scalable, and context-sensitive representation of aggressive behavior. 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 behavioral 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 behavioral 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 behavior of another animal. These expectations are informed by prior experiences, general behavioral knowledge, and the animal's current internal state, such as its arousal level.
Sensory Input: The animal receives sensory information from the other animal, including cues such as size, posture, movement, and other observable behaviors.
Orientation Response: After processing the sensory input, animal orients itself 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.

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.

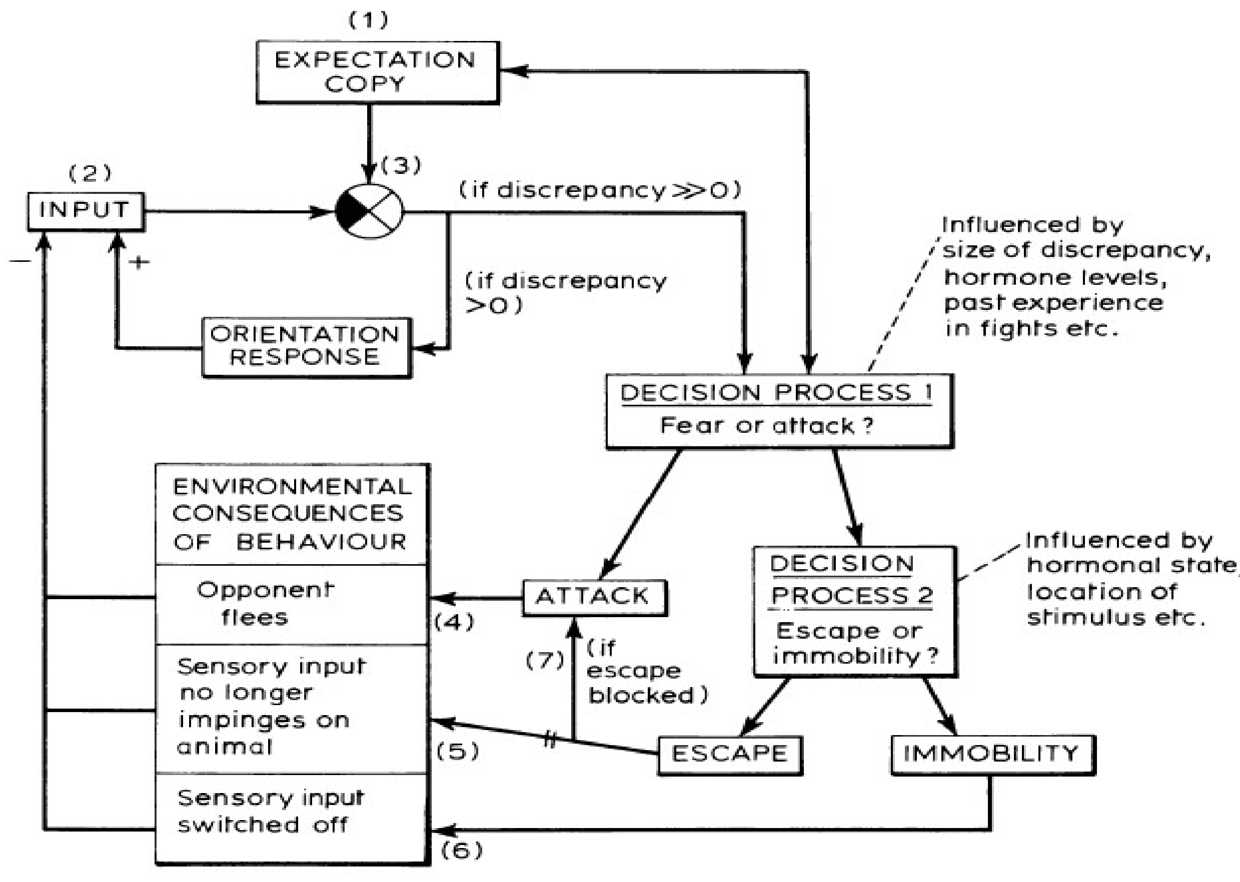

Figure 3. Archer organization model [5]

The Archer Control Theory model provides a structured framework for understanding how biological systems regulate behavior 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 behaviors 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 behavioral 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 behavioral 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 behavior [32]. The implementation process involves several core steps. First, the system states representing distinct behaviors 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 behavior. A typical rule might be: "If familiarity with the 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 behavior. 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 the another animal. This methodology provides a robust framework for simulating ethologically valid aggression responses in artificial systems.

To apply this ethologically inspired behavior model, the process begins with categorizing scenarios that provoke aggression. The model identifies how such situations elicit behavioral 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 nonbinary, fluid nature of real animal behavior. Before implementation, specific terms and rules are defined and expressed using fuzzy logic to capture animal behavior's nuanced and complex nature.

State Variables: The fuzzy "Aggression" behavior model incorporates four primary state variables, as illustrated in Figure 4. Three of these "Attack," "Escape," and "Immobility" represent observable behavioral 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 behavioral 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 behavioral 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 behaviors are associated with aggression or defense, rather than predation or food acquisition.

"Escape": This variable encompasses behaviors 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 behavior model identifies a set of key observational variables that inform the system's state transitions [20]. 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 behavior 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 the 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 behavior 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 behaviors. 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 behaviors.

"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 behavioral responses. For instance, prior exposure to threatening situations can predispose the animal toward defensive behaviors such as fear or aggression in similar future contexts.

Figure 4 presents the fuzzy model for simulating animal aggressive behavior, 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 behavioral 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 behavior. This enables a nuanced representation of behavioral 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 behavior modeling. defensive behaviors such as fear or aggression in similar future contexts.

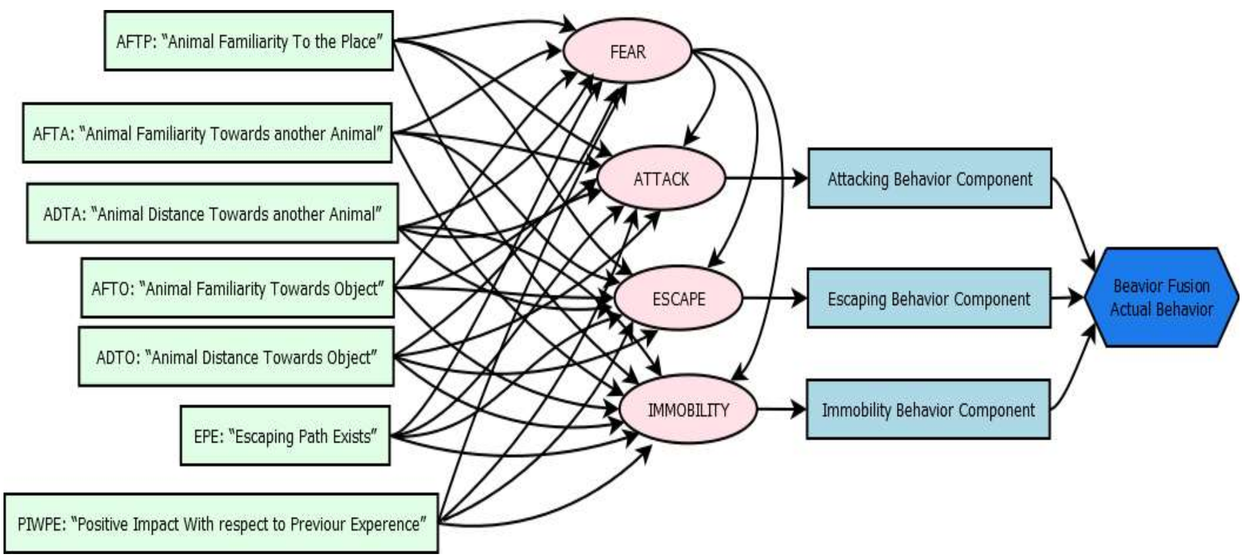

Figure 4. Animal Aggressive Behaviour Fuzzy model

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

3.1 Model Overview and Implementation Guidelines

To implement the fuzzy behavior 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) [33], which facilitates the construction of behavior components and their behavior 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 behavior 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”** behavior 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 behaviors. Fear responses are particularly prevalent when animals enter unfamiliar environments, though even familiar objects in strange contexts can alter behavioral 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 behavior. Collectively, these scenarios provide a robust foundation for constructing the fuzzy state rule bases, enabling the model to dynamically represent behaviors such as Fear, Aggression, Escape, and Immobility in a context sensitive and interpretable manner.

In fuzzy rule-base format, the FEAR Fuzzy Rule-base ($\boldsymbol{R}_{\mathrm{FEAR}}$) 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 ($\boldsymbol{R}_{\text{ATTACK}}$) 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.

Animal behaviors 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 *behavioral 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 behaviors 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 behavior 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 behavior, 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 behavioral outcomes.

In parallel, behavioral 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 behaviorally 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 behavior. 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 behavior components Fear, Attack, Escape, and Immobility are modulated by varying observations within the fuzzy model of aggressive behavior [20]. The analysis decomposes each behavior 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 [34], [35]. 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.

Figure 5(a): This graph shows changes in Fear based on ADTA and EPE. 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): This graph represents changes in Attack behavior. 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(c): This graph illustrates changes in Escape behavior. 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): This graph shows changes in Immobility behavior. 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).

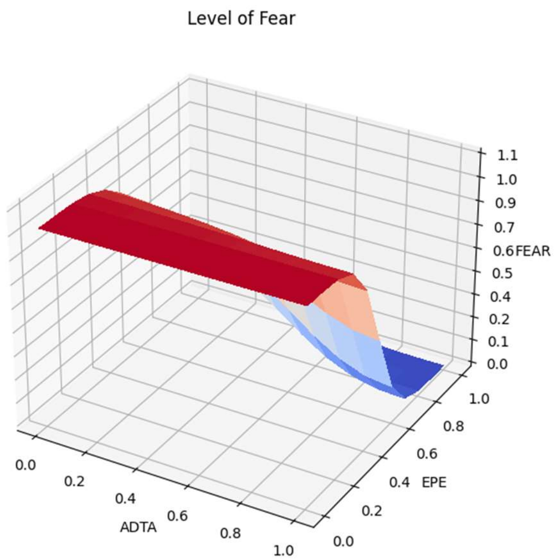

Figure 5 (a). Level of Fear Behaviour

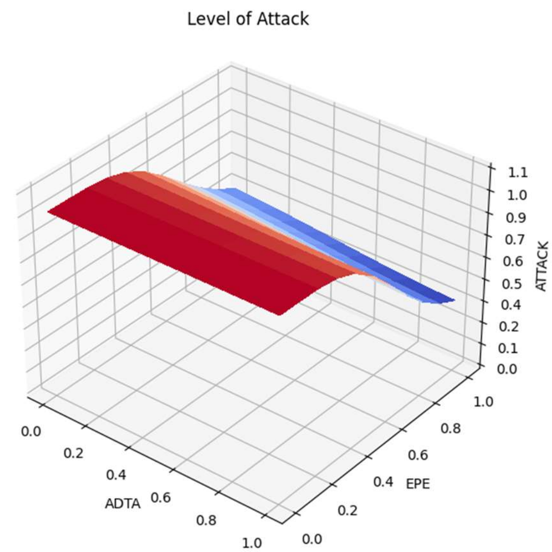

Figure 5 (b). Level of Attack Behaviour

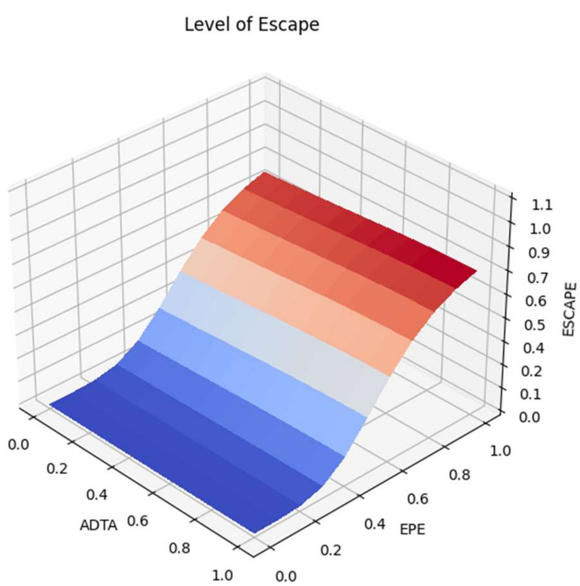

Figure 5 (c). Level of Escape Behaviour

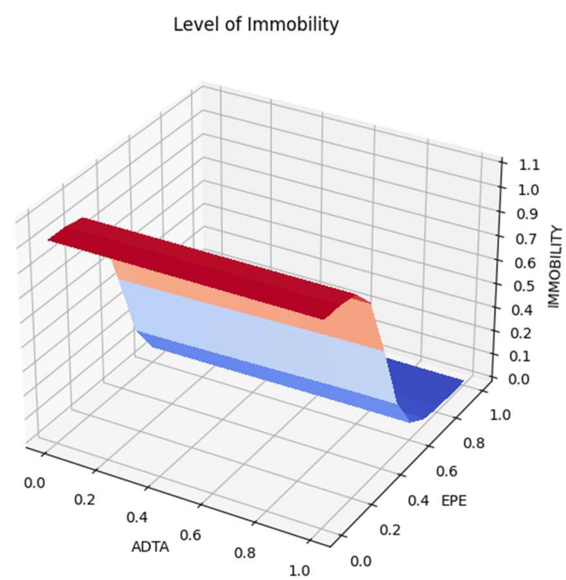

Figure 5 (d). Level of Immobility Behaviour

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

These examples demonstrate how variations in input observations directly affect behavioral 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 behavioral 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 behavior 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 behavior in both animals and autonomous systems.

Behavior	High Behavior Conditions	Low Behavior 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 1: Summary of Behavioral 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 behavioral 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 behavioral 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 behavior. 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 behaviors, with associated visualizations (Figures 7 and 8) illustrating how these strategies unfold in both spatial and behavioral dimensions.

3.2.1 Escape Behaviour

Escape behavior 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 behavior 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 behavior, 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 behavioral profile. As the 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 behavioral 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 behavior. 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 behavioral adaptations observed in prey species. Notably, the trajectories of R1 and R2 are interdependent, exhibiting behavioral synchronization that reflects real-world social modulation. R1's escape behavior 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 behavioral 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 behavior modulation are essential for effective operation.

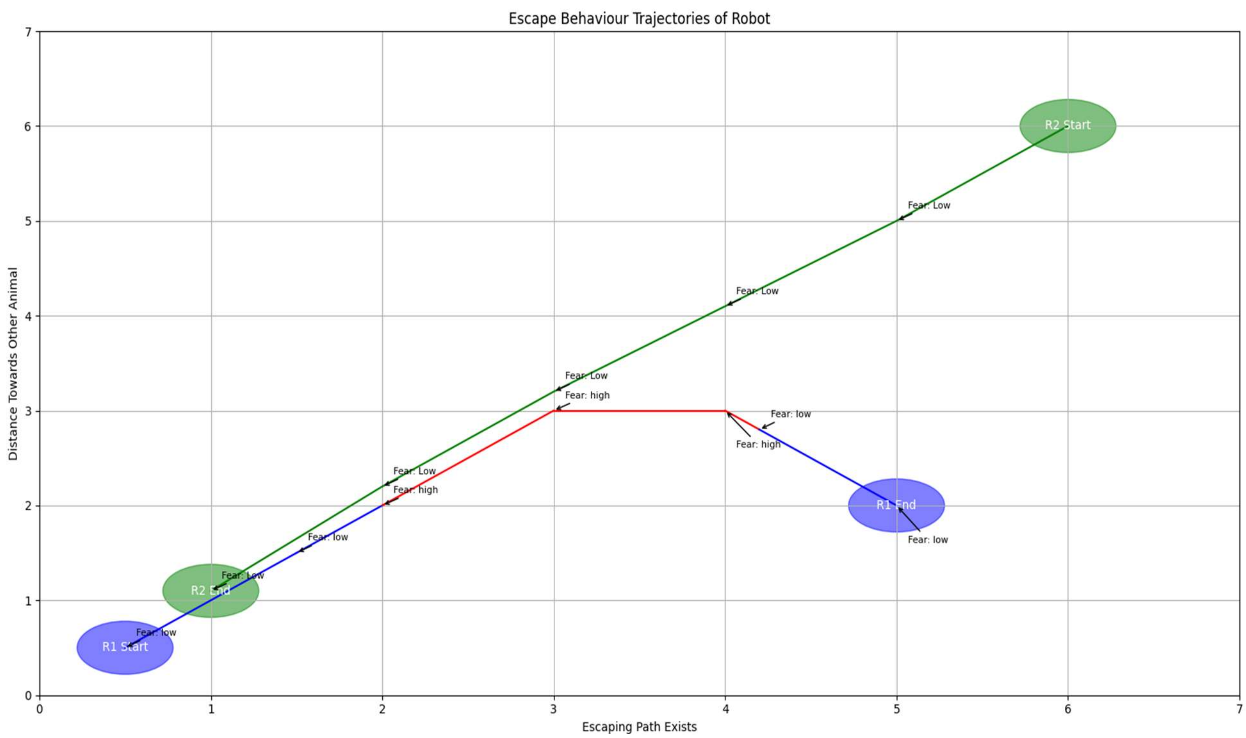

Figure 6. Trajectories for Escape Behaviour, where colours of the paths are representing the level of the "Fear"

Algorithm: Fuzzy Logic-Based Escape Behavior for Robots
Input:
- Initial Positions: Robot_1 (0.5, 0.5), Robot_2 (6, 6)
- Behavioral Parameters: ADTA, FEAR, EPE

- Thresholds: Critical Distance (D) at which Robot_1’s fear level increases

Initialize:

- Robot_1 (low fear) moves towards Robot_2’s start position
- Robot_2 (high familiarity) moves towards Robot_1’s start position

While robots are moving:

- Compute distance (CD) between them
- Evaluate FEAR using fuzzy logic
- If CD ≤ D: Robot_1's FEAR Increase
  - If EPE exists: Trigger escape (Robot_1’s trajectory turns red)
  - Else: Continue towards coordinates

Behavioral synchronization:

- Robot_1’s escape alters Robot_2’s movement
- If CD increases, FEAR decreases (trajectory turns blue,Robot_1 escaped from danger)

End Condition:

- If Robot_2 reaches near to Robot_1’s start position, And Robot_1 escaped successful from threat, stop and log behaviors

Output:

- Robot_1’s trajectory visualization (Blue → Red → Blue)
- Robot_1’s adaptive response
- Simulated natural escape behavior in robotics

3.2.2 Attack Behaviour

While escape behavior centers on evasion and retreat, attack behavior 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 behavior control system that simulates aggression dynamics inspired by animal interactions. This fuzzy rule-based framework captures the inherent uncertainty and complexity of aggressive behavior in multi-agent systems. Each robot’s movement is visualized through color-coded trajectories that trace their spatiotemporal interactions. These visual patterns mirror behavioral 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 behavioral escalation from neutral to aggressive triggered by increasing proximity to R2. The behavior 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 the 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 behavior, akin to territorial charging or dominance displays in animals.

Simultaneously, R2 interprets R1’s behavioral 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 behavior 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 behavioral transitions, grounded in environmental and social stimuli.

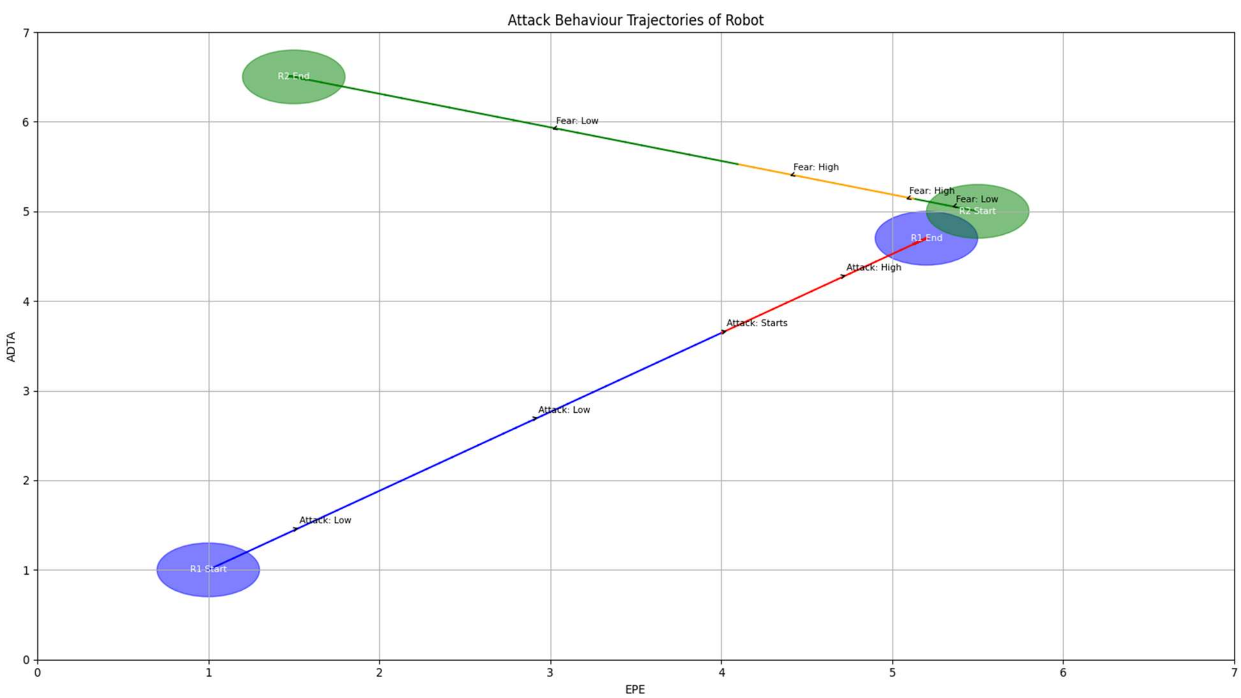

Figure 7. Trajectories for Attack Behaviour, where colours of the paths are representing the level of the “Attack”

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

Algorithm: Fuzzy Logic-Based Attack Behavior for Robots

Input:
- Initial Positions: Robot_1 (1,1), Robot_2 (5.5, 5.5)
- Behavioral Parameters: ADTA, FEAR, AFTP, AFTA
- Thresholds: Critical Distance (D) at which Robot_1's attack level increases

Initialize:
- Robot_1 (low aggression, blue) moves towards near Robot_2 initial position
- Robot_2 (no fear, green)

While Robot_1 is moving:
- Compute distance (CD)
- Evaluate fuzzy parameters (ADTA, AFTP, AFTA, FEAR)
- If CD ≤ Critical:
  - Increase Robot_1's aggression (trajectory turns red)
  - Robot_2's fear getting high (trajectory turns orange)
  - Robot_1 attacks (show high aggression) robot_2, and robot_2 leaves its place to avoid damage.

If CD Increases Again:
- Robot_1 reduces aggression, and attack level will go to low
- Robot_2 fear level decreases, low level to show a calm state (trajectory turns green)

End Condition:
- If Robot_1 reaches its goal successfully, stop and log behaviors

Output:
- Robot_1's adaptive response and trajectory visualization (Blue → Red)
- Robot_2's adaptive response (Green → Orange → Green)
- Simulated animal-like attack behavior in robotics

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

Furthermore, these simulations highlight the effectiveness of fuzzy behavior-based systems in enabling robots to engage in complex social dynamics, including multi-agent coordination, emotional modulation, and contextual learning. The seamless behavioral 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 behavior 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.

Conclusion

This research introduces a novel fuzzy behavior model, developed in the FBDL language, to simulate aggressive behaviors 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 behavioral 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 behavioral 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 behavior-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 behaviors in both virtual simulations, such as TurtleBot, and physical mobile robots, marking a significant advancement in applying biological behavior 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

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”.

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.
- *Mamdani Type-1 Fuzzy Inference System*: Introduced by Ebrahim Mamdani, this inference architecture uses Type-1 fuzzy logic, where each input has a crisp membership value in [0, 1]. It supports rule-based, interpretable decision making and is widely used in control systems for its balance of expressiveness and computational tractability.

Mathematical Formalism

In the proposed fuzzy-behaviour framework, a robotic agent determines its active behavioural state B_i based on both:

- Internal affective states F_j (e.g. FEAR, ATTACK etc.), and
- External Context Variables C_k (ADTA, AFTA, AFTP, EPE etc.).

The mapping can be expressed as:

$$\text{Behavioral State } B_i = f(F_j, C_k)$$

Each continuous input variable X_k (e.g., distance = 2 meters, EPE = 1) is fuzzified into fuzzy linguistic terms $Lx_k \in \{\text{Low, Medium, High}\}$ through corresponding membership functions:

$$\mu_{Lxk}(x_k) \in [0,1]$$

For example, a variable like EPE (Escape Possibility Estimate) might be fuzzified as:

$$X_k = \text{EPE} \Rightarrow Lx_k \in \{\text{Low, Medium, High}\}$$

Each linguistic label has a membership function $\mu Lx_k\ (x_k) \in [0,1]$ that quantifies how much an input value belongs to that fuzzy set.

The behavioral rules are expressed as:

R^B: **IF** AFTA is *Low* **AND** EPE is *Low* **THEN** Fear is *High*

Each rule uses fuzzy logic (via min-max inference) to compute an output membership degree for each behavior. The fuzzy output for each behavior Bi is computed using Mamdani inference:

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

Whereas $\min_j$ applies the weakest truth value (degree) among all input conditions in the rule. The $\max_i$ aggregates the strongest activation from any rule contributing to behavior B_i. The behavior with the highest final membership activation μ_{Bi} is selected as dominant.

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).

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.

Scientific Contribution and Novelty

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.

Chapter 4: Implementing Aggressive Behavior 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 behavior-based modeling. This research focuses on embedding ethologically inspired aggressive behaviors specifically escape and attack into robotic systems using fuzzy behavior-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 behavior 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) [36] in combination with tools such as Gazebo and RViz to simulate biologically plausible behavior. 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 behaviors into ROS represents a key step in bridging biological and synthetic systems. Animal behaviors such as escape and attack are adaptive survival mechanisms shaped by a combination of sensory input, internal state, and contextual awareness. Escape behavior 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 behavior, 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 behaviors 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 behavior 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 behavior, synthetic or biological.

4.2 Methodologies for Biologically Inspired Behavior Modeling in Robotics

This section presents two complementary methodologies aimed at developing context-sensitive, biologically inspired behaviors in autonomous robotic systems. Each method addresses unique aspects of behavioral 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 behaviors in robots.

4.2.1 Knowledge-Based Ethologically Inspired Behavior Design

The knowledge-based ethological design framework integrates behavioral insights from the field of ethology specifically, the study of animal behavior under natural conditions into robotic system development. This interdisciplinary methodology supports the creation of biologically plausible robot actions by translating observed animal responses into functional robotic behaviors. 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 behavioral patterns, including action triggers, behavioral 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 behaviors and the robotic platform's physical and computational constraints.

Following model integration, robotic experiments are conducted under controlled and variable environmental conditions [20]. These experiments assess the robot's ability to replicate the targeted behavior accurately and adaptively. Quantitative and qualitative data obtained from these trials are analyzed to evaluate behavioral fidelity and performance consistency. Discrepancies between observed and expected behaviors 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 behavior 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.

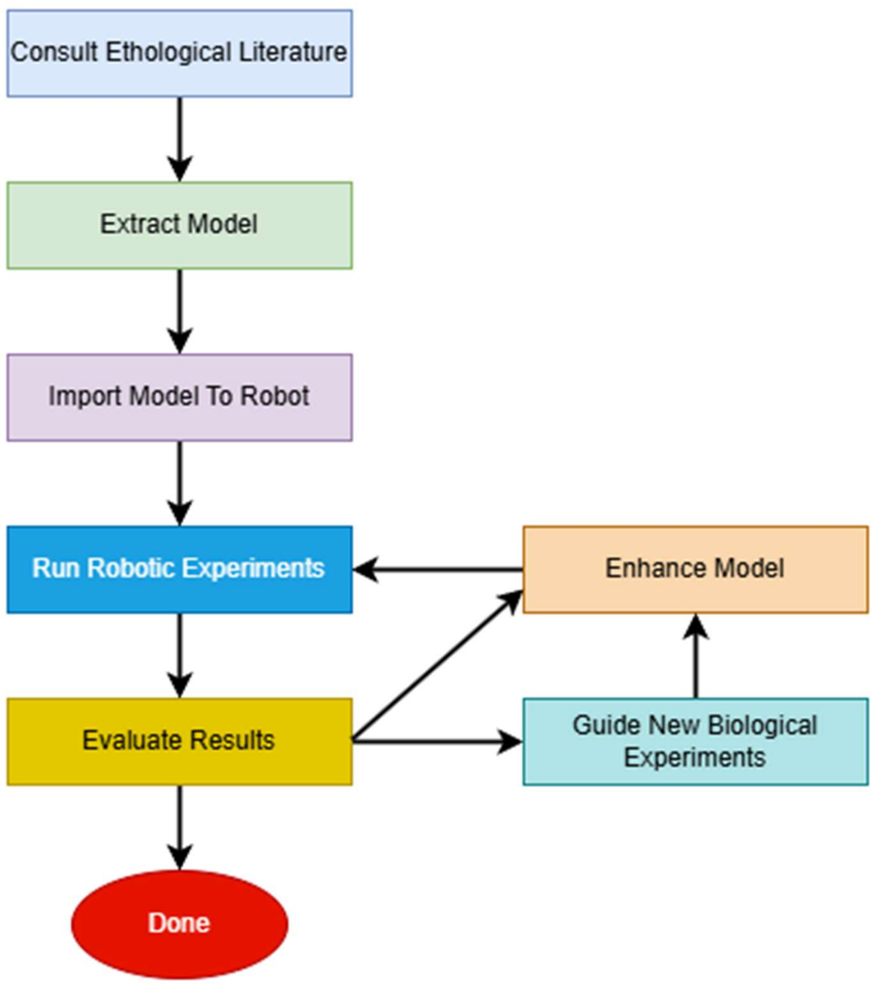

Figure 8. A knowledge-based ethological approach to robot behavior design.

4.2.2 Situated Action-Based Behavior Design

Situated action-based behavior design emphasizes the robot's capacity to interpret and respond to real-time environmental stimuli through context-dependent behaviors. In contrast to traditional rule-based systems that rely on pre-scripted decision trees, this methodology foregrounds situational awareness, behavioral 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 [20]. 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 behavioral requirement. Contextual behavioral responses are then formulated for each identified situation. These responses are derived from empirical observations of animal behavior or synthesized using domain-specific control strategies. Behavioral 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, camera, IMU).

Robotic trials are subsequently performed to evaluate behavioral effectiveness and adaptability. Feedback from these experiments is used to refine behavioral 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. The situated action design model incorporates a hierarchical control structure that allows flexible switching between behavioral 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. In disaster response, autonomous robots are required to navigate debris-laden and unstable terrains, where environmental conditions change unpredictably, necessitating context-aware behavioral 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 behavior and environmental cues is essential. 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 intervention. Finally, in marine and environmental monitoring, the capacity for autonomous, context-sensitive behavior 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.

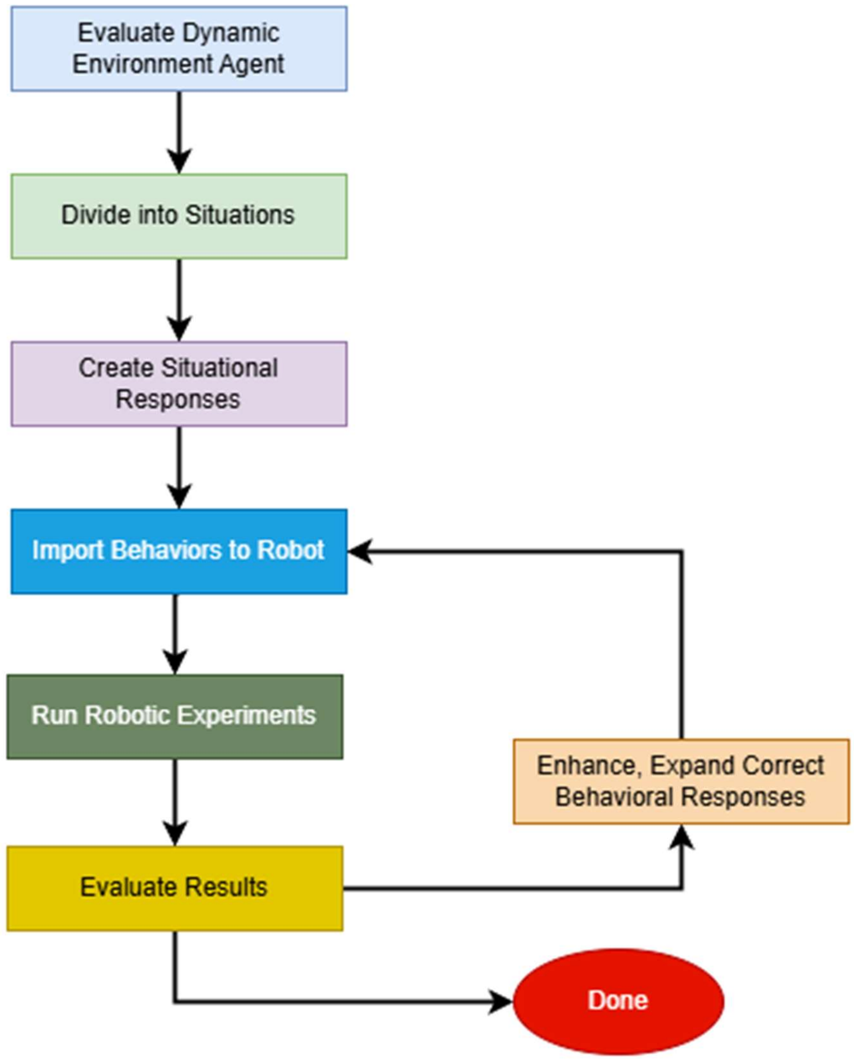

Figure 9. Design procedure for Situated Action-Based Design.

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

4.3 System Architecture and Implementation

To embed ethologically inspired behaviors such as escape and attack into robotic systems, a modular architecture was developed using the Robot Operating System (ROS) [37] 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 behavior 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, Behavior 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 behavior 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 behavior, 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 behavioral 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 behaviorally 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 behavioral expression.

4.3.2 Behavior 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 behavioral 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 behavioral 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 behavioral 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.
Behavioral State Transition Management where supervisory logic governs switching between behaviors 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 behavioral 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 behavioral decision is made, the Motion Execution Layer translates it into a physical trajectory using ROS’s navigation stack. For escape behavior, the robot selects paths that maximize distance from the identified threat, calculated using the SLAM-derived cost maps. For attack behavior, 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 behavior 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 behavioral 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
- /behavior_state: Currently active behavior (e.g., Escape, Attack)
- /cmd_vel: Motor commands derived from the selected behavior 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 behaviors into robotics through the fuzzy behavior-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 behaviors, 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 behaviors 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 behaviors, 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 behavior, contributing to the development of intelligent, ethically aligned robotic systems.

4.5 Behavior implementation

Implementing ethologically inspired behaviors 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 behavioral responses, such as retreating, confronting, or freezing in response to dynamic stimuli. Unlike conventional rule-based systems, this approach leverages models of natural behavior observed in animals, particularly in predator-prey and threat-avoidance contexts, to inform robotic decision-making.

The implementation of such adaptive behaviors 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, behavior arbitration mechanisms, and behavior 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 behaviors, 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 behaviors within a ROS-based simulation environment, where real-time data streams and fuzzy logic modules collaboratively govern the robot's behavior under controlled but dynamic conditions.

The successful embedding of such ethologically grounded behaviors 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], [20], biologically inspired behavior embedding improves both autonomy and resilience, positioning robotic systems as capable agents in complex, high-risk settings.

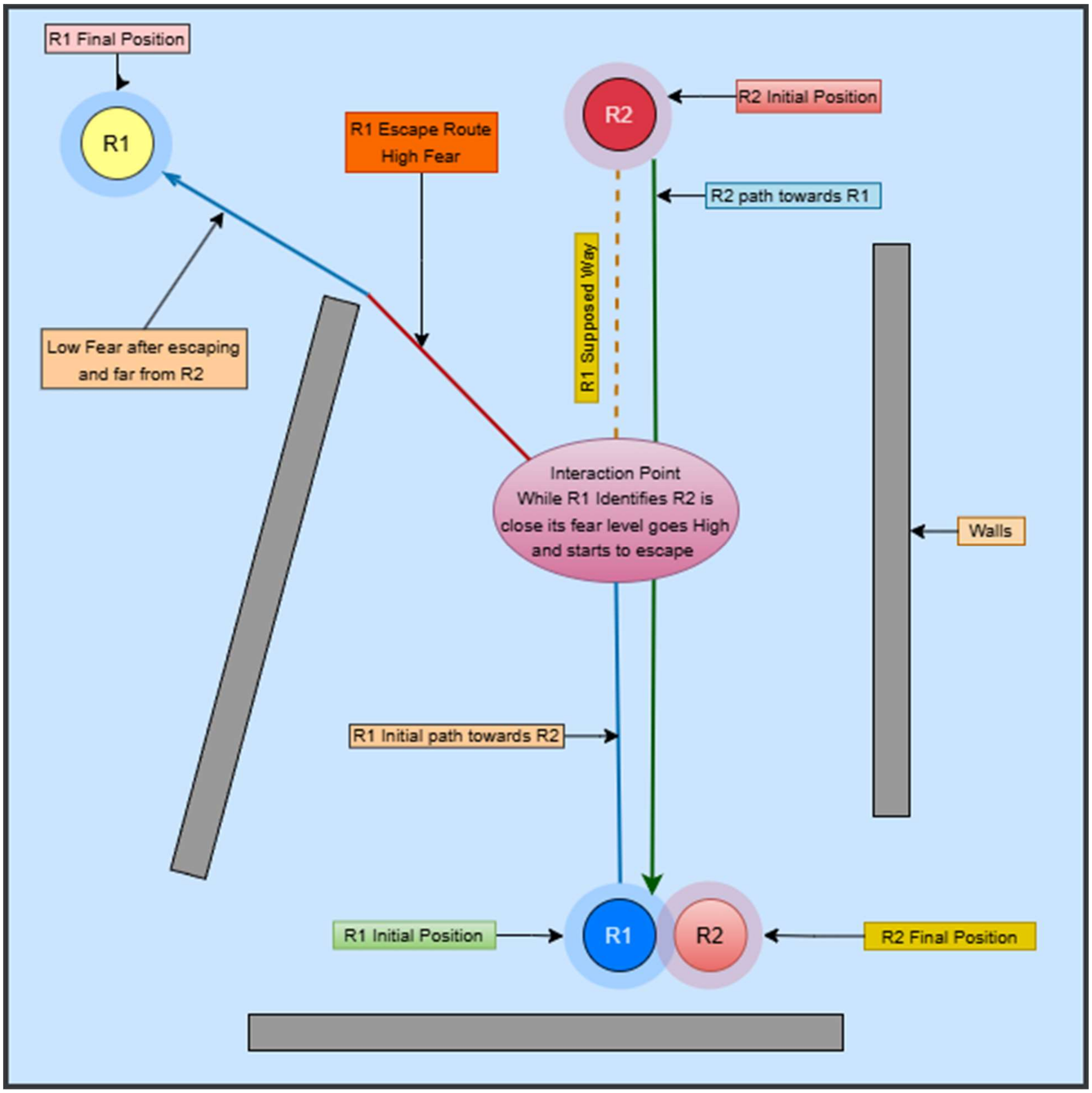

Figure 10. Escape Behaviour of Robot_1

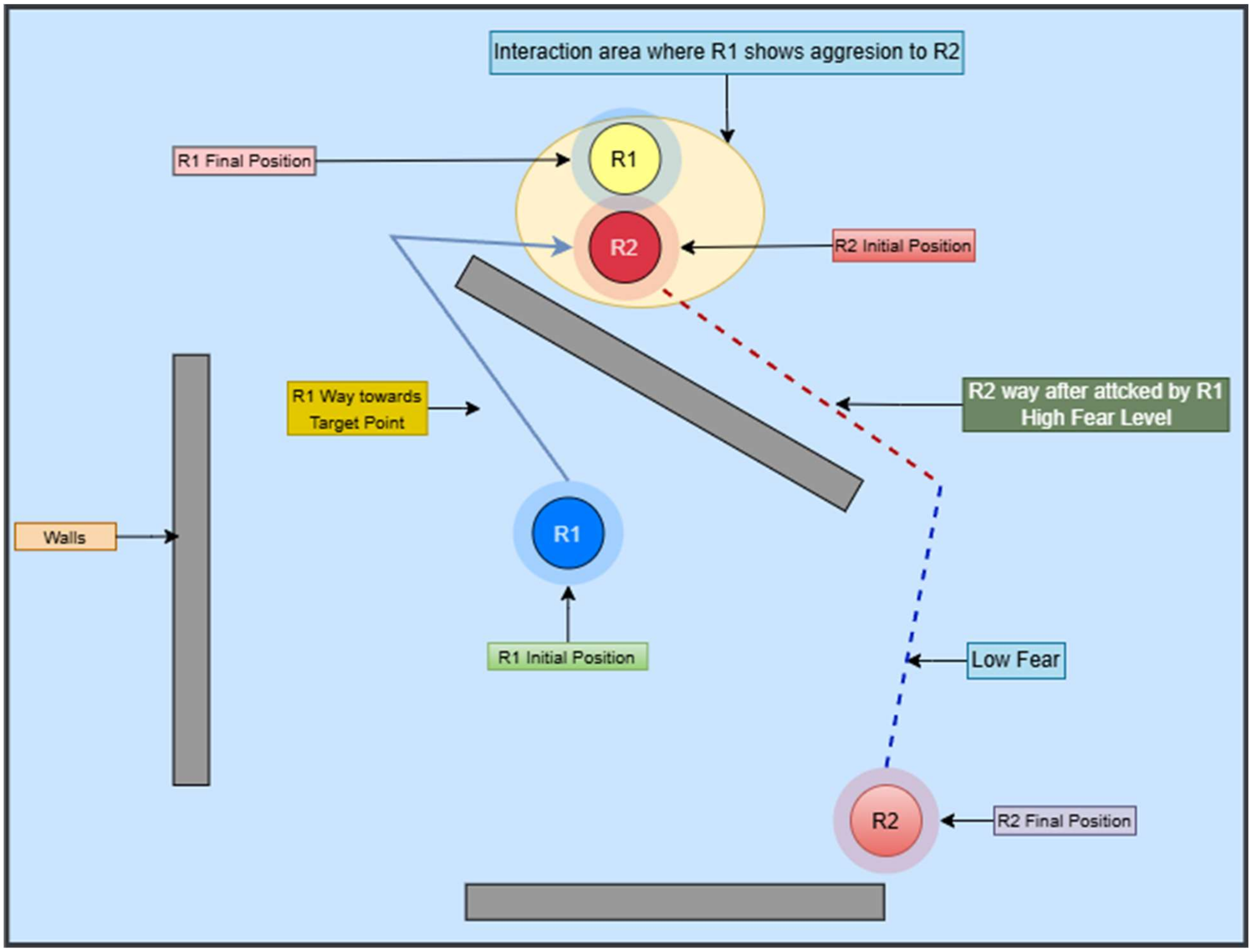

Figure 11. Attack Behavior of Robot_1.

4.5.1 Implementing the Escape Behaviour

The escape behavior 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 behavior-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 behavior 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 behavioral 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, behavior fusion and coordination mechanisms come into play, integrating multiple behavioral 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 behavior arbitration module, ensuring seamless control flow between perception and motor execution.

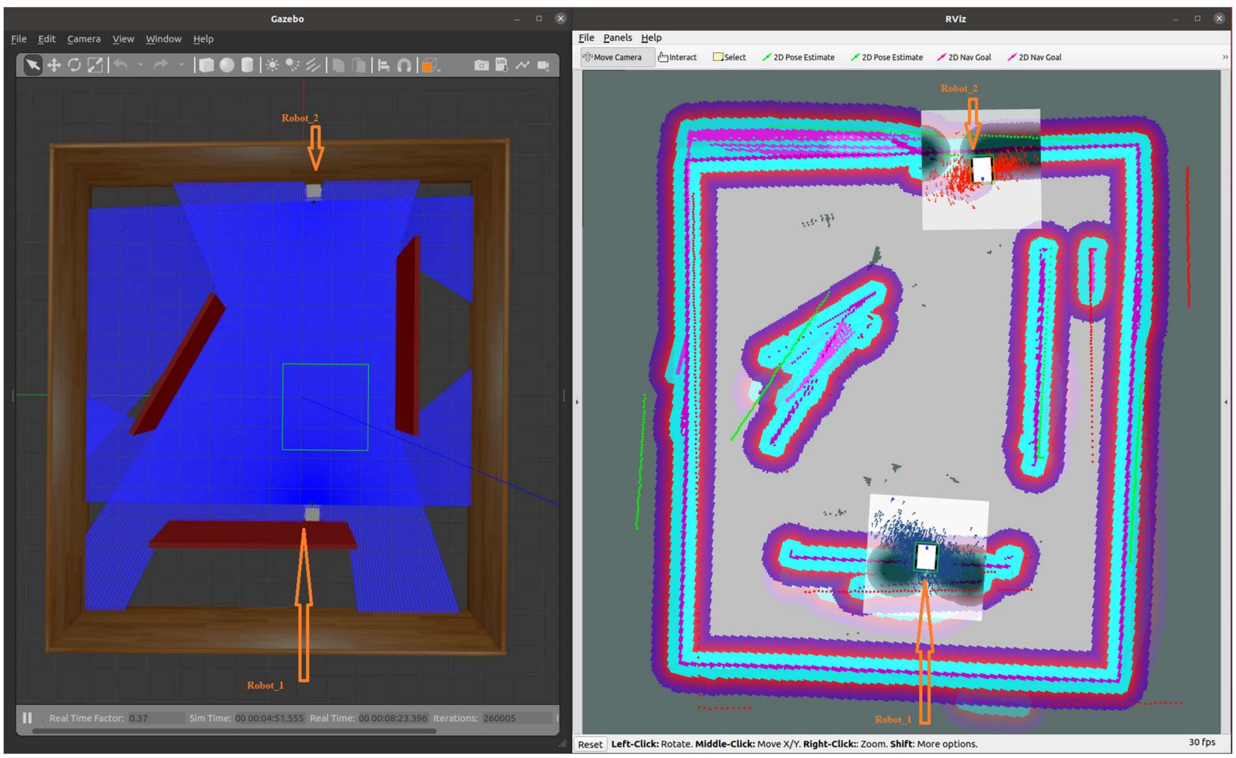

Figure 12(a). Initial Position of Robots: both robots start at designated positions.

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, behavior coordination, and fusion mechanisms. Robot_1's behavior 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 behavioral models for embedding context-sensitive escape behaviors in autonomous robotics.

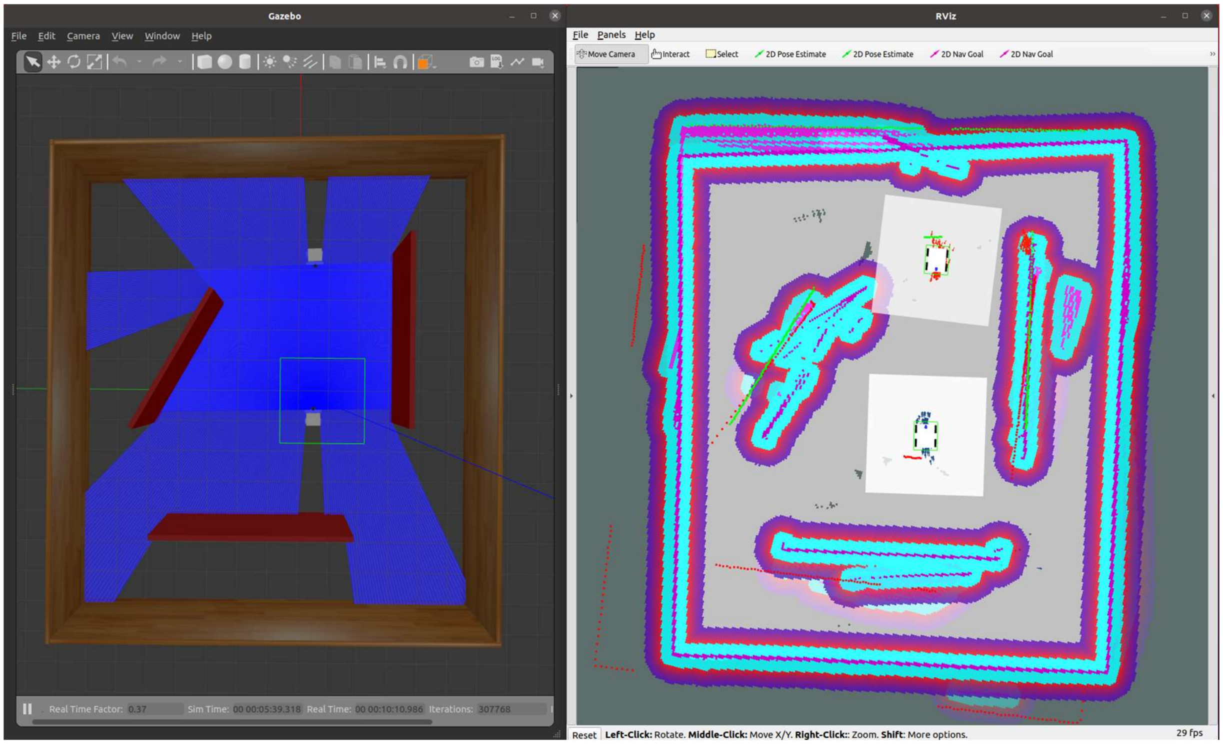

Figure 12(b). Movement Stage: robots move towards each other.

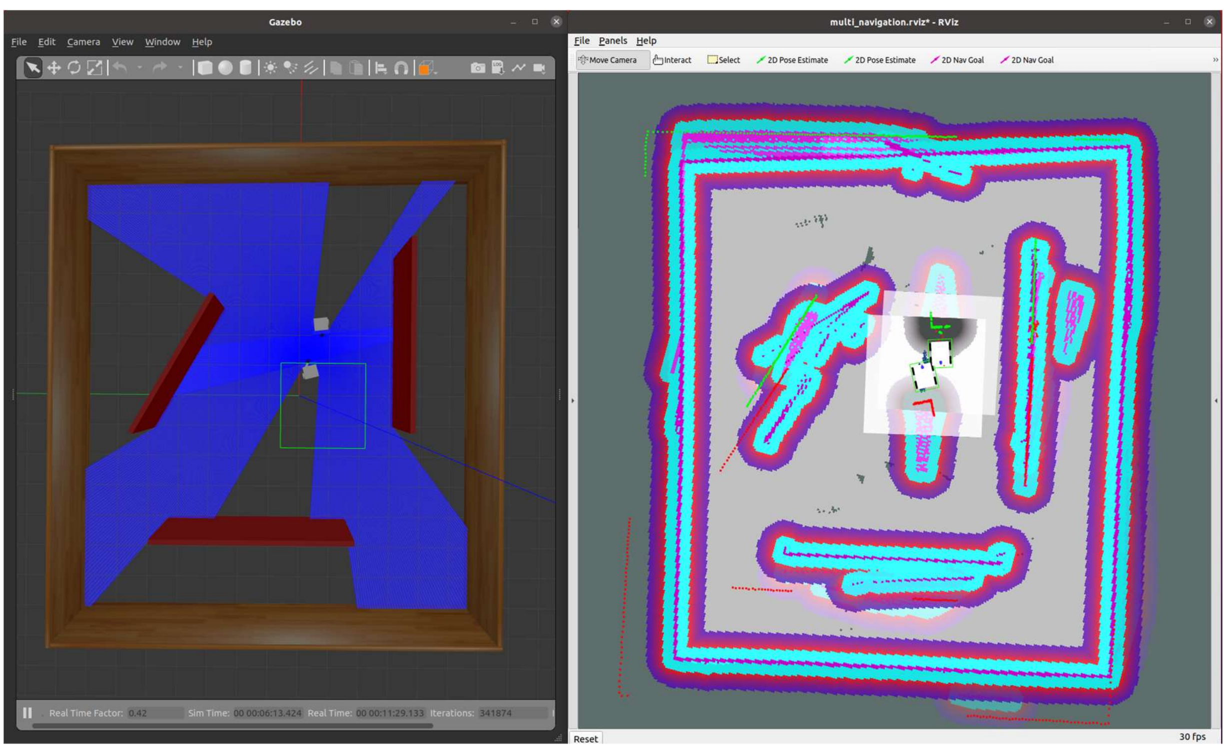

Figure 12(c). Detection and Fear Assessment: Robot_1 detects Robot_2 and assesses fear based on proximity and environment unfamiliarity.

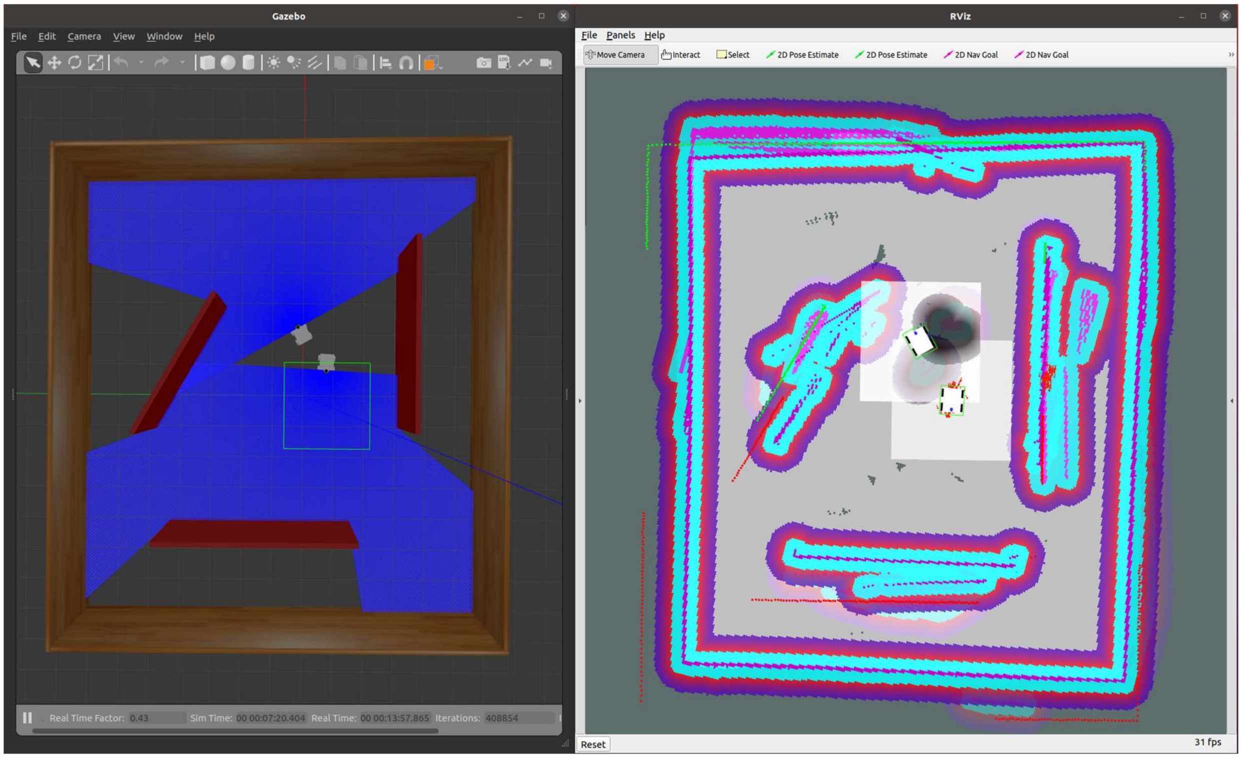

Figure 12(d). Escaping: High fear, and the presence of an escape route triggered Robot_1's Escape.

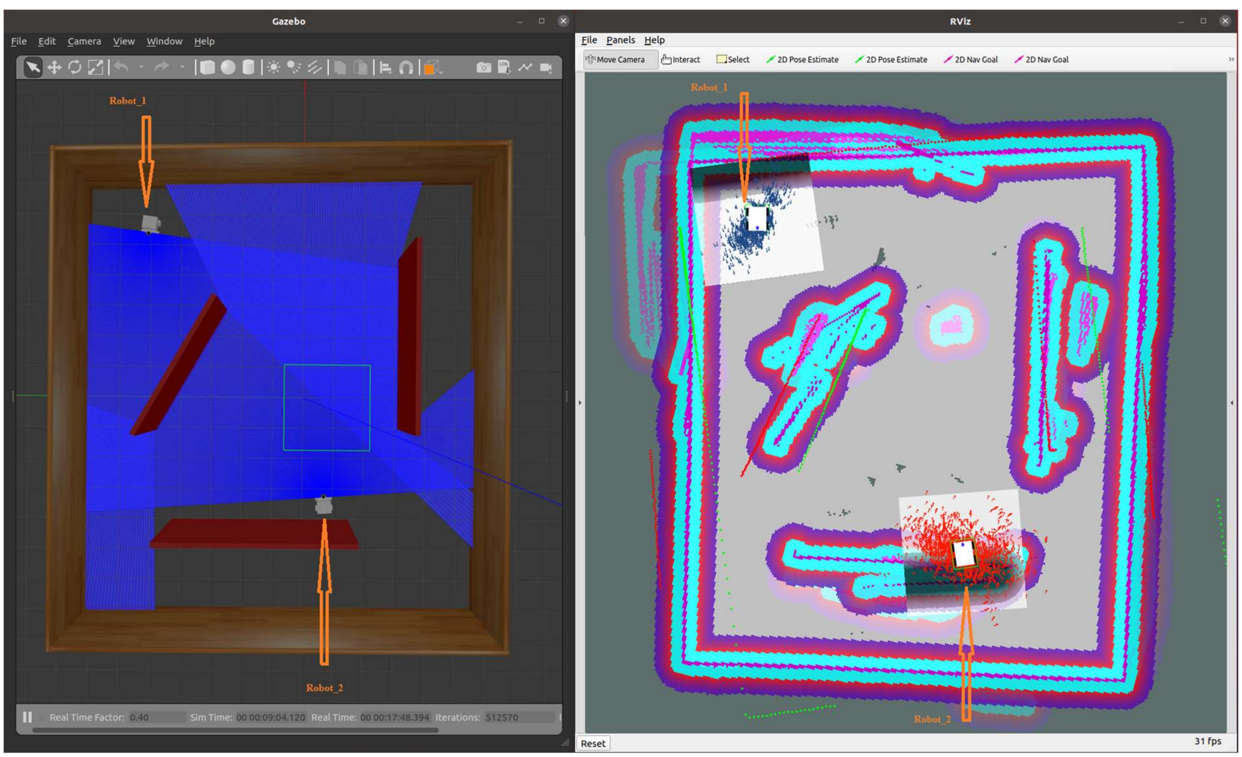

Figure 12(e). Robot_1 successfully escapes, illustrating the effective use of fuzzy logic, behaviour coordination, and fusion.

4.5.2 Implementing the Attack Behaviour

The embedding of attack behavior 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), 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.

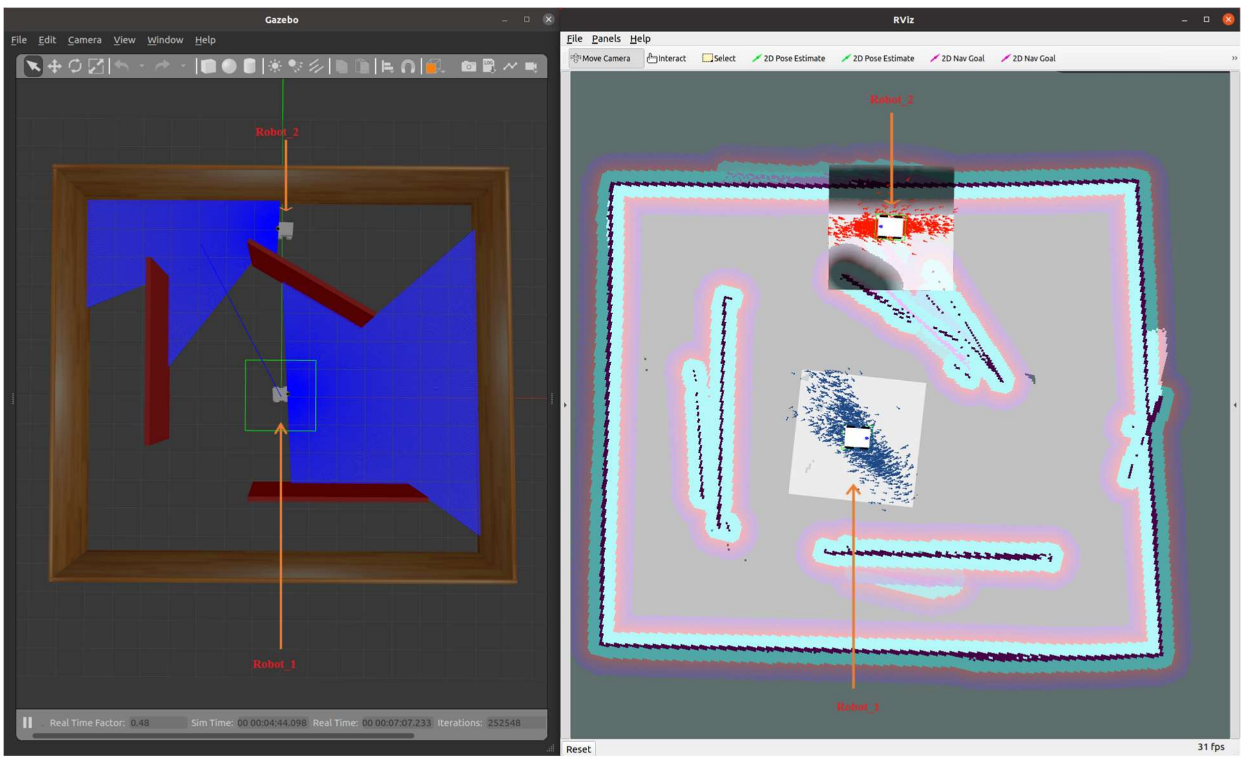

Figure 13(a). Robots Initial Position

The simulation employs fuzzy component behavior, behavior fusion, and behavior 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 behavior encoded in its fuzzy logic rule base. Behavior coordination synchronizes both agents' reactions: Robot_1's aggressive pursuit is dynamically linked to Robot_2's avoidance behavior, reflecting ethologically inspired predator-prey dynamics. These synchronized responses result from behavior fusion mechanisms, which resolve potential conflicts between overlapping behavioral priorities and ensure coherent interaction between multiple fuzzy controllers.

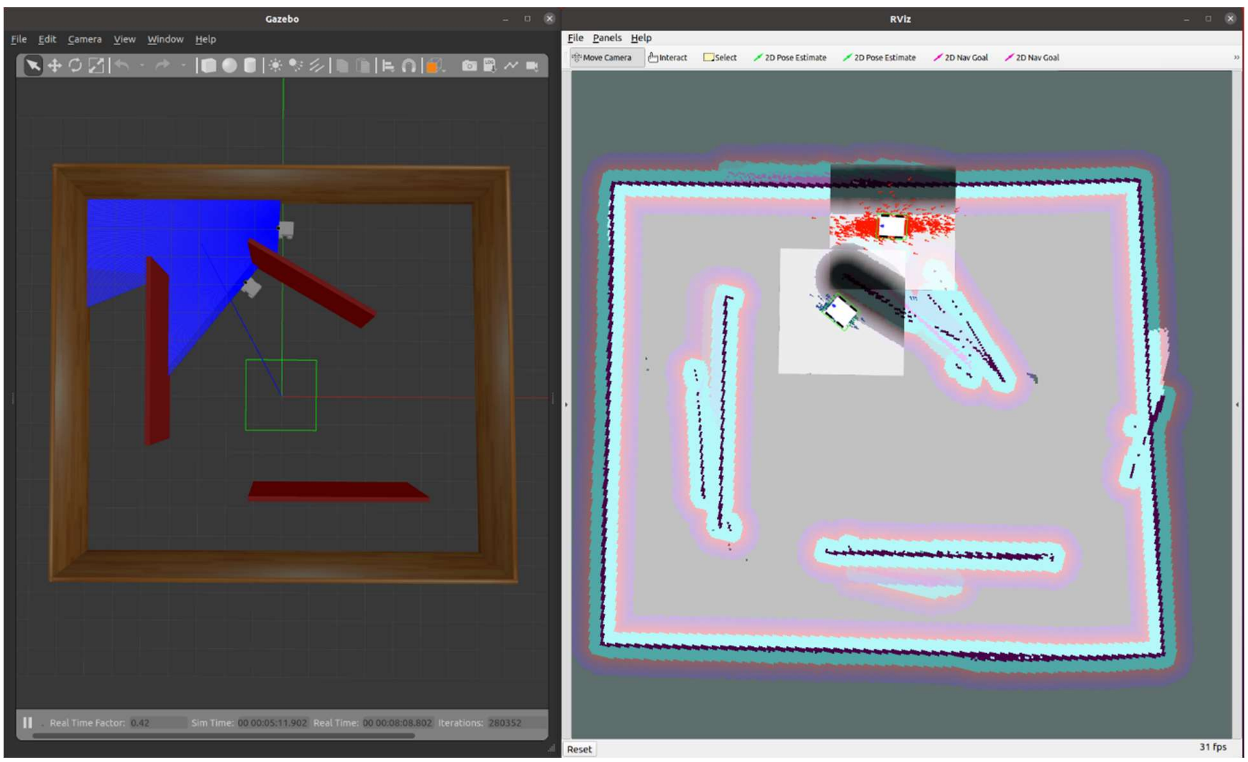

Figure 13(b). Robot_1 starts moving towards its goal task

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 behavior 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 behavior embedding. The ability to simulate nuanced behaviors 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 behavior 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 behavior embedding enhances decision-making under uncertainty advancing both autonomy and safety in intelligent robotic ecosystems.

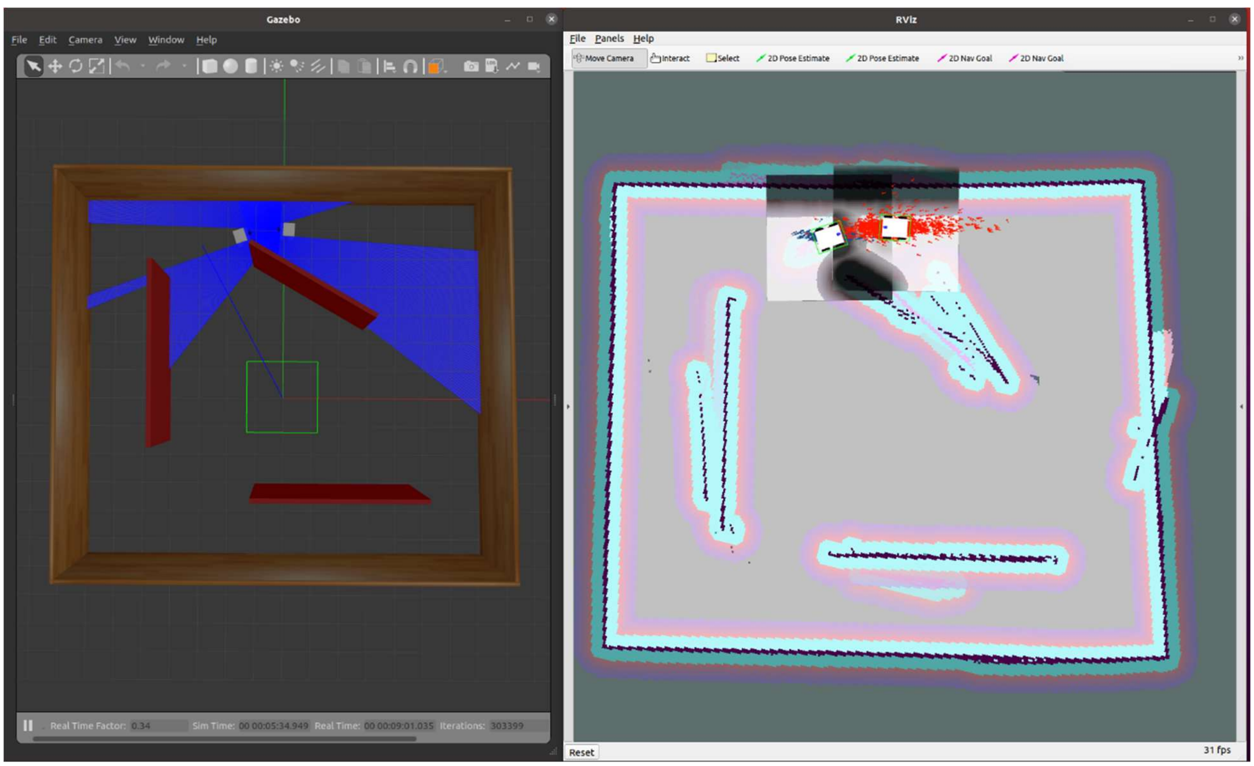

Figure 13(c). Robots are close to each other, and Robot_2 detects an unknown animal robot approaching.

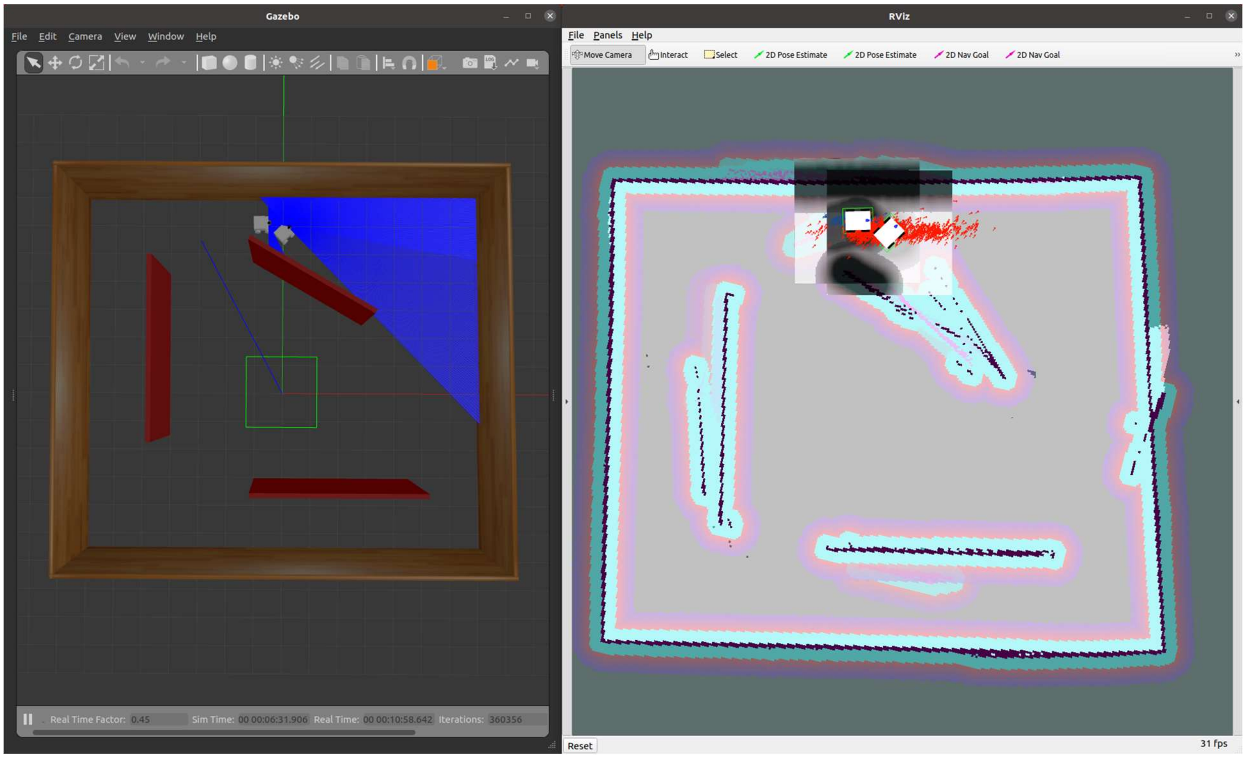

Figure 13(d). Robot_2 Start Leaving from its place.

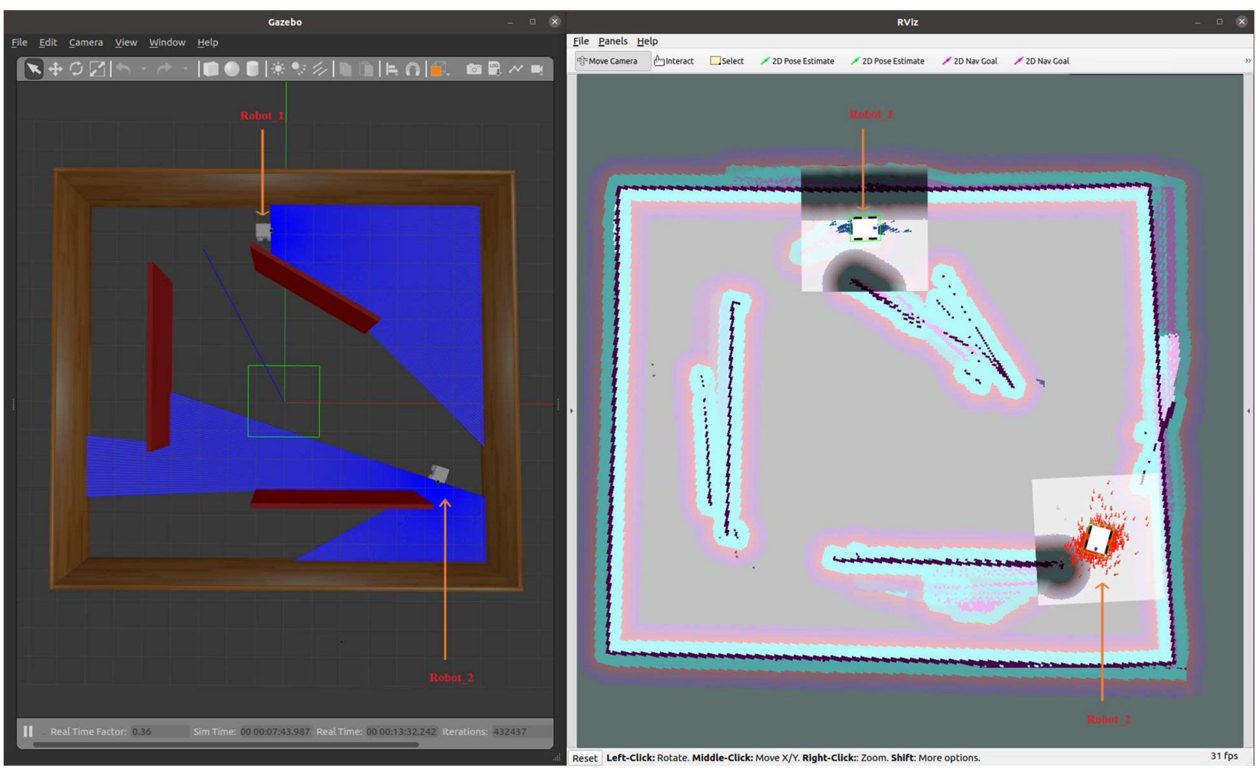

Figure 13(e). Robot_1 successfully showed its attack behavior, and Robot_2 is far from Robot_1

4.5.3 Classification Metrics Report of Escape and Attack Behaviour

The figure 14(a)-(b) presents the classification performance report, which is derived from a systematic evaluation of a fuzzy logic-based behavior modeling framework embedded in autonomous robotic agents. It specifically measures the model's ability to accurately classify context-sensitive behaviors such as Escape and Attack under dynamic environmental and operational conditions. This evaluation is grounded in a well-defined rule-based fuzzy inference system, where each behavior is governed by a set of biologically inspired fuzzy rules. For example:

Escape behavior is activated by rules such as:

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

Attack behavior is governed by logic like:

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

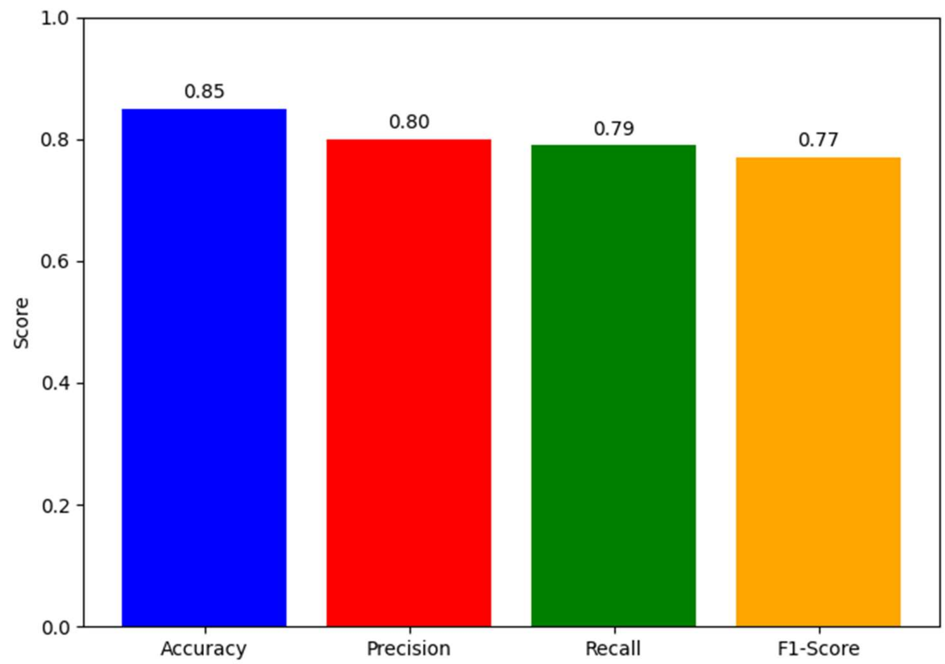

Figure 14 (a). Escape Behaviour Classification Metrics

The performance metrics precision, recall, F1-score, and accuracy were computed from simulation trials conducted within the Robot Operating System environment. During testing, the fuzzy controller continuously evaluated real-time sensory inputs (such as AFTA, AFTP, and AFTO) along with dynamic variables like robot speed and proximity. The system was assessed on its ability to adaptively select appropriate behavioral responses under varying conditions. The resulting classification report provides a quantitative validation of the system's decision-making accuracy, rule activation robustness, and context-sensitive adaptability. These results confirm the effectiveness of the proposed ethologically inspired fuzzy behavior architecture in supporting realistic and responsive navigation in autonomous robots.

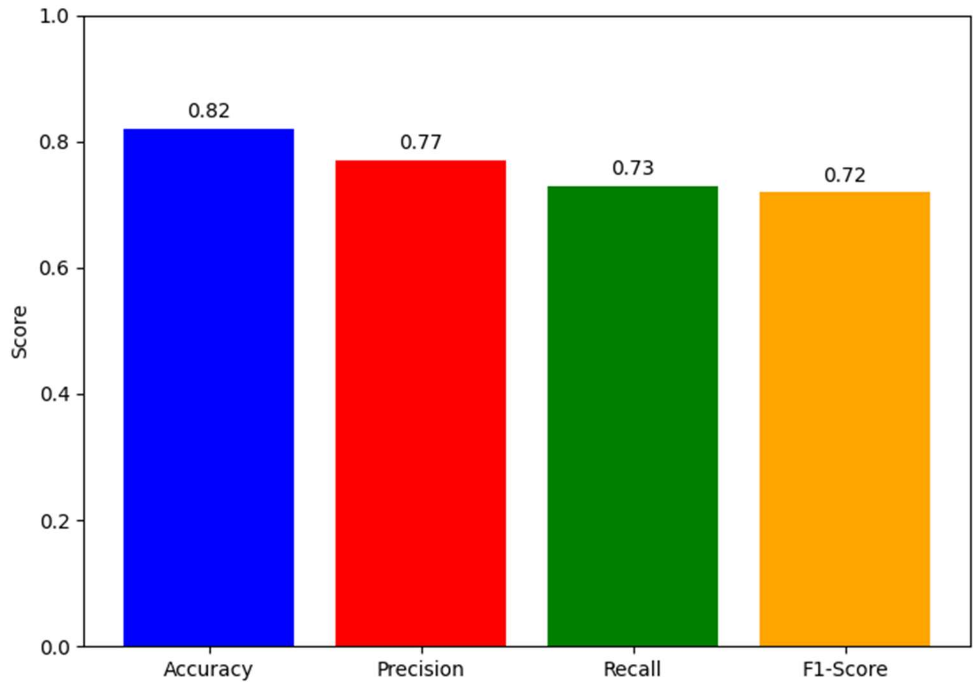

Figure 14 (b). Attack Behaviour Classification Metrics

Conclusion

This example demonstrates the successful integration of ethologically inspired behaviors specifically escape and attack into autonomous robotic systems using a fuzzy behavior-based framework. By leveraging ROS, Gazebo, LIDAR, and fuzzy inference, the system enables robots to perceive environmental stimuli, assess internal affective states, and execute adaptive, context-aware responses. Unlike rigid binary models, fuzzy logic supports graded, biologically realistic decision-making that yields lifelike behavior. A critical component of the system is SLAM, which allows the robot to construct a map of its environment while simultaneously tracking its position, ensuring continuous localization and spatial awareness. SLAM enhances the robot’s ability to align behavior with environmental structure, enabling real-time adaptation in dynamic scenarios. This approach not only improves robotic autonomy and resilience in uncertain environments but also grounds artificial behavior in ethological principles. The outcomes have broad implications for multi-agent coordination, human-robot interaction, and deployment in real-world applications such as search and rescue, surveillance, and collaborative robotics. By bridging the fields of robotics and ethology, this work contributes to the advancement of intelligent systems that are both technically proficient and behaviorally interpretable.

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 behavior science and robotics by enabling emotion-driven real-time behavior switching based on both internal affective states and external stimuli.

Scientific Contribution

- *Robotic Instantiation of Ethological Behavior*: This research marks the first robotic realization of Archer's biological aggression model, enabling real-time behavior 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 behavior 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 Behavior Evaluation → Inference Engine → Motion Execution, supporting both simulation and hardware deployment.

Mathematical and System Formalism

The behavioral state of the robot, denoted by $S \in \{\text{Escape, Attack, Immobility}\}$, is computed via fuzzy inference over perceptual and experiential variables:

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

These inputs represent key perceptual and experiential factors, such as distance to threats, familiarity with entities or environments, escape possibility, and prior interactions. Each variable is fuzzified using trapezoidal membership functions μX_i, which convert crisp sensor values into linguistic terms like Low, Medium, and High.

Behavioral rules are defined using FBDL, were combinations of input terms yield specific behavioral activations. For example, the rule

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

Encodes a biologically plausible response. A fuzzy behavior fusion mechanism aggregates the outputs of multiple such rules, resolving conflicts by selecting the behavior with the highest activation value:

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

This process enables the robot to adaptively and interpretably switch between behaviors in real time, based on its internal state and external context.

Empirical Validation & Simulation-Based Evidence

Real-Time Escape Behavior (Figure 10 and 12 (a–e)):

- Robot_1 evaluates its environment (AFTA, ADTA, EPE).
- On detecting Robot_2, it triggers a high fear response and escape is evaluated and executed.
- The Robot_1 performs smooth, adaptive maneuvers, reflecting ethological Escape behavioral realism.

Coordinated Attack Simulation (Figure 11 and 13 (a–e)):

- Robot_1 identifies Robot_2's location and initiates approach using aggression model.
- Robot_2 responds with a fear-based escape, validating cross-agent behavioral inference.
- The behavioral arbitration module dynamically transitions between attack and avoidance states, yielding lifelike, emergent interaction.

SLAM Integration and Spatial Awareness:

- Uses gmapping for continuous localization and mapping.
- Ensures context-sensitive behavior even in GPS-limited environments (i.e., inside buildings, unknown terrain).
- Motion planning adapts to real-time occupancy grids from SLAM outputs.

System-Level Testability and Reproducibility

- Each behavior (Escape, Attack, Immobility) is tied to an explicit rule-base and ROS node.
- Gazebo simulation validate rule triggering across controlled conditions (e.g., varying EPE, ADTA, Robot speed).
- Behavior transitions are visualized in Rviz, with real time velocity commands and state markers.
- The system works well in ROS simulation environment and can also work in real-world TurtleBot hardware setups.

Applications and Ethical Implications

- *Search and Rescue:* Robots avoid hazards, escape collapse zones, or autonomously retreat from danger.
- *Autonomous Surveillance:* Agents can assess threat levels and react with appropriate aggression or withdrawal.
- *Human-Robot Interaction:* Enables emotionally resonant behavior without reliance on pre-scripted dialogue trees.

The model also raises ethical considerations related to autonomy, emotional expressiveness, and intent interpretation addressed through design transparency and state interpretability.

Novelty and Impact.

- Novel implementation of ethologically derived fuzzy state machines operating in high-resolution spatially aware ROS environments.
- Demonstrates that affective robotics can be grounded in biological models, not only heuristic rules or reinforcement policies.
- Provides a reusable open-source modular framework for further research in multi-agent emotion-aware 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 (VFF) 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 [38], [39].

Ethology, the scientific study of animal behavior, 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 behaviors 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 [40]. Mobile robots with cognitive capabilities are increasingly essential in critical domains such as warehouse automation, disaster response, patrolling, and search-and-rescue missions [41], 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 [42]. 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 [43], [44], [45].

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.

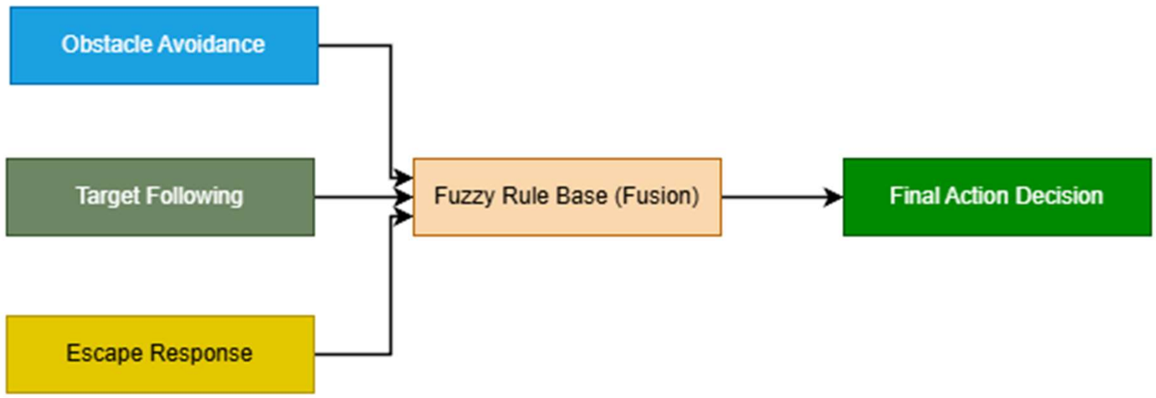

Figure 15. Fuzzy Behavior Fusion Process

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 [46]. 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 [47].

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 the 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 a stronger repulsive effect 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.

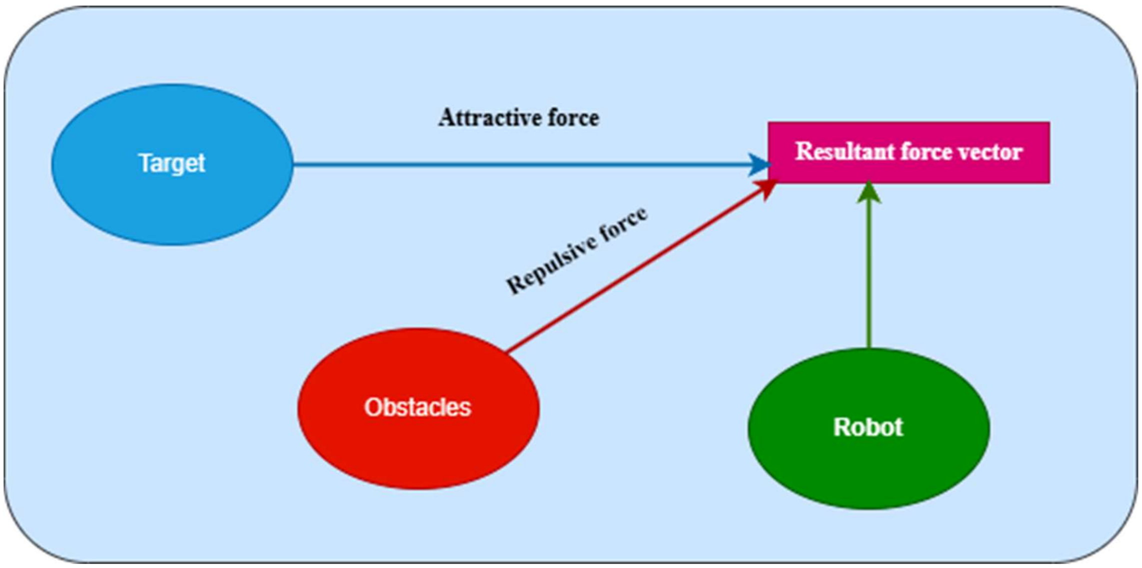

Figure 16. Concept of Virtual Force Field (VFF) Navigation

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 (1):

$$F(i,j) = \frac{F_{cr}\,C(i,j)}{d^2(i,j)}\left[\frac{x_i - x_0}{d(i,j)}\hat{x} + \frac{y_i - y_0}{d(i,j)}\hat{y}\right] \tag{1}$$

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, which the robot utilizes to safely maneuver around obstacles.

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

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 [48].

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. 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 [49].

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 [50]. 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 [51].

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(VFF): 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 behavior coordination serves as the central mechanism governing how various behaviors are combined and executed in response to environmental stimuli. The fuzzy rules of behavior coordination consist of **If** *[conditions] and* **Then** *[actions]* statements that define relationships between input variables (e.g., environmental conditions) and output behaviors (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*

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 behavior model can be found in [20]. 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

To demonstrate this integration, the proposed study analyzes the "Escape" behavior as modeled in the ethologically inspired aggression framework [20], where the corresponding fuzzy rule bases are implemented using the Fuzzy Behavior 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 behavior 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 behavior but influences other state variables. Fear is a complex reaction involving physiological, behavioral, 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 behavior 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 behaviors.
Animal Distance Towards Object (ADTO): The distance between an animal and an object, with unfamiliar objects potentially eliciting fear or defensive behavior.

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. 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. 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 Behavior 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 behavioral 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 Behavior Descriptive Language (FBDL) definitions are designed to address a wide range of behaviorally relevant scenarios. 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 behaviors 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 behaviors 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*

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

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

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

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:

ADTA - Animal Distance Toward Another Animal

ADTO - Animal Distance Toward Object

AFTP - Animal Familiarity Toward Place

AFTO - Animal Familiarity Toward Object

EPE - Escape Path Exists

These variables represent perceptual observations that inform the robot's understanding of its surroundings and potential threats or escape opportunities.

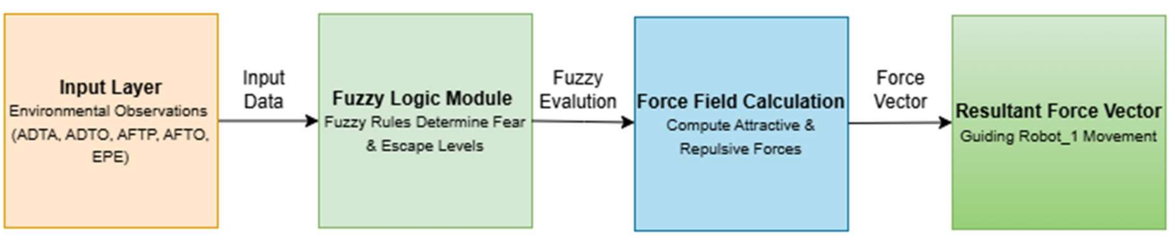

Figure 17. Conceptual Diagram of the Fuzzy Behaviour Fusion with VFF navigation model

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 behavior, 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.

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 behavior of Robot_2, a potential threat, and a static obstacle, both of which test the robot's capacity for avoidance and path adaptation.

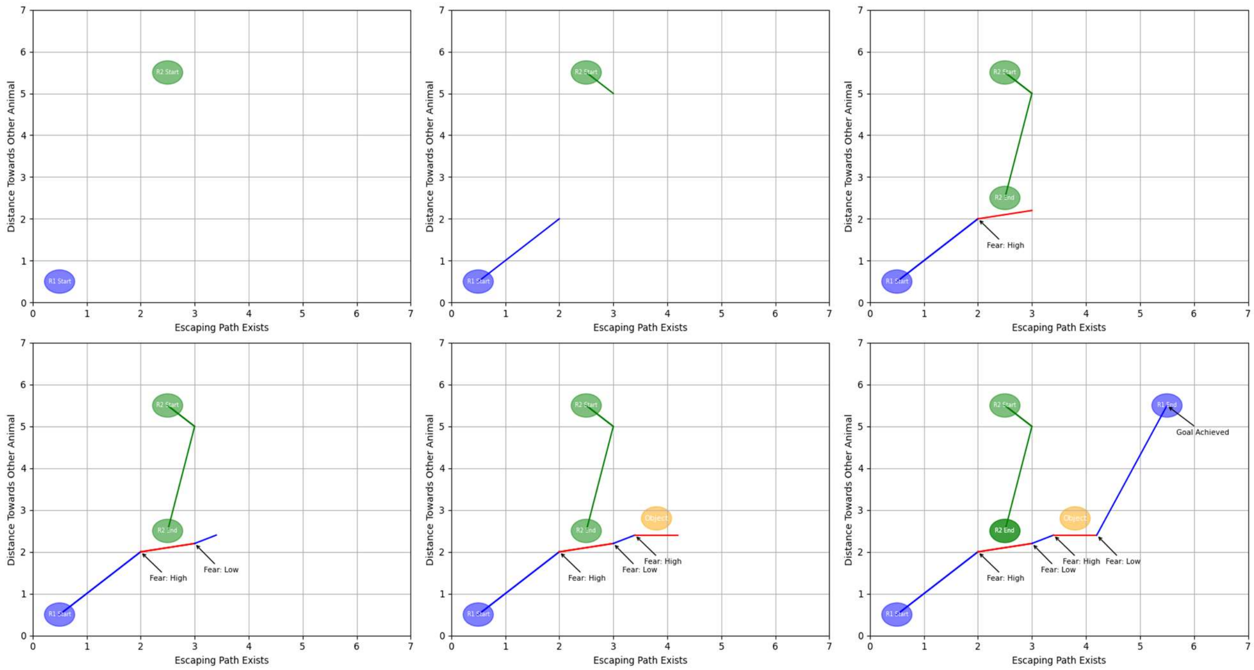

Figure 18. Represents the Trajectories for Animal Escape behaviour

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 (as described in Section 5.5), 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.

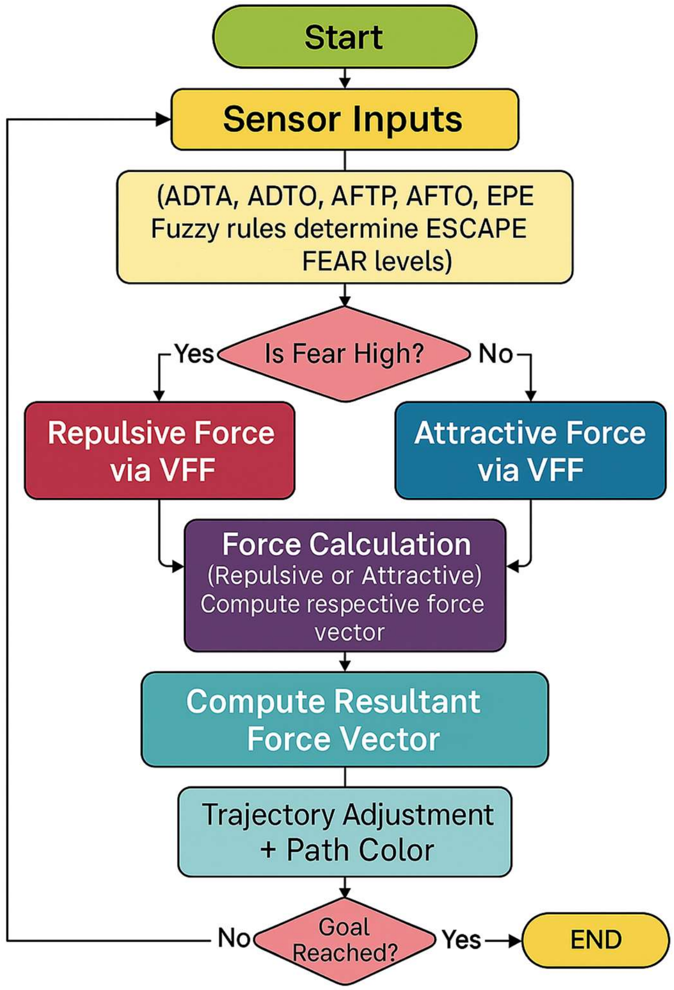

Figure 19. VFF-Fuzzy Behaviour flowchart.

The virtual force field utilizes equations (2) and (3) to measure the overall effect of repulsive forces, while equations (4) and (5) measure the attractive forces on the robot's motion.

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

$$Y_{cr} = - F_{cr}\left(\frac{Y_i - Y_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_o)^2}}\right), \tag{3}$$

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.

$$X_{ca} = F_a \left(\frac{H_x - X_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}} \right), \tag{4}$$

$$Y_{ca} = F_a \left(\frac{H_y - Y_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}} \right), \tag{5}$$

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, F_a 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 a stronger weight to the 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 behavioral modulation based on fuzzy inference and VFF vector dynamics: Blue: Calm, goal-seeking behavior (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 [37]. 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.

The simulation utilizes a range of ROS tools to ensure real-time behavioral 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 Integration for Spatial Intelligence a critical backbone of the hybrid navigation system is the integration of Simultaneous Localization and Mapping (SLAM). SLAM enables the robot to construct and update an internal map of the environment while simultaneously localizing itself within that map. This is crucial in dynamic settings where GPS-based or external localization is unavailable or inadequate.

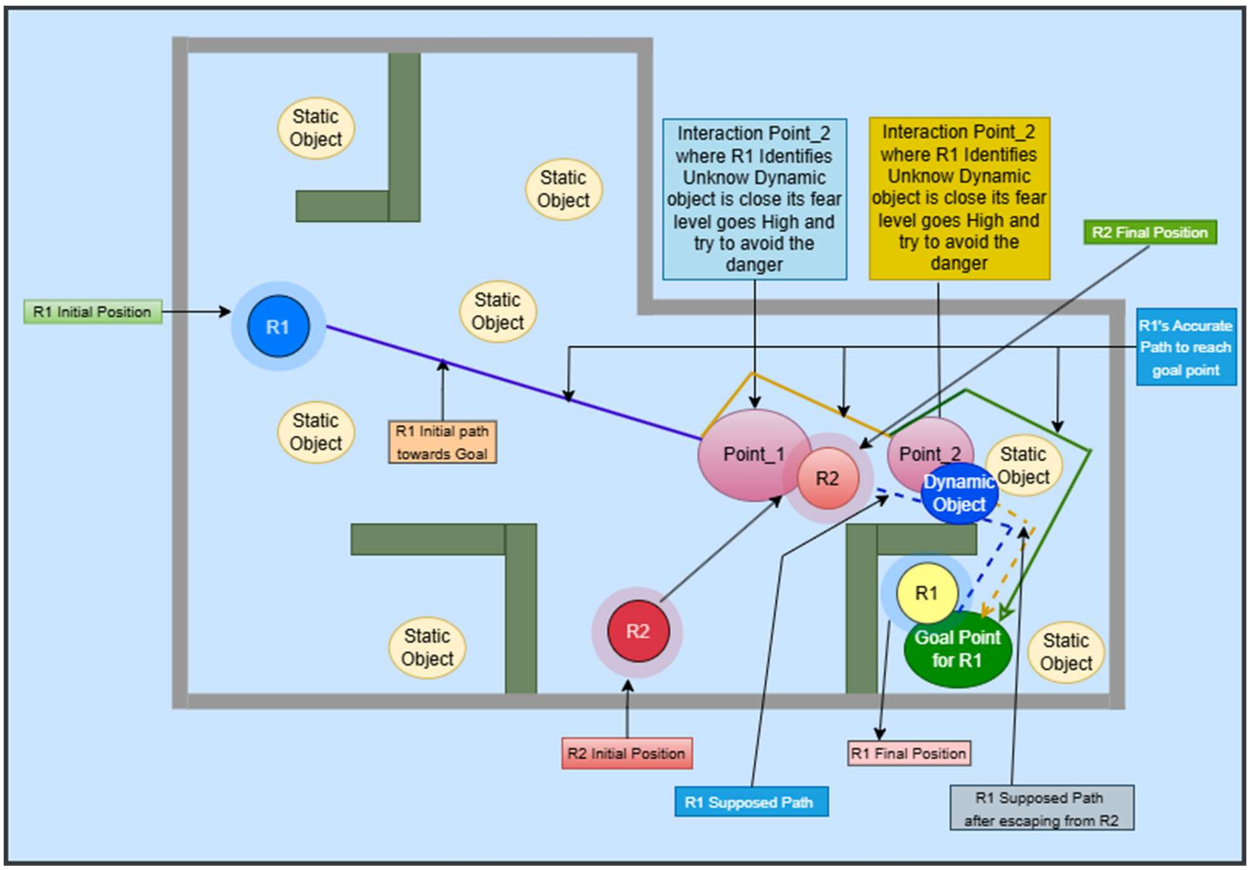

Figure 20. Basic Concept of the Hybrid Architecture.

In this simulation SLAM is implemented using ROS-compatible tools such as gmapping, which continuously update an occupancy grid map based on LIDAR data. 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 behavior in response to obstacles including Robot_2 and unexpected objects using fuzzy behaviour control with VFF.

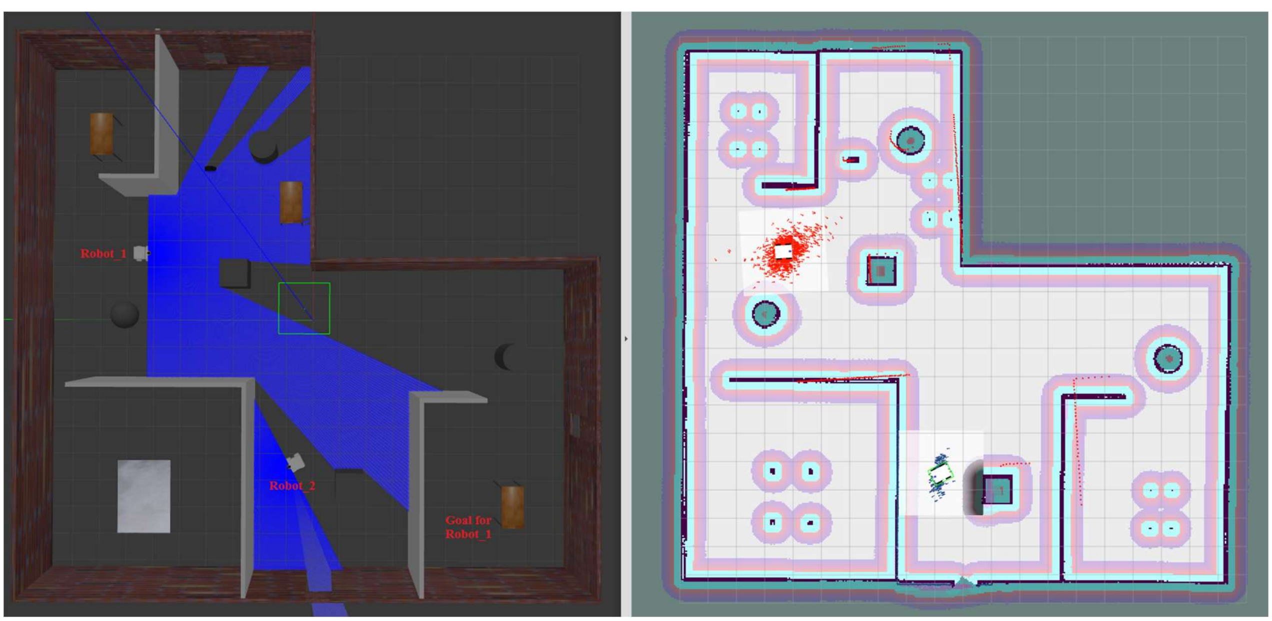

Figure 21(a) Initial stage of robots

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.

Role of VFF and Fuzzy Coordination in Behaviour Generation: The VFF system forms the reactive motion backbone, It: Calculates attractive vectors toward the goal. 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.

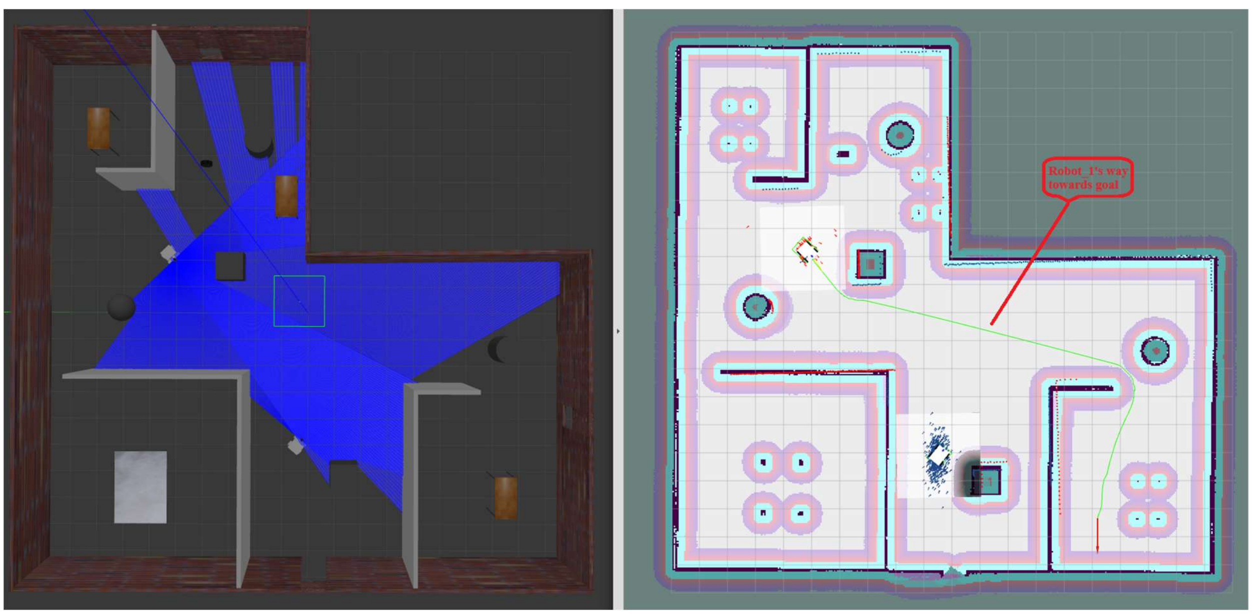

Figure 21(b) Robot_1 starts to move towards its goal.

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 behavior 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.

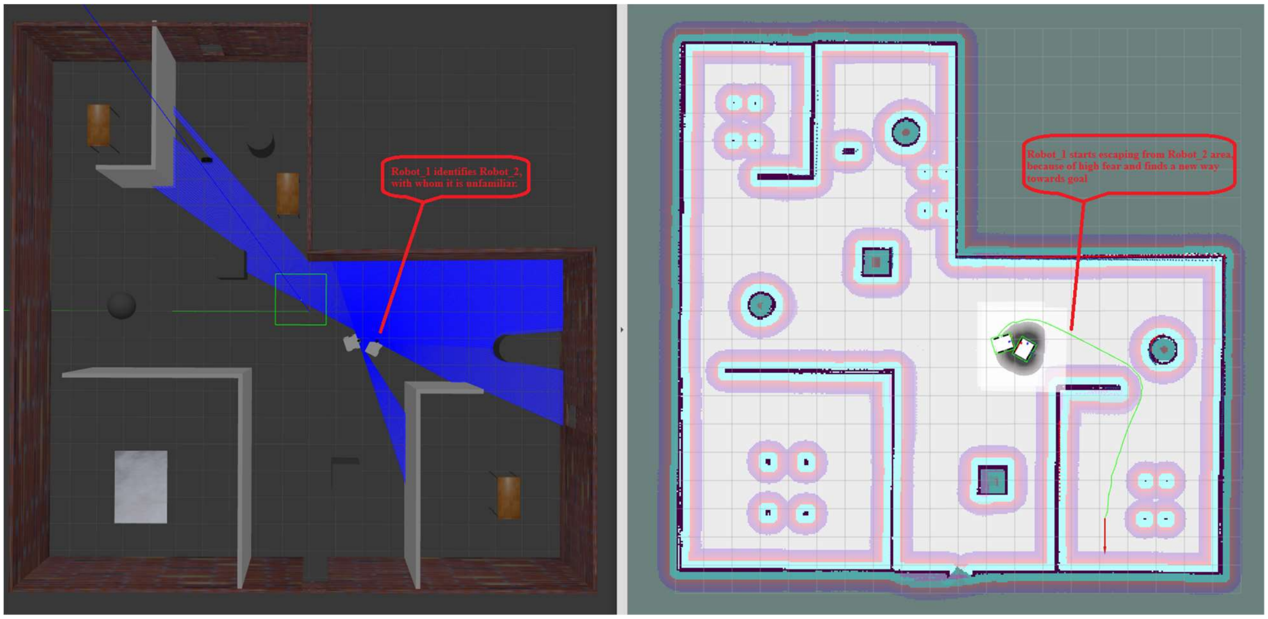

Figure 21(c) Robot_1 detects Robot_2

The hybrid model operates in three coordinated stages: Behavior Components, Behavior Coordination, and Behavior Fusion (VFF) as descibed in the introduction and implementation section of this chapter. *Behavior 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 behavior is triggered.

Behavior 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 prioritized ESCAPE behavior with increased weight.

Behavior Fusion (VFF) the system merges the weighted behaviors 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 behaviors and continuous adaptation to environmental stimuli.

As depicted in figure 21(d), after successfully evading from 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.

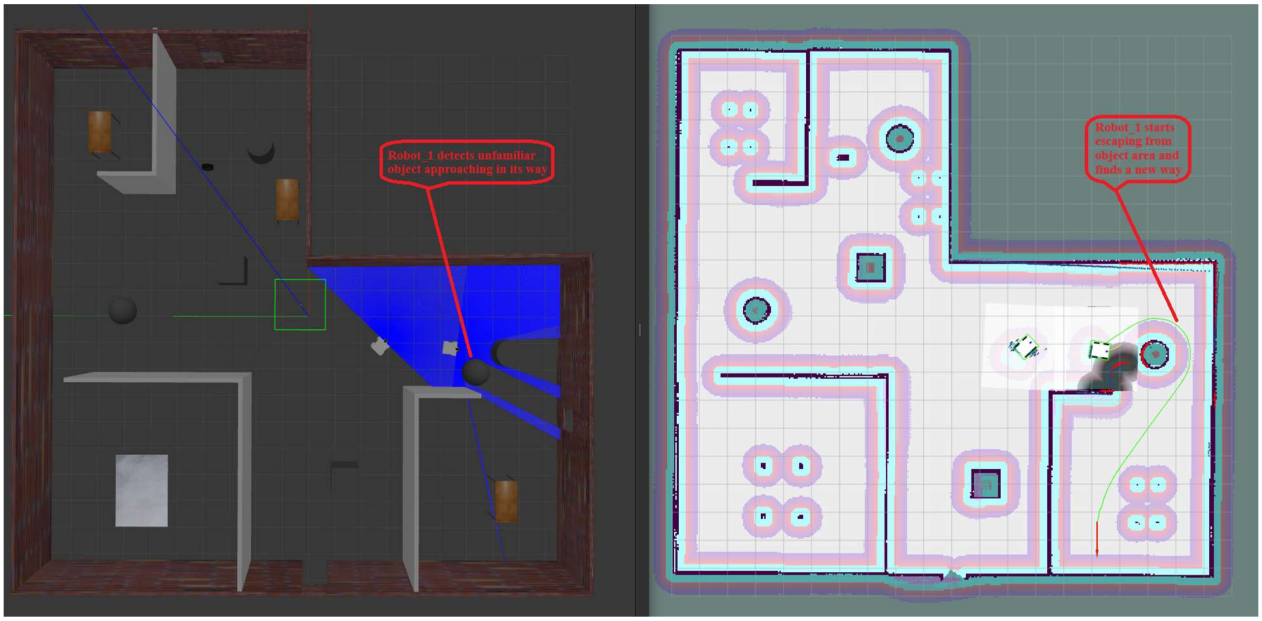

Figure 21(d) Robot_1 identifies the unfamiliar object that comes in its way.

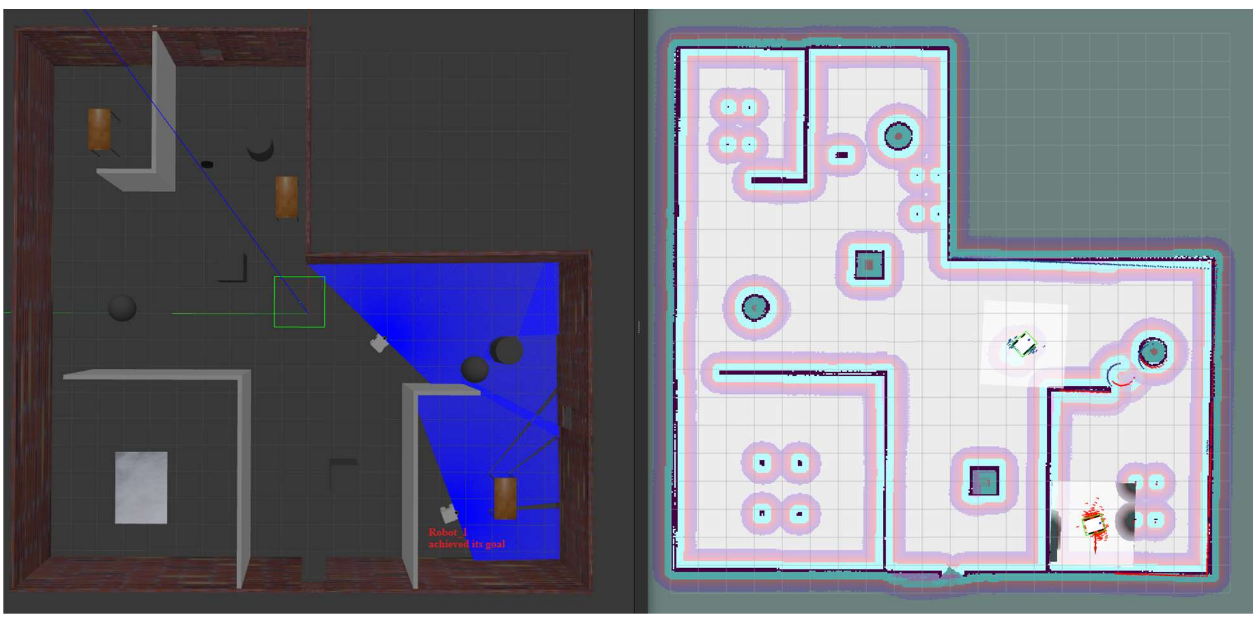

Figure 21(e) Robot_1 successfully achieved its goal.

Figure 21(e) concludes the simulation by illustrating Robot_1's successful arrival at its target after dynamically avoiding both Robot_2 and a 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 behavior 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 Report of Hybrid Model

The classification metrics for the Fuzzy Behaviour-Based Control Framework integrated with the Virtual Force Field presented in figure 22, highlight the system's capacity for adaptive and biologically inspired decision-making in dynamic environments, . This hybrid model combines a fuzzy coordination layer which dynamically assigns behavioral weights based on real-time sensory inputs with the VFF navigation method, which computes attractive forces (e.g., toward goals) and repulsive forces (e.g., away from obstacles). These forces are proportionally scaled by fuzzy-derived weights, resulting in a composite motion vector that enables safe, efficient, and context-aware navigation.

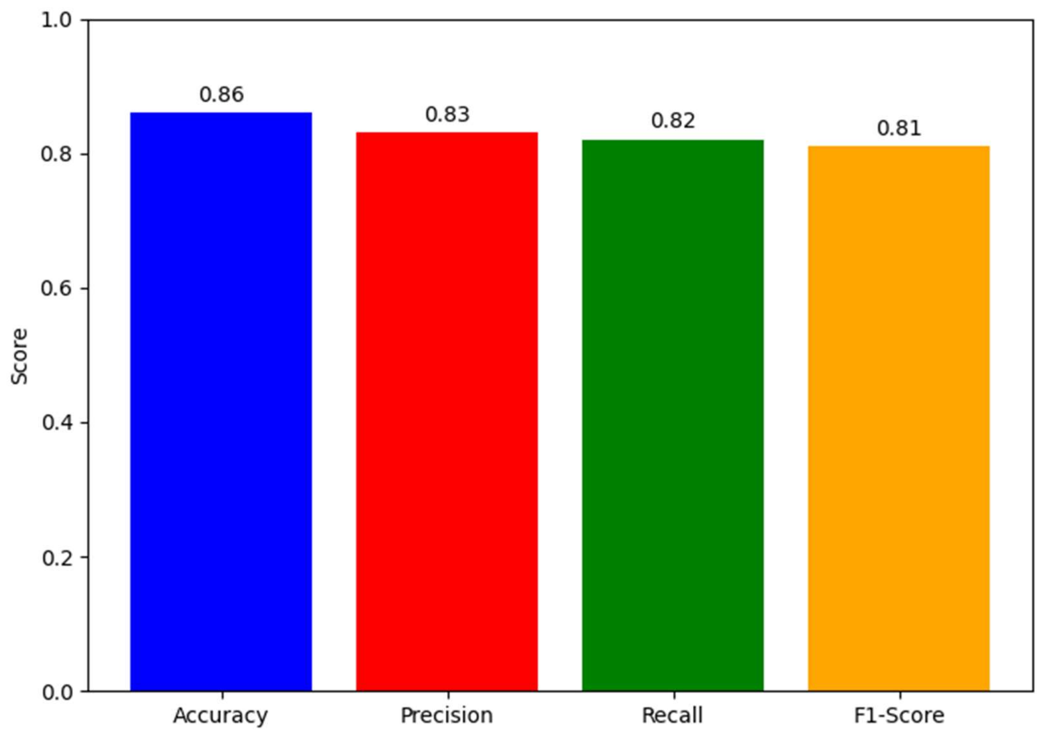

Figure 22. Hybrid Model Classification Metrics

Performance metrics such as precision, recall, F1-score, and accuracy were derived from simulations in ROS. During testing, the fuzzy controller processed inputs like AFTA, ADTA, and AFTO to evaluate behavioral urgency. Decision-making was governed by a structured fuzzy rule base defined in the Fuzzy Behaviour Description Language (FBDL). For example:

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

The rule ensures that the system prioritizes escape behavior when threat conditions are detected. These weighted behaviors are then fused by the VFF module into a unified action directive. The resulting classification report provides quantitative validation of the system's accuracy in real-time decision-making, robustness in rule activation, and adaptability to environmental uncertainty. Overall, the results demonstrate the effectiveness of the proposed ethologically inspired control architecture for real-world and simulated robotic applications.

Conclusion

This study proposes 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 system operates in three stages: behaviour components (e.g., Escape, Goal Pursuit), a fuzzy coordination layer that assigns contextual weights based on inputs like 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 are scaled by the fuzzy-assigned weights, resulting in a unified motion vector that reflects both environmental stimuli and internal state evaluations. Implemented in ROS with LIDAR and SLAM support, the framework enables real-time, context-aware path planning in dynamic environments. Simulations confirm its ability to replicate ethologically plausible escape behaviours, demonstrating smooth transitions between actions and robust decision-making under uncertainty. This integration of high-level reasoning and low-level motion control supports scalable deployment in logistics, service robotics, and human-robot interaction.

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.

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.

System Architecture and Mathematical Formalism

The hybrid control model comprises a dual-layered architecture: a fuzzy emotional module and a force vector computation engine.

- A fuzzy emotional coordination module that classifies behavioural states (e.g., Escape) based on input variables X={AFTA, AFTP, AFTO, EPE, ADTA}. Each input is fuzzified using trapezoidal membership functions, and FBDL-defined rule bases.
- A VFF computation module generating motion vectors scaled by fuzzy-derived emotional weights.
- For example:

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

This triggers dynamic force computation:

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

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

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

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

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

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

- The final motion vector becomes:

$$\vec{F}result = \vec{F}attractive + \vec{F}repulsive * \mu\text{FEAR}$$

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.

Empirical Validation and Simulation

The framework was implemented in ROS and tested in Gazebo with real-time visualization in RViz. Using LIDAR and SLAM, the robot autonomously mapped its environment and responded to dynamic threats. Simulation results (Figures 21(a)–(e)) show real-time behaviour modulation:

- Fear-driven repulsive amplification redirects the robot during encounters with Robot_2 or unknown objects.
- Colour-coded trajectories (blue = low fear, red = high fear) reflect internal emotional states inferred by fuzzy rules.

In threat scenarios where the rule:

IF AFTA = *Low* **AND** ADTA = *Low* AND *EPE* = *High* **THEN** Escape = *High*

is activated, the robot executes an evasive path with elevated repulsion. Each architectural component sensor data acquisition, fuzzy evaluation, vector computation is modular and testable within ROS, supporting unit-level verification and debugging.

Novelity and Impact

This thesis introduces a novel fuzzy-modulated force mechanism, enabling robots to adjust avoidance behavior 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 21, 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 and immobility into fuzzy rule sets, the system simulates biologically grounded behaviors. 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, LIDAR sensing for obstacle detection, and SLAM for real-time localization and mapping. The architecture was rigorously tested using Gazebo-RViz simulations, demonstrating robust, adaptive, and interpretable behavior. The cohesive integration confirms the system's scientific validity and practical applicability for real-world deployment in emotion-aware robotic systems.

Applications

The proposed hybrid control framework enables adaptive, emotionally responsive navigation in dynamic environments, with significant implications across various 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 behaviors (e.g., fear-based retreat) help agents avoid unstable or unfamiliar zones, enhancing resilience and mission success.

Human-Robot Interaction (HRI): Robots exhibit interpretable behaviors 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 behavior modeling.

Chapter 6: Conclusion and Future Work

6.1 Conclusion

This research has presented a comprehensive investigation into the embedding of ethologically inspired emotional behaviors 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

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".

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 behavioral 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 behavioral 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 Behavior control in robotic environment

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 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 behavior 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 behavior selection in dynamic settings. By leveraging modular behavior coordination, the system supports scalable multi-agent interactions and robust behavior 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 behavior modeling but also offers a foundation for ethical and socially aware robotic design.

6.1.3 Thesis III: Hybrid VFF based Fuzzy Behaviour Fusion for Navigation

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.

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 Behavioral 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 behaviors such as nurturing, social bonding, group coordination, dominance, and territoriality. These behaviors are central to both human and animal interactions, and their robotic analogs could significantly enrich empathetic and socially adaptive HRI systems. Studying behavioral 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 behavioral science.

6.2.2 Advancing Machine Learning Integration

Although fuzzy logic provides interpretable and controllable behavior 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 behavioral 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 behaviors 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 Behavior Analysis Models

Further research is warranted in developing advanced models for sentiment detection, contextual emotion prediction, and multimodal behavior 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 behavioral assessment could support rich, adaptive interactions in domains ranging from caregiving and therapy to collaborative robotics and ambient intelligence. Enhanced behavioral inference would not only improve robot autonomy but also contribute to more natural and emotionally congruent human-robot relationships.

Publications

No.	Authors	Title	Publication Details	Type & Indexing
1	Lone, Mohd Aaqib; Khanday, Owais Mujtaba; Kovács, Szilveszter	Implementation Guidelines for Ethologically Inspired Fuzzy Behaviour-Based Systems	INFOCOMMUNICATIONS JOURNAL 16:3, pp. 43-56 (2024). DOI | WoS | Scopus	Journal Article | Q3 (CS, EE) | HASSESVI, HASSESX
2	Lone, Mohd Aaqib; Szilveszter Kovacs	Implementation Guidelines for Ethologically Inspired Fuzzy Behavior-Based Systems	17th Miklós Iványi Symposium, Abstract Book (2021), p. 92	Book Abstract
3	Khanday, Owais Mujtaba; Samad, Dadvadipour; Lone, Mohd Aaqib	Effect of Filter Sizes on Image Classification in CNN	IAES Int. J. of Artificial Intelligence 10:4, pp. 872-878 (2021)	Journal Article | Q3 AI/EE/IS | Scopus
4	Ganie, Aadil Gani; Samad, Dadvadipour; 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 (1992-8645 1817-3195) : 99 11 pp 2567-2577	Journal Article | Q4 | Scopus
5	Lone, Mohd Aaqib; Szilveszter Kovacs	A Survey on Ethologically Oriented Fuzzy Behavior-Based System Implementations	16th Miklós Iványi Symposium, Abstract Book (2020), Paper 131	Book Abstract
6	Lone, Mohd Aaqib; Khanday, Owais Mujtaba; Gani, Aadil Ganie	A Survey on Robot Behavior and Distance Estimation in IndoorGML Maps	American Journal of Electronics & Communication 1:3, pp. 1-7 (2021)	Journal Article | Survey
7	Maen, Alzubi; M, Almseidin; Lone, Mohd Aaqib; Szilveszter Kovacs	Fuzzy Rule Interpolation Toolbox for GNU OCTAVE	ICETA 2019, IEEE, pp. 16-22	Conference Paper | Scopus
8	Lone, Mohd Aaqib; Zsolt, Toth	Ontology Based Navigation Solutions	Tavaszi Szél 2019 Konferencia, p. 437	Book Abstract

9	Lone, Mohd Aaqib; Khanday, Owais Mujtaba; Ganie, Aadil Gani	Survey on Indoor Navigation Solutions	JOURNAL OF SOFTWARE ENGINEERING AND INTELLIGENT SYSTEMS 6:2 (2021)	Journal Article | Survey
10	Lone, Mohd Aaqib; Zsolt, Toth	Distance Estimation In IndoorGML Maps	Theory Meets Practice in GIS, Debrecen (2019), pp. 9-18	Conference Paper
11	Owais, Mujtaba Khanday; Samad, Dadvadipour; Lone, Mohd Aaqib	Forecasting the Spread of COVID-19 in Hungary	Preprint (2020)	Repository | Preprint
12	Ganie, Aadil Gani; Samad, Dadvadipour; Lone, Mohd Aaqib; Khanday, Owais Mujtaba	Covid-19 Situation in Hungary using Time Series Analysis	ICACTCE'21, pp. 1-4 (2021)	Conference Paper

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