UNIVERSITY OF MISKOLC

FACULTY OF MECHANICAL ENGINEERING AND INFORMATICS

ETHOLOGICALLY INSPIRED FUZZY BEHAVIOUR BASED SYSTEMS

PHD THESIS

Prepared by

Mohd Aaqib Lone

BACHELOR OF INFORMATION TECHNOLOGY

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Head of Doctoral School

Prof. Dr. László Kovács

Full Professor

Scientific Supervisor

Prof. Dr. Szilveszter Kovacs

Full Professor

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Preface

The development of intelligent machines capable of autonomous operation in complex, dynamic environments has long been a central goal in artificial intelligence and robotics. While substantial progress has been made in areas such as mechanical control, sensory perception, and cognitive reasoning, the integration of affective, ethologically grounded behaviours remains relatively underexplored. This dissertation addresses that gap by investigating how emotional constructs specifically fear, escape, and attack, as conceptualized in ethology can be modelled computationally, expressed behaviourally, and deployed operationally within autonomous robots.

Grounded in Archer's ethological framework of aggression and fear in vertebrates, this research examines how such adaptive responses can be translated into robotic behaviour that is both functionally intelligent and socially interpretable. The central premise is that embedding emotional constructs into machine behaviour enhances not only the realism and expressiveness of autonomous agents but also their ability to interact safely, intuitively, and adaptively with humans and dynamic environments. The dissertation is structured around three core contributions, each representing a step toward integrating Archer's model into artificial systems.

The first contribution introduces the Fuzzy Behaviour Description Language (FBDL) a novel, machine-executable interpretation of Archer's theory. It enables robots to generate interpretable, context-sensitive emotional responses using fuzzy logic. The second contribution implements this framework in the Robot Operating System (ROS), enabling real-time behavioural transitions through integration with LIDAR and SLAM for perception and localization. This allows robots to fluidly modulate behaviours such as escape and attack in dynamic scenarios. The third contribution presents a hybrid system that combines Virtual Force Field (VFF) navigation with fuzzy emotion-based control, allowing robots to make graded decisions based on continuous variables such as threat proximity, environmental familiarity, and internal emotional states. This enhances their responsiveness and safety in human-centric and unpredictable settings.

Collectively, these contributions establish a novel framework for affective robotics, bridging behavioural ethology, fuzzy logic, and autonomous navigation. The work advances the fields of artificial emotional intelligence, socially aware robotics, and interpretable machine behaviour. I am deeply grateful to my supervisor, collaborators, and all those who supported this interdisciplinary journey. I hope this research offers both theoretical insight and practical inspiration for the development of emotionally responsive machines.

Part 1. Summary of the Research Task

1.1 Introduction

Autonomous robots are increasingly deployed in dynamic and unpredictable environments where they must engage in navigation, collaboration, and interaction with other agents including humans. While traditional robotic control systems perform reliably in structured settings and deterministic tasks such as mapping and trajectory planning, they often falter when operating in conditions marked by uncertainty, social complexity, or ambiguous sensory inputs. One of the key limitations is their inability to exhibit adaptive, context-aware behaviours similar to those found in biological organisms particularly those behaviours modulated by emotions.

In biological system, emotional responses such as fear, aggression, or escape are not merely affective states but evolved mechanisms that guide survival and adaptive decision-making. Ethology, the scientific study of animal behaviour, has shown that such emotions arise through dynamic evaluations of threat, familiarity, and past experience [1]. Embedding this kind of biologically meaningful behaviour in robots opens the possibility for machines that are more responsive, interpretable, and socially attuned [2, 3].

Despite advancements in fields like cognitive robotics and affective computing, the implementation of real-time emotional responses grounded in biological theory remains a significant gap. Many robotic systems model emotions as symbolic tags or rely on opaque statistical methods that lack transparency. What is needed is a principled framework that integrates emotional processing into behavioural control, enabling robots to respond to uncertainty with nuanced, naturalistic behaviours.

This research addresses that need by proposing a fuzzy logic-based control architecture inspired by Archer's ethological model of fear and aggression. It hypothesizes that using fuzzy inference to formalize emotional constructs enables robots to reason with ambiguity, produce graded behavioural responses, and navigate more intelligently in multi-agent settings. The work introduces a Fuzzy Behaviour Description Language (FBDL) [4], implements fuzzy state transitions in the Robot Operating System (ROS), and integrates emotional appraisal with Virtual Force Field (VFF) navigation. Collectively, these contributions create a foundation for emotionally responsive robots that operate ethically and intuitively in real-world environments.

1.2 Context and Motivation

The core motivation for this research stems from the ambition to build robots that behave not only through mechanistic control but also through emotional intelligence that mirrors biological reasoning. Drawing upon ethology, this study models fundamental emotional behaviours namely fear, escape, and aggression as seen in animal responses to environmental threats [5]. These behaviours, when embedded in robots, allow machines to act in ways that feel more natural and intuitive to human users. Fuzzy logic serves as the computational bridge for this modelling task. Unlike binary systems that enforce strict true/false evaluations, fuzzy logic accommodates partial truths and ambiguity essential properties when dealing with emotions and adaptive behaviour. Archer's ethological theory of aggression and fear provides the conceptual backbone, guiding the formulation of behavioural rules that respond to variables such as threat distance, environmental familiarity, and escape feasibility.

The principal challenge lies in translating this biologically rich model into a machine-executable language that enables real-time behavioural modulation. Through the creation of FBDL, fuzzy inference models, and their integration into ROS, this work aims to bridge the gap between natural behaviour theory and practical robotic implementation.

1.3 Objectives

The first objective of this research is to design and develop the Fuzzy Behaviour Description Language (FBDL), a modular and human-readable language that enables researchers to encode behaviours such as fear, escape, and aggression using fuzzy logic. By allowing the formalization of complex behavioural rules in a declarative syntax, FBDL facilitates collaboration between robotics engineers and ethologists, thus creating a shared framework for interdisciplinary development.

The second objective is to construct a fuzzy inference model grounded in Archer's theory. This involves defining fuzzy membership functions for key environmental variables such as the proximity to a threat, familiarity with surroundings, and escape potential and designing a rule base to govern emotional state transitions. The model must support smooth and graded behavioural shifts, such as transitioning from escape to attack, and it is validated through systematic simulations and controlled experiments.

A third objective is to embed the fuzzy behavioural model into a robot control architecture built on the Robot Operating System (ROS). Within this framework, a Fuzzy State Machine (FSM) processes real-time sensory input from devices like LIDAR and SLAM and evaluates emotional states based on predefined fuzzy rules. The FSM outputs behaviours such as escape or attack in real-time, ensuring the robot can operate autonomously in unpredictable scenarios.

Finally, the work seeks to integrate the fuzzy behaviour controller with a Virtual Force Field (VFF)-based navigation system. This hybrid architecture enables robots to adjust their motion plans not just based on geometric constraints but also on internal affective states. For example, higher fear levels increase repulsion forces and lead to wider path deviations. This fusion of emotional state and path planning equips robots with the capacity to act more fluidly and appropriately in complex environments.

1.4 Significance and Scope

This research contributes to the fields of affective robotics, fuzzy systems, and bio-inspired control by introducing a computational framework that mirrors the emotional modulation found in animal behaviour

[5, 6, 7, 8]. Situated at the intersection of ethology, fuzzy logic, autonomous systems, and VFF-based motion planning, it presents a novel approach to developing context-sensitive, emotion-driven robotic behaviour.

Its primary significance lies in enabling robots to exhibit graded and interpretable responses that reflect biologically inspired emotional states. Such capabilities are increasingly crucial in domains requiring human-robot interaction, adaptive navigation, or social collaboration. By grounding robotic behaviour in validated biological models and pairing it with fuzzy logic reasoning, the system ensures both functional adaptability and transparency.

The scope of the thesis is intentionally focused and practical: it models animal aggression behaviours using fuzzy logic, implements them in a real-time robotic control framework, and validates the outcomes through simulations and empirical tests. While it does not aim to model the full emotional spectrum or support all application domains, it demonstrates the feasibility and value of integrating emotional intelligence into autonomous robots. This lays the groundwork for future research into socially compatible and emotionally aware machines.

Part 2: Methodology: Investigations and Experiments

This research presents an interdisciplinary methodology that integrates ethology, fuzzy logic, and robotics to design emotionally responsive autonomous systems [Aaqib1-Aaqib7]. At its core is Archer's ethological model of aggression and fear, which provides a biologically grounded template for modeling adaptive behaviour in animals [5]. This model is computationally translated into a robotic control architecture using fuzzy logic, enabling robots to simulate behaviours such as escape, attack, and immobility in response to varying environmental stimuli. The Fuzzy Behaviour Description Language (FBDL) [4] was developed to formalize these behaviour rules, making them interpretable, modular, and executable within robotic platforms. The methodology encompasses theoretical modeling, software implementation, simulation-based testing, and analysis of emergent multi-agent dynamics.

2.1 Ethological Foundations

Ethology, the study of animal behaviour, provides evolutionary models of adaptive responses such as fear, escape, and aggression. Classical works by Tinbergen, Lorenz, and Archer have guided the abstraction of behavioural hierarchies and motivational systems [5, 9, 10, 11]. These models were foundational for constructing robotic behaviours that are reactive, context-aware, and biologically plausible.

This research adopts Archer's model to simulate aggression and fear, focusing on how animals modulate behaviour based on environmental familiarity, proximity to threats, and prior experience [5]. By abstracting these principles, ethologically inspired control strategies were adapted for autonomous robots to support socially intelligible interactions.

2.2 Fuzzy Behaviour-Based Systems

This system offers a powerful and flexible framework for implementing ethologically inspired behaviours in autonomous robots [12, 13]. Fuzzy systems allow robots to interpret input data with flexibility and to respond in a more adaptive, human-like manner. In the context of ethological robotics, fuzzy logic serves as the computational layer that mediates between sensory inputs and emotional or instinctive responses. At the core of these systems are fuzzy rule-based structures that encode expert knowledge through **IF**[*Condition*] **THEN**[*Statements*] rules. For example:

If AFTP = *Low* **AND** AFTA = *Low* **AND** ADTA = *Low*, **THEN** FEAR = *High*

Here, AFTP (Animal Familiarity Toward Place), AFTA (Animal Familiarity Toward Another), and ADTA (Animal Distance Toward Another), together all these define a robot's perceived emotional context. Fuzzy Logic Controllers (FLCs) that encapsulate individual behaviours like attack, escape, or immobility; Behaviour Arbitration, which manages conflicts between competing actions based on emotional appraisal and sensory stimuli; and Behaviour Fusion, which integrates outputs to form a coherent control signal [14]. This architecture enables robots to make fluid, graded behavioural transitions that reflect the ambiguity and dynamism of real-world scenarios. Figure 1 illustrates the logic of fuzzy behaviour system.

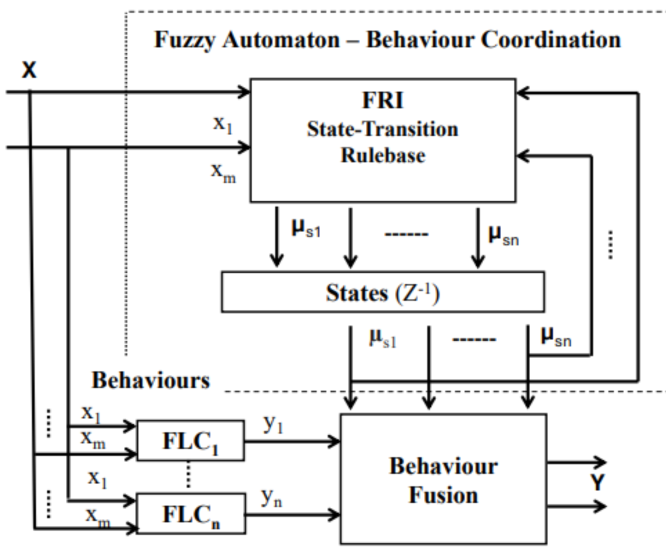

Figure 1. The applied Fuzzy Behaviour-based System [15]

2.3 Modelling and Implementation of Aggression Behaviour

This study models aggressive behaviour in autonomous robots by translating Archer's ethological theory of fear and aggression into a fuzzy control architecture [5]. Archer's model describes how animals evaluate threats through a dynamic loop of internal states, environmental perception, and behavioural adaptation (figure 2). The process begins with the formation of expectations based on past experiences and current internal conditions. When external stimuli such as another agent's movement or posture are detected, the animal compares them against these expectations. A significant mismatch raises arousal levels and prompts a behavioural choice: escape, attack, or immobility. Fear-dominant situations typically lead to escape if a viable path is available. If escape is not feasible, the organism may resort to immobility or aggression, depending on situational constraints.

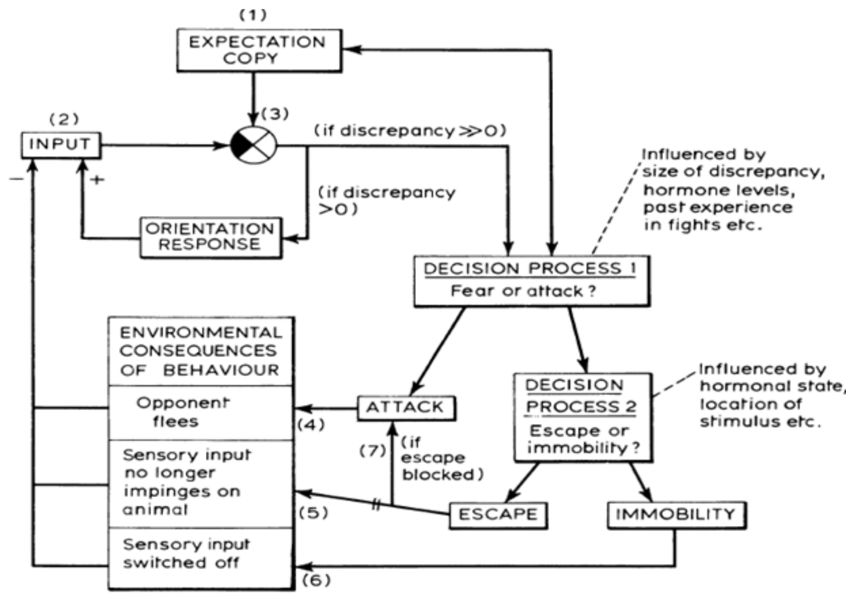

Figure 2. Archer organization model [5]

To translate this model into a robotic control system, a Fuzzy State Machine (FSM) is employed. The system defines four key state variables: Attack, Escape, and Immobility as observable actions, and Fear as a hidden state influencing transitions. *Fear* reflects internal physiological and emotional responses to threats and often manifests through posture or movement. *Attack* denotes defensive or offensive action; *Escape* refers to evasion; and *Immobility* is a passive survival response. Transitions among these states are governed by observational variables, including: Animal Familiarity towards Place (AFTP), Animal Familiarity towards Another Animal (AFTA), Animal Distance towards another animal (ADTA), Animal Familiarity towards Object (AFTO), and Animal Distance towards Objects (ADTO) (AFTO and ADTO are the extensions of Archer's model for robotic context), Escape Path Exists (EPE), Positive Impact With Previous Experiences (PIWPE). All these input variables are mapped into fuzzy sets such as Low, Medium, or High, allowing flexible and context-sensitive reasoning. For example:

If AFTP = *Low* **AND** AFTA = *Low* **AND** ADTA = *Low*, **THEN** FEAR = *High*.

This rule reflects how low familiarity with surroundings and close proximity to others can elevate fear, triggering avoidance or defensive behaviours. The FSM continuously evaluates such rules in real time based on sensory data primarily from LIDAR and SLAM and adjusts behaviour accordingly. The resulting architecture produces adaptive, biologically plausible behaviours that are computationally tractable and interpretable. It allows robots to exhibit complex emotional responses such as aggression or evasion not as static reactions, but as fluid, state-dependent strategies shaped by environmental context and internal appraisal.

2.4 Experimental Setup and Behavioural Testing

The proposed fuzzy behaviour-based control system was validated through simulation within the Robot Operating System (ROS) environment [16, 17]. The simulation utilized Gazebo for dynamic environment modelling and RViz for real-time visualization. Robotic agents were equipped with LIDAR sensors and integrated Simultaneous Localization and Mapping (SLAM) to facilitate environmental perception and accurate self-localization. Test scenarios involved navigation through varied environments, characterized by differing levels of threat, object familiarity, and obstacle density. Behavioural responses were governed by fuzzy-logic rules derived from ethological principles. For example:

Escape Rule: **If** EPE is High **and** Fear is High, **then** Escape is High.

Attack Rule: **If** AFTA is Low, **and** ADTA is Low, **and** EPE is Low, **then** Attack is High.

Multi-agent scenarios were designed to test the system's ability to manage complex social interactions. In one case, Robot_1 detected Robot_2 as a threat and initiated an escape response based on elevated fear levels. In another, Robot_2 interpreted Robot_1's retreat as a threat, triggering an aggressive response. A third scenario introduced simultaneous exposure to a moving robot and an unfamiliar object, prompting Robot_1 to execute an emotionally modulated escape using fuzzy rule evaluation and Virtual Force Field (VFF) fusion. These experiments demonstrated the system's capacity to generate adaptive, context-sensitive behaviours in real time, in response to both animate and inanimate stimuli. System performance was assessed using precision, recall, F1-score, and accuracy, confirming consistent and appropriate behavioural transitions. The smooth shifts between escape and attack behaviours highlighted the effectiveness of the fuzzy state machine in capturing naturalistic emotional dynamics.

2.5 Data Collection Methods and Discoveries

This research employed a hybrid data collection methodology combining simulation and real-world robotic testing to validate the proposed fuzzy behaviour-based control model. In simulation, the Fuzzy Behaviour Description Language (FBDL) [4] was used to define and implement fuzzy rules via publicly available libraries [18, 19]. Environmental inputs such as threat proximity, familiarity, and past experience were systematically varied. Robots equipped with LIDAR and SLAM generated real-time spatial data, which the fuzzy state machine processed to infer emotional states like fear, aggression, and escape. Behavioural outputs were visualized through state transition diagrams and trajectory plots, aiding iterative refinement of rules and membership functions.

The experimental design followed two complementary methodologies. The knowledge-based approach translated Archer's ethological model into structured fuzzy rules, while the situated action approach emphasized adaptive behaviour in response to unanticipated environmental changes. This combination ensured both theoretical grounding and practical robustness. System performance was evaluated using standard classification metrics precision, recall, F1-score, confusion matrices, and accuracy demonstrating reliable, context-sensitive responses. The fuzzy rule base included approximately 36 interpretable, testable rules, each contributing to biologically plausible decision-making.

A key finding is the natural compatibility between fuzzy logic and ethological models. Both accommodate uncertainty, gradation, and non-binary reasoning are essential for modelling emotional behaviour. Fuzzy logic effectively captured nuanced shifts in emotional states as functions of multiple situational variables. This interdisciplinary integration of ethology, robotics, and computational logic resulted in a behaviour control system that is adaptive, explainable, and scalable. The architecture supports extensions to more complex emotions and multi-agent interactions, offering a viable path toward socially intelligent, emotionally responsive robots for dynamic real-world environments.

Part 3: Scientific Results

3.1 Fuzzy Rule-Base, Graphical Representation, and Trajectory Implementation for the Aggression Model

3.1.1 Fuzzy Behaviour-Based Modeling for Aggression Behaviour Using FBDL

To implement fuzzy behavioural modelling for aggression, Fuzzy Behaviour Description Language (FBDL) [4] is employed. FBDL is a rule-based modelling language that incorporates fuzzy rule systems and Fuzzy Rule Interpolation (FRI) [15] [20], enabling the construction and coordination of behavioural components in a transparent, human-readable format. This approach ensures interpretability of rule-based knowledge representation. The fuzzification process uses linguistic variables defined as fuzzy sets over continuous universes, enhancing computational flexibility and semantic clarity. The model supports both numerical simulations and integration with machine learning algorithms for optimization using real-world data [Aaqib2]. The FBDL definition of the input and state variable universes are:

```
universe "Universe label"
        "low" 0 0
        "high" 1 1
end
```

For example, the input universe AFTP in FBDL can be defined as:

```
universe "AFTP"
description "Level of the Animal Familiarity towards Place."
    "low" 0 0
```

"high" 1 1

end

Here, AFTP represents the input variable describing animal familiarity with the place. Fuzzy rules can then be defined using linguistic terms like Low and High.

In FBDL format a fuzzy rule expressing Low Fear (when the animal is highly familiar with the place, animal, and object) is presented as:

Rule *"Low"* **When** "AFTP" is "*High*" **And** "AFTA" is "*High*" **And** "AFTO" is "*High*" **end**

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.

3.1.2 Construction of Fuzzy Rule for Ethological Aggression Behaviour

The fuzzy rule bases model key affective states are FEAR, ESCAPE, ATTACK, and IMMOBILITY under conditions such as: AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, these scenarios correspond to real ethological triggers, like territorial invasion, predator-prey dynamics, and approach-avoidance conflicts [Aaqib1, Aaqib2].

The **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.

The **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

The **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. Similarly in the same way Immobility rulebase in FBDL is described.

3.1.3 Graphical Representation of Behavioural Dynamics

The figures 3(a)-(d) presents the Graphical representation of Aggression behaviours [Aaqib2]. Simulations were run by varying key inputs such as ADTA (Animal Distance Towards Another) and EPE (Escape Path Exists), with all other parameters held constant. The output behaviours were visualized graphically: Figure 3(a): Fear increases with decreasing distance and no escape. Figure 3(b): Attack peaks under threat proximity with no EPE. Figure 3(c): Escape is high when unfamiliarity and EPE coexist. Figure 3(d): Immobility dominates when both escape and attack are infeasible.

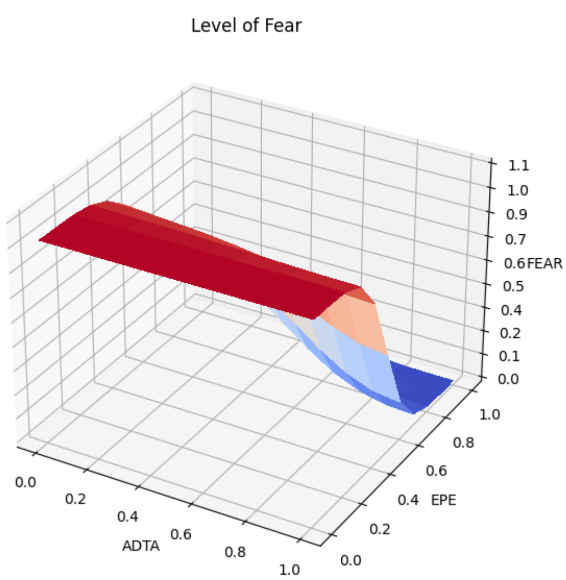

Figure 3 (a). Level of Fear Behaviour

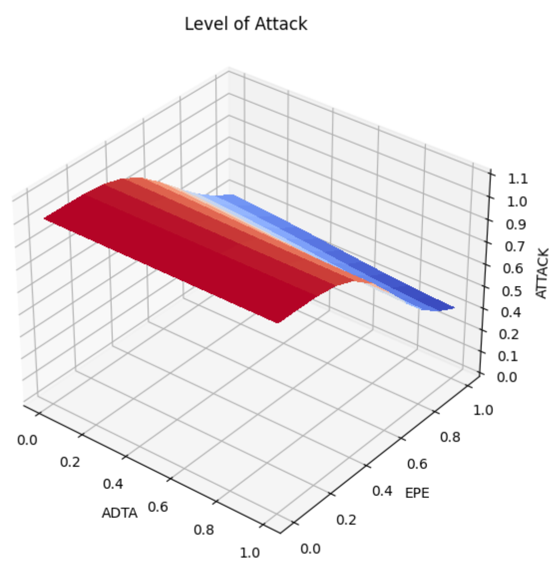

Figure 3 (b). Level of Attack Behaviour

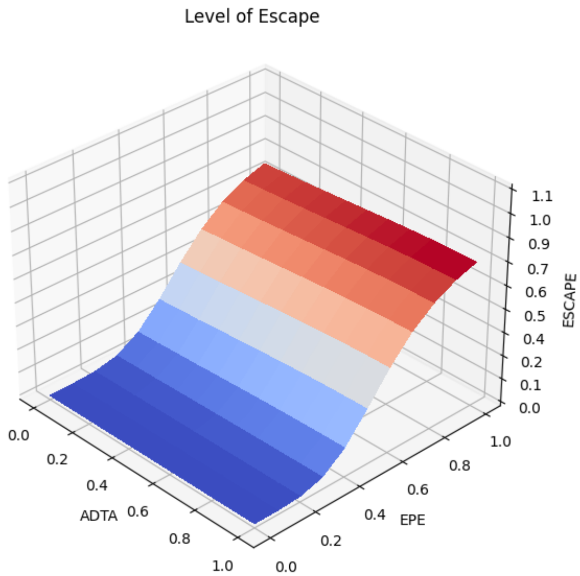

Figure 3 (c). Level of Escape Behaviour

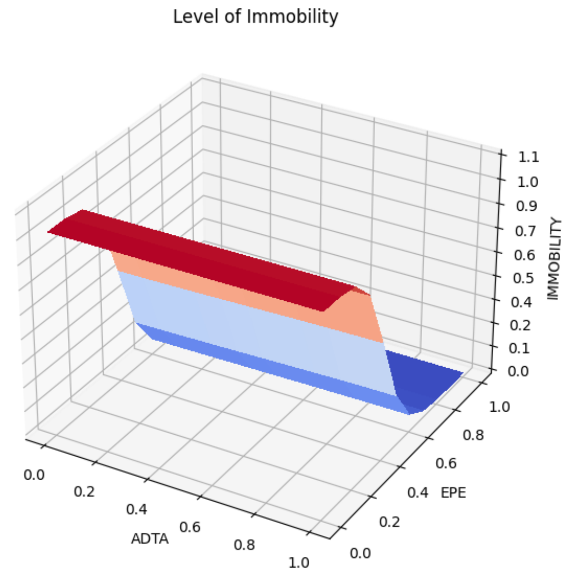

Figure 3 (d). Level of Immobility Behaviour

Figure 3 (a), (b), (c), (d). Graphical Representation of Behaviours

3.1.4 Escape Behaviour Trajectory Simulation

Algorithm 1: Fuzzy Logic-Based Escape Behaviour for Robots

```
Input:
   Robot_1_Start ← (0.5, 0.5)
   Robot_2_Start ← (6, 6)
   Parameters ← {ADTA, FEAR, EPE}
   Threshold_Distance ← D  (Critical distance for fear increase)
Initialize:
   Set Robot_1 fear_level ← LOW
   Set Robot_2 familiarity_level ← HIGH
   Move Robot_1 toward Robot_2_Start
   Move Robot_2 toward Robot_1_Start
While Robot_1 and Robot_2 are moving:
   CD ← ComputeDistance(Robot_1.position, Robot_2.position)
   FEAR ← EvaluateFuzzyLogic(ADTA, FEAR, CD)
   If CD ≤ Threshold_Distance:
      Increase Robot_1 fear_level
      If EPE exists:
         TriggerEscape(Robot_1)
      Else:
         ContinueMovement(Robot_1)
   SynchronizeBehaviour(Robot_1, Robot_2)
   If CD increases:
      Decrease Robot_1 fear_level
      SetTrajectoryColor(Robot_1, BLUE)
EndCondition:
   If Robot_2 reaches near Robot_1_Start location and Robot_1 escaped successfully:
      StopSimulation()
```

    LogBehaviourData()
Output:
  - Robot_1 trajectory: BLUE → RED → BLUE
  - Adaptive escape response recorded
  - Simulated natural escape behaviour in robotics

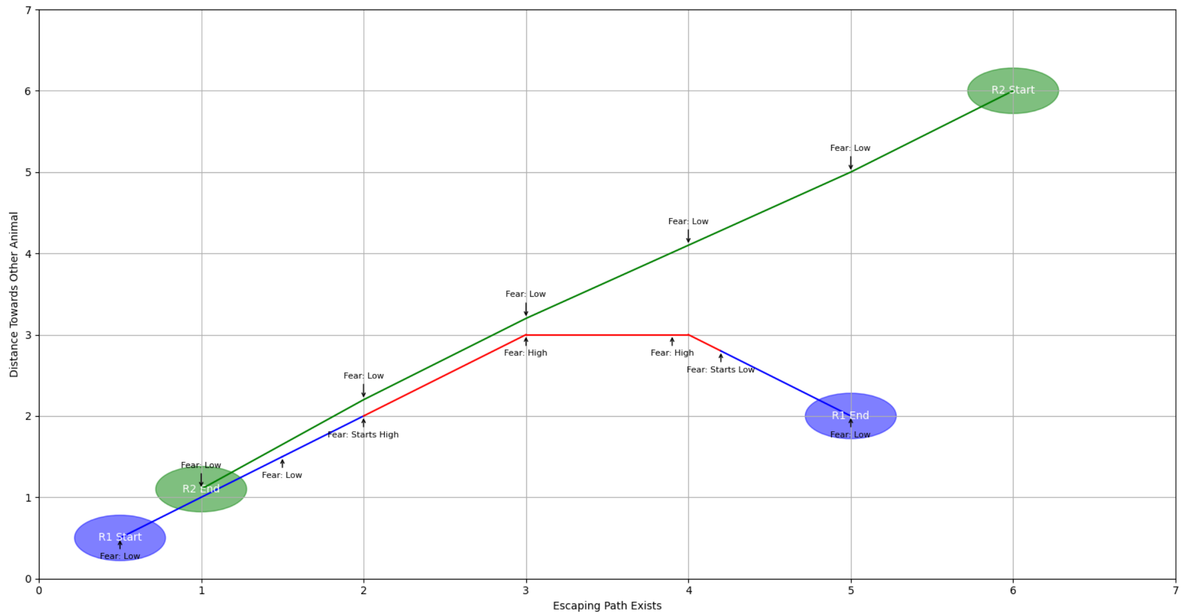

Figure 4. Trajectories for Escape Behaviour, where colours of the paths are representing the level of the "Fear" [Aaqib2]

3.1.5 Attack Behaviour Trajectory Simulation

Algorithm 2: Fuzzy Logic-Based Attack Behaviour for Robots
Input:
  Robot_1_Start ← (1, 1)
  Robot_2_Start ← (5.5, 5.5)
  Parameters ← {ADTA, FEAR, AFTP, AFTA}
  Threshold_Distance ← D (Critical distance for aggression increase)
Initialize:
  Set Robot_1 aggression_level ← LOW (BLUE)
  Set Robot_2 fear_level ← NONE (GREEN)
  Move Robot_1 toward near Robot_2_Start
  Keep Robot_2 stationary initially
While Robot_1 is moving:
  CD ← ComputeDistance(Robot_1.position, Robot_2.position)
  FuzzyParams ← EvaluateFuzzyLogic(ADTA, AFTP, AFTA, FEAR, CD)
  If CD ≤ Threshold_Distance:
    Increase Robot_1 aggression_level
    SetTrajectoryColor(Robot_1, RED)
    Increase Robot_2 fear_level
    SetTrajectoryColor(Robot_2, ORANGE)
    Robot_2 evades position to avoid damage
  If CD increases again:

```
        Decrease Robot_1 aggression_level
        SetTrajectoryColor(Robot_1, BLUE)
        Decrease Robot_2 fear_level
        SetTrajectoryColor(Robot_2, GREEN)
EndCondition:
    If Robot_1 presents Aggression successfully:
        StopSimulation()
        LogBehaviourData()
Output:
    - Robot_1 trajectory: BLUE → RED
    - Robot_2 trajectory: GREEN → ORANGE → GREEN
    - Adaptive attack behaviour recorded
    - Simulated animal-like attack behaviour in robotics
```

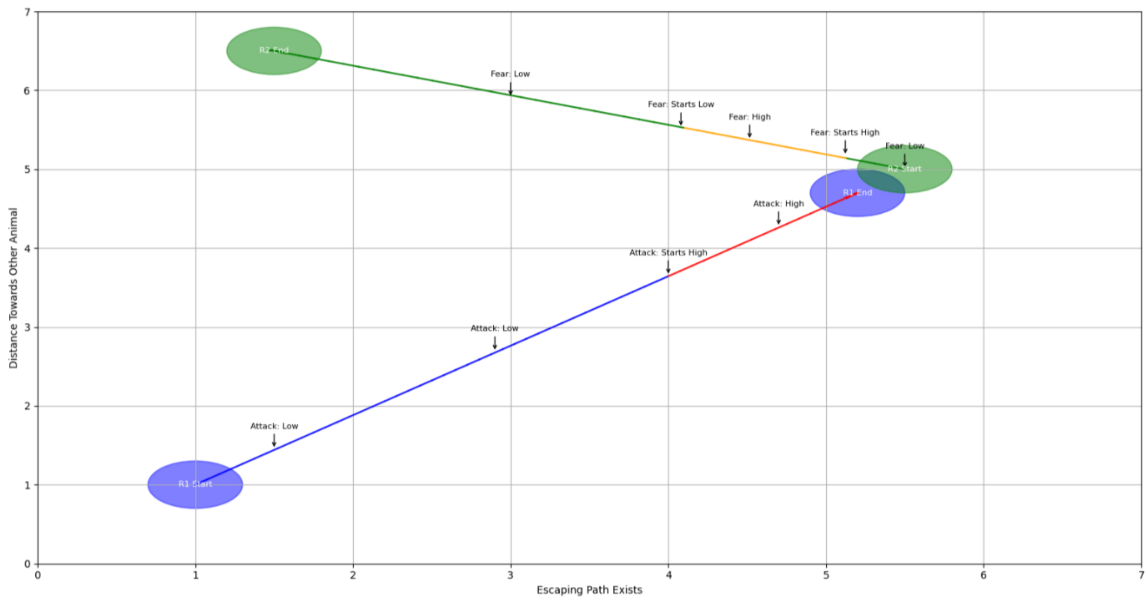

Figure 5. Trajectories for Attack Behaviour, where colours of the paths represent the level of the "Attack" [Aaqib2]

3.2 Implementing Aggressive Behaviour in ROS robotic environment

Biologically inspired robotic behaviours can be effectively developed using two complementary methodologies: Knowledge-Based Ethological Design and Situated Action-Based Behaviour Design [Aaqib1, Aaqib2, Aaqib3]. Both aim to emulate animal-like responses by integrating principles from ethology with real-time environmental interactions. The ethological approach draws on observed animal behaviours, mapping them onto robotic sensorimotor systems through an iterative process of simulation and refinement. This allows robots to replicate complex behaviours such as territorial defence or predator-prey interactions [21, 22, 23, 24, 25]. In contrast, the situated action-based method emphasizes real-time responsiveness by decomposing dynamic environments into discrete "situations," each associated with specific behavioural responses. Robots interpret live sensory input and select appropriate actions using hierarchical control. Together, these methods enable context-sensitive, adaptive behaviours that are both biologically grounded and operationally robust.

3.2.1 System Architecture and ROS Implementation

A modular control architecture was developed in ROS [16, 17] to implement biologically inspired behaviours such as escape and attack. The system comprises four layers: Perception, Behaviour Evaluation, Fuzzy Inference, and Motion Execution. The *Perception Layer* uses LIDAR, SLAM, and vision sensors to collect real-time data and extract environmental variables such as AFTA, AFTP, ADTA, EPE, and PIWPE, which form the basis for behavioural decision-making. These inputs are processed in the Behaviour *Evaluation Layer*, where raw sensor data is converted into fuzzy linguistic terms for semantic interpretation. This layer also incorporates behavioural memory by computing historical metrics that influence current threat perception. At the core, the *Fuzzy Inference Engine* applies ethologically inspired rules using the Fuzzy Behaviour Description Language. It supports fuzzy rule interpolation, coordination of multiple rule bases (e.g., Escape, Attack, Immobility), and supervisory logic to manage behaviour transitions based on confidence levels. For example, a combination of high fear and high EPE triggers an escape response. The *Motion Execution* Layer translates behaviour outputs into physical actions using ROS navigation tools: escape behaviour increases distance from threats, while attack behaviour decreases it. Paths are visualized in RViz with colour-coded states and executed via motor control through topics such as /scan, /map, /fuzzy_inputs, and /cmd_vel. A central controller node synchronizes all layers, ensuring coordinated and adaptive multi-agent behaviour [Aaqib4, Aaqib5].

Escape behaviour was validated in a ROS-based simulation (Figures 6(a)-6(e)) featuring two autonomous robots navigating an obstacle-filled environment. Robot_1, governed by fuzzy logic, continuously assessed threats using LIDAR and proximity sensors [Aaqib2]. When Robot_2 was detected and fear exceeded a threshold while an escape path was available, Robot_1 performed an adaptive maneuver demonstrating biologically inspired, fear-driven behaviour. The simulation begins with both robots at rest (Figure 6(a)); as they move toward each other (Figure 6(b)), their trajectories adapt according to their internal behavioural models. LIDAR continuously updates proximity and environmental features, while behaviour fusion integrates trajectory analysis, object proximity, and movement direction to shape Robot_1's responses. Upon detecting Robot_2 (Figure 6(c)), Robot_1 evaluates the situation using its fuzzy rule-based system, factoring in familiarity (AFTA), environmental knowledge (AFTP), relative distance (ADTA), and escape path availability (EPE). If the fear level is *high* and EPE is *high*, the arbitration module triggers an escape maneuver (Figure 6(d)), coordinating perception and motor control for a seamless transition.

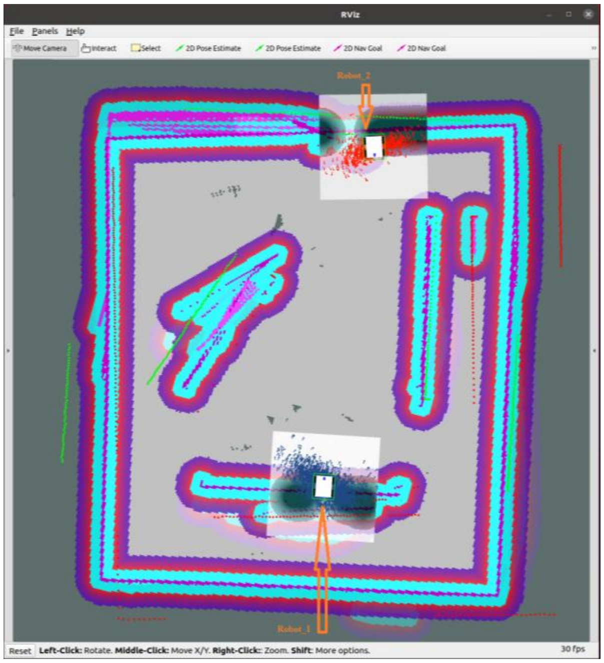

Figure 6 (a). Initial Position of Robots.

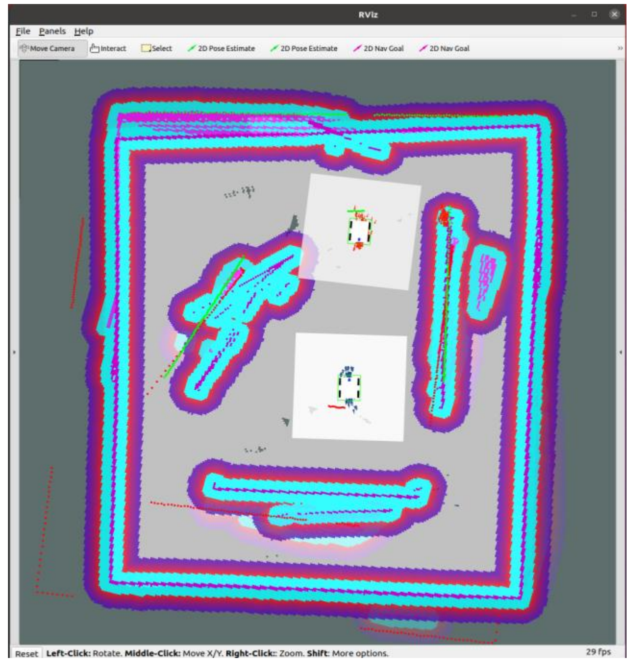

Figure 6(b). Movement Stage.

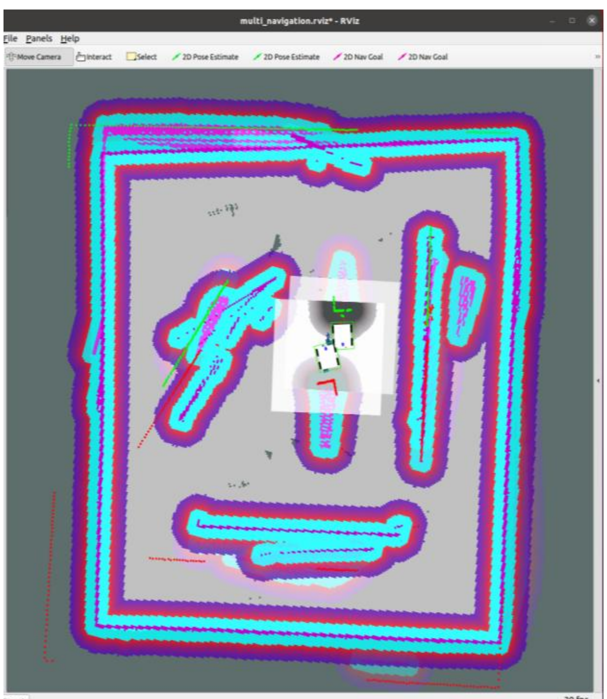

Figure 6(c). Robot Detection and Fear Assessment.

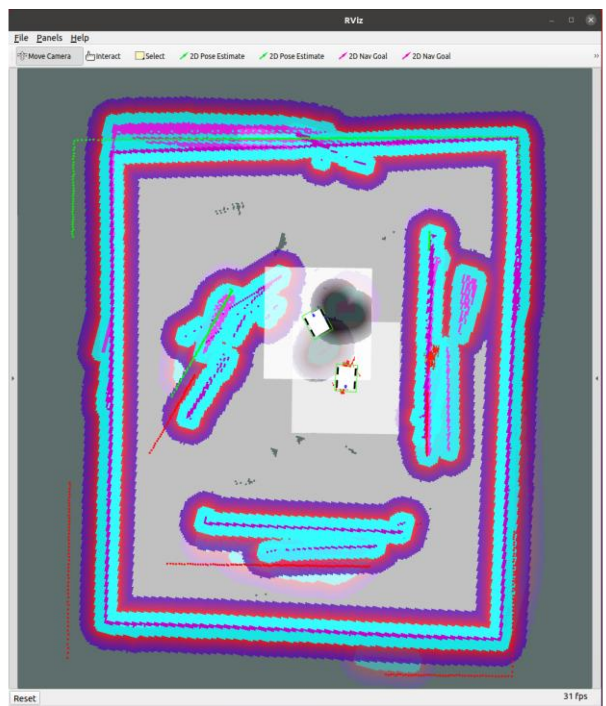

Figure 6(d). Robot_1's Escaping

Finally, Figure 6(e) shows Robot_1 successfully distancing itself from Robot_2 and exiting the threat zone. This demonstrates the effective integration of fuzzy logic, behaviour coordination, and fusion mechanisms, resulting in realistic, context-sensitive escape behaviour that closely mirrors biological adaptability. The simulation confirms the viability of fuzzy behavioural models for embedding adaptive, ethologically inspired behaviours in autonomous robotics.

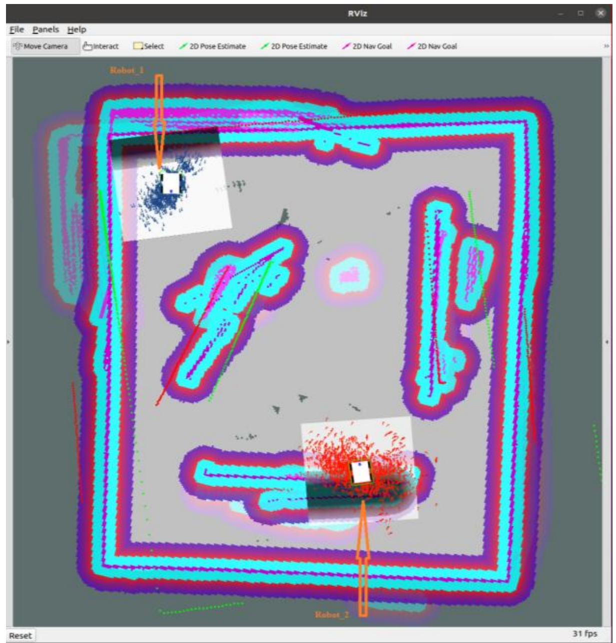

Figure 6(e). Robot_1 successfully escapes, illustrating the effective use of fuzzy logic, behaviour coordination, and fusion.

Similarly, *attack behaviour* simulation was tested in a same way and in attack scenario Robot_1 was tasked with approaching Robot_2 in a confined space [Aaqib2]. Triggered by low fear and close proximity, Robot_1 initiated aggression based on fuzzy rules. In response, Robot_2 retreated, evaluating the threat level in real time. This interaction successfully replicated predator-prey dynamics, validating the fuzzy system's ability to produce synchronised and lifelike aggression in autonomous agents.

3.2.2 Escape and Attack Behaviour Classification Metrics

Figures 7(a)-(b) present the classification performance of the proposed fuzzy logic-based behaviour modelling framework in autonomous robots. The evaluation measures the system's ability to classify context-sensitive behaviours specifically Escape and Attack under dynamic and uncertain conditions. Metrics such as accuracy, precision, recall, and F1-score were calculated from approximately 50 ROS-based simulation trials, which varied in threat proximity, obstacle layout, robot speed, and environmental familiarity.

To assess practical effectiveness, the fuzzy controller was benchmarked against a traditional reactive controller [13, 14, 26, 27, 28]. Key performance indicators included task completion time, collision count, behaviour-switching latency, and classification accuracy, as shown in Table 1. Additionally, Table 2 offers a conceptual comparison between the fuzzy ethological model and established architectures like

Subsumption, BDI, and Neuro-Fuzzy Systems, highlighting the proposed framework's strengths in emotional modelling, biological plausibility, and interpretability.

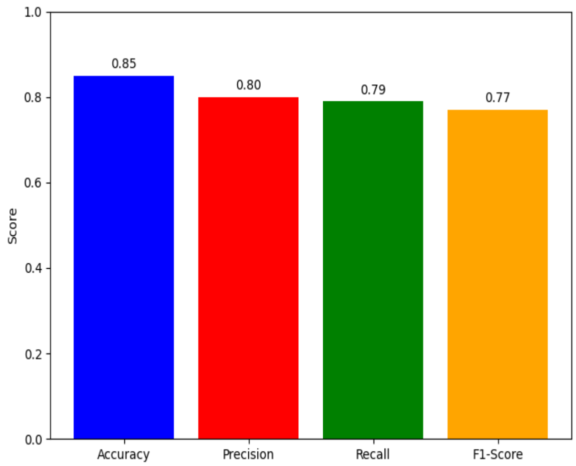

Figure 7(a). Escape Behaviour

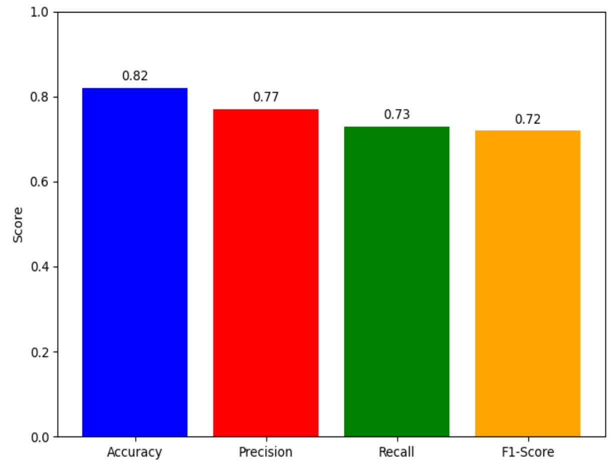

Figure 7(b). Attack Behaviour

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

Table 1. Fuzzy Behaviour Based Vs Baseline Controller

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

Interpretability	Moderate	High (symbolic), but often abstract	Low ("black box")	High; rules are biologically and ethologically grounded
Training Data Needs	None	Not data-driven	Require large datasets	Rule-based; no training required

Table 2. Comparison of Traditional and Fuzzy Ethological Control Systems.

3.3 Fuzzy Behaviour-Based Control Framework with Virtual Force Field

This work presents a hybrid robotic control framework that enables lifelike, adaptive, and context-aware navigation in real time, particularly within unstructured and dynamic environments. Inspired by animal behaviours such as fear and escape, the system integrates a fuzzy behaviour model with the VFF method to simulate emotion-modulated decision-making. Unlike conventional VFF implementations, which operate independently, this approach uses VFF as a behaviour fusion mechanism guided by internal emotional states derived from environmental cues like obstacle proximity and agent familiarity. Fuzzy inference assigns context-sensitive weights to competing behaviours such as obstacle avoidance, goal pursuit, and escape which are blended to produce smooth and reactive motion.

3.3.1 Fuzzy Behaviour Fusion

Fuzzy behaviour fusion involves integrating multiple behavioural outputs into a coherent response based on real-time context [29, 30, 31]. In this model, the Behaviour Coordination module uses fuzzy inference to assign relevance weights to each behaviour, allowing them to contribute proportionally to the final decision. Each behaviour generates a directional motion vector, and the Fusion Module integrates them by computing a net force vector. This biologically inspired method mimics how animals adaptively weigh multiple action tendencies depending on internal states and situational cues. For example, when threats are detected, escape behaviour receives higher weight, intensifying repulsive forces to guide the robot away from danger [32, 33]

3.3.2 Virtual Force Field Navigation

Virtual Force Field (VFF) navigation is a reactive control strategy where virtual attractive forces pull the robot toward its goal, and repulsive forces push it away from obstacles. By continuously calculating a net force vector, the robot dynamically adjusts its path in real-time [34, 35, 36]. Although VFF is efficient and simple, it suffers from issues like local minima and decision conflicts in complex environments. To address these limitations, this work embeds VFF as the fusion engine within a fuzzy behaviour-based framework [Aaqib5, Aaqib6]. Here, the repulsive and attractive forces are not treated equally but are scaled by fuzzy-assigned weights. For example, if the robot detects a threat, the Escape behaviour's weight increases, intensifying the repulsive force and adjusting the motion vector accordingly. This hybrid approach improves adaptability and decision accuracy [37, 38, 39, 40]. To quantify the influence of repulsive forces on the robot's motion, the system applies the mathematical model defined in Equation (1):

$$\mathrm{F}\ (i, j) = \frac{\mathrm{FcrC(i,j)}}{\mathrm{d2\ (i,j)}} \left[\frac{x_i - x_0}{\mathrm{d(i,j)}}\ \hat{x}\ +\ \frac{y_i - y_0}{\mathrm{d(i,j)}}\ \hat{y}\right] \qquad (1)$$

The mathematical model calculates repulsive forces based on obstacle proximity and certainty (Equation 1), summing them to produce a total repulsive force Fr shown in equation (2).

$$Fr = \textstyle\sum_{\mathrm{I,\ j}} F\ (i, j) \qquad (2)$$

3.3.3 Construction of Fuzzy Rule and Trajectory Implementation for Fuzzy Behaviour Based Control Framewok with Virtual Force Field Navigation

The hybrid control framework replicates biologically grounded behaviours, such as fear-driven escape, by combining fuzzy inference with VFF navigation in a modular architecture. It comprises three components: *Behaviour Coordination,* which uses fuzzy rules to evaluate environmental inputs and assign weights to behaviours like Goal Pursuit, Obstacle Avoidance, and Escape; *Component Behaviours,* which independently propose motion vectors; and *Behaviour Fusion,* where *VFF* combines these vectors using attractive and repulsive forces scaled by fuzzy-assigned weights. Unlike traditional VFF, this system adapts to internal emotional states such as Fear, which increases the influence of Escape behaviour in threatening contexts. The fuzzy system operates on observations (e.g., AFTP, AFTA, ADTA, AFTO, ADTO, EPE) and state variables (Fear, Escape), with inputs classified as High or Low and interpreted through FBDL rules as detailed in Section 3.1.1 [Aaqib1, Aaqib2].

Figure 8 illustrates a trajectory representation where Robot_1, assigned a goal at coordinates (5.5, 5.5), adapts its path in real time to avoid a moving threat such as a Robot_2 and a dynamic obstacle. As it progresses, Robot_1 continuously monitors environmental inputs such as proximity (ADTA), familiarity (AFTA, AFTO), and escape path availability (EPE). These inputs are processed by the fuzzy inference system to evaluate internal emotional states specifically Fear and Escape which dynamically influence behavioural priorities. The VFF-based fusion module then computes a motion vector by blending attractive forces toward the goal with repulsive forces from threats, each scaled according to its fuzzy-assigned weight. This results in a smooth, context-sensitive trajectory that enables the robot to navigate safely while exhibiting lifelike, emotionally modulated behaviour based on ethological principles [Aaqib7].

The Trajectory adaptation process works as:

Input evaluation: The system continuously monitors sensor inputs like ADTA, AFTA, AFTO, EPE.

Behaviour weighting: The fuzzy coordination module assigns weights based on rules (e.g., If ADTA=Low AND AFTA=Low AND EPE=High, then ESCAPE=High).

Force computation: Repulsive forces (from threats/obstacles, equation 3). Attractive forces (towards goal, equation 4).

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

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

The final motion vector becomes a weighted sum:

$$\vec{F}\text{result} = \vec{F}\text{attractive} + \vec{F}\text{repulsive} * \mu\text{FEAR} \quad (5)$$

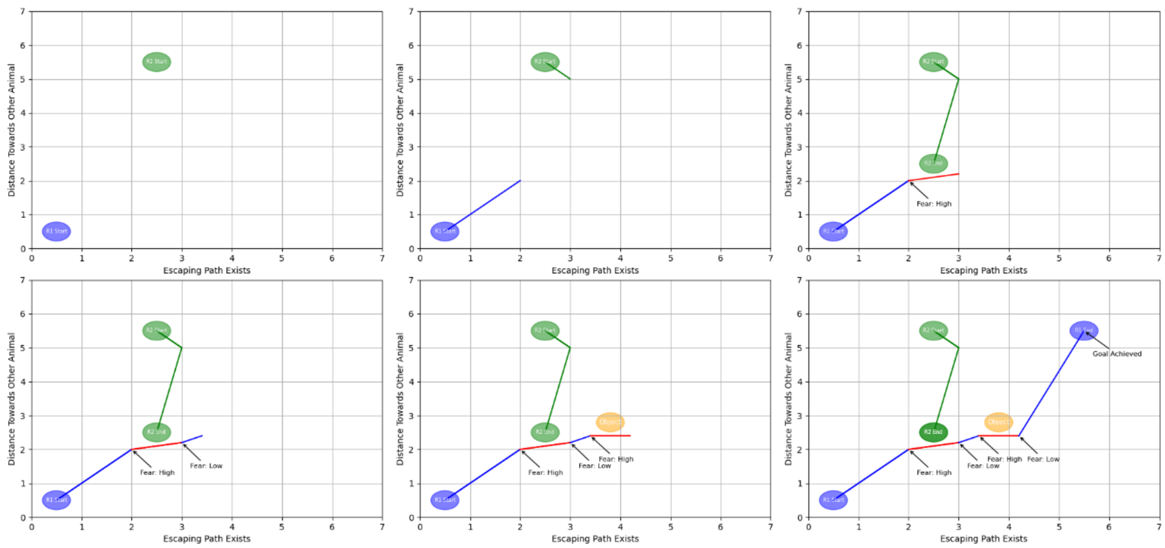

Figure 8. Represents the Trajectories for Animal Escape behaviour

3.3.4 ROS Simulation Environment and Classification Metrics Evaluation

The proposed hybrid control framework was evaluated in a ROS-based simulation environment. This architecture integrates real-time fuzzy logic reasoning with reactive force-based motion planning, enabling adaptive, context-aware navigation. Key ROS tools include RViz for visualizing sensor data and trajectories, Gazebo for realistic 3D simulation, and LIDAR for accurate obstacle detection. SLAM (gmapping) supports map building and localization, critical in GPS-denied environments. SLAM data informs both the Fuzzy Coordination Moduleassessing proximity, familiarity, and escape path availability to determine emotional states such as fear and the VFF Module, which computes attractive and repulsive forces. These forces are weighted by fuzzy logic to generate a motion vector for real-time, biologically inspired trajectory adaptation [Aaqib7].

The test scenario involves two robots navigating a bounded environment with static and dynamic obstacles (Figures 9(a)-9(e)). Robot_1 has assigned a goal, while navigating it may get interrupted by Robot_2 (a moving threat) as well as unexpected objects. In the initial stage (Figure 9(a)), both robots are positioned in the environment. As Robot_1 moves toward its target (Figure 9(b)), Robot_2 explores the space, increasing the chance of encounter. LIDAR detection of Robot_2 (Figure 9(c)), combined with unfamiliarity and decreasing distance, raises Robot_1's fear level. The fuzzy coordination system classifies the escape level as high, meeting the triggering conditions: (i) high fear, (ii) close proximity (ADTA=low), and (iii) a clear escape path (EPE = high). VFF supports this response by amplifying the repulsive force vector and temporarily reducing goal attraction.

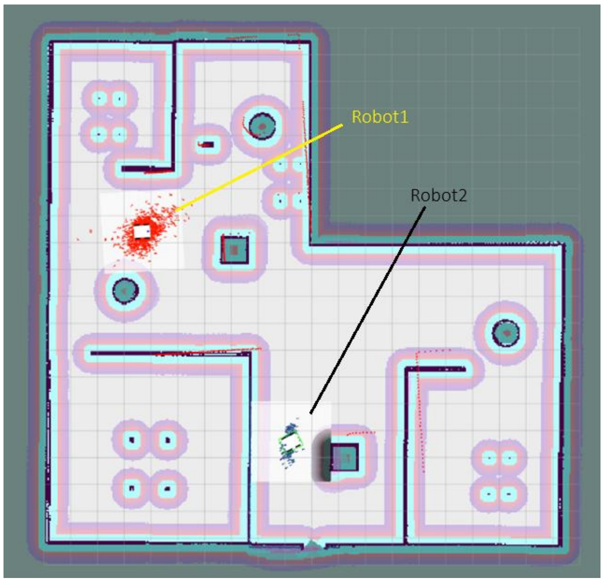

Figure 9(a) Initial stage of robots

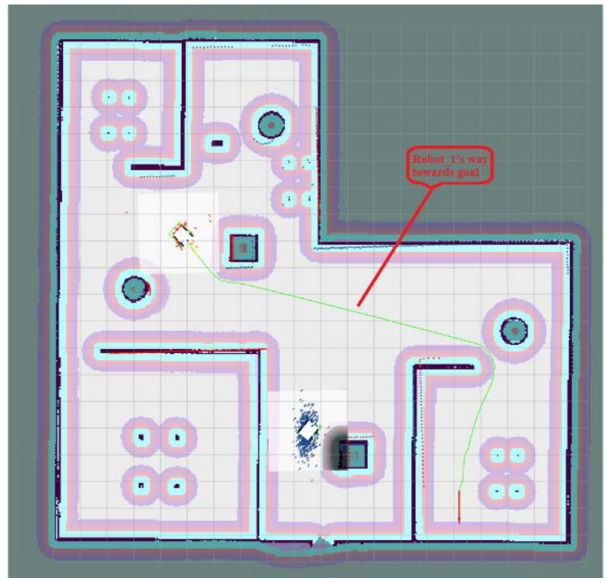

Figure 9(b) Robot_1 starts to move towards its goal.

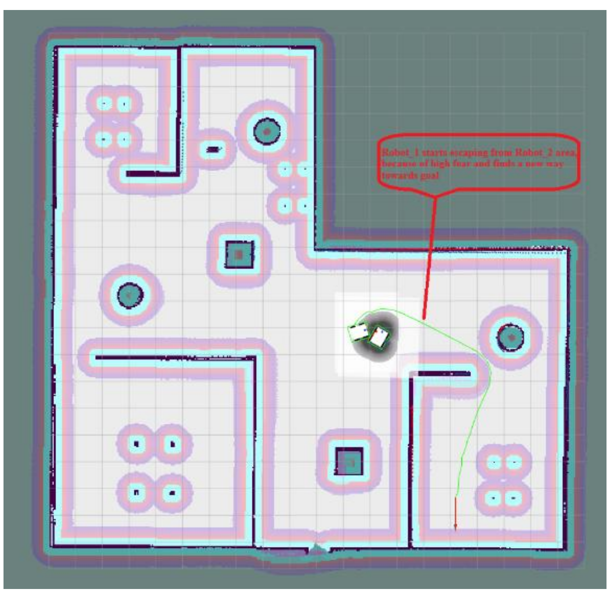
Figure 9(c) Robot_1 detects Robot_2.

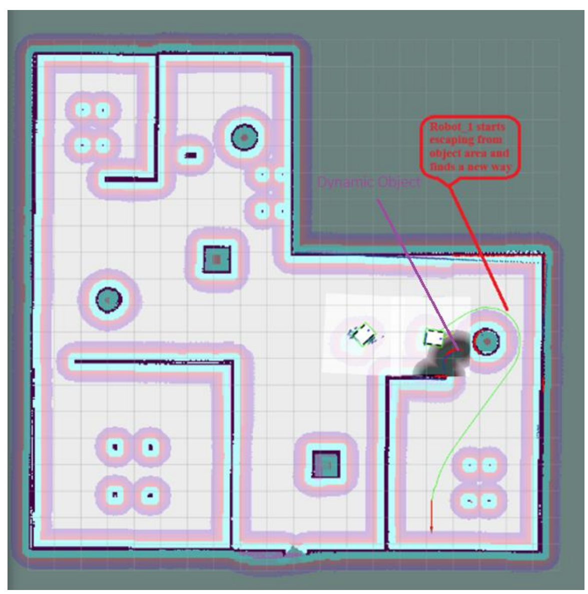

Figure 9(d) Object Detection by Robot_1.

The hybrid model operates in three coordinated stages: Behaviour Components (discrete actions such as ESCAPE or GOAL PURSUIT), Behaviour Coordination (fuzzy inference assigning behaviour weights based on fear level, familiarity, and obstacle proximity), and Behaviour Fusion (VFF merging weighted behaviours into a single unified force vector). This structure ensures smooth transitions and continuous adaptation to environmental stimulus. For example, in Figure 9(d), after evading Robot_2, Robot_1 encounters a new unknown object. Reduced distance (ADTO = low) again triggers ESCAPE, with VFF recalculating repulsive forces and suppressing goal attraction until the danger subsides. Once clear, the fuzzy controller restores goal attraction, guiding Robot_1 to its destination. Figure 9(e) shows the successful completion of the mission despite dynamic and unpredictable challenges. These results demonstrate the system's robustness, with VFF providing continuous low-level control and the fuzzy fusion system modulating actions based on internal states such as fear. By embedding biologically inspired mechanisms like fear-driven escape into the control logic, the framework mimics naturalistic intelligence and achieves adaptive, interpretable navigation in complex environments.

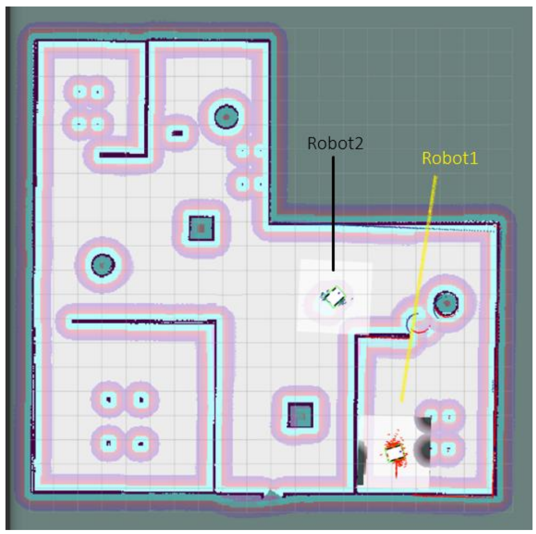

Figure 9(e) Robot_1 successfully achieved its goal.

Classification Metrics: Figure 10 illustrates the classification performance of the proposed Fuzzy Behaviour-Based Control Framework integrated with VFF navigation. This hybrid architecture enhances decision-making by combining a biologically inspired fuzzy coordination layer which dynamically assigns behaviour weights based on real-time sensor inputs with the traditional VFF algorithm that computes attractive and repulsive forces. These vectors are scaled using fuzzy-modulated weights, producing emotion-aware, context-sensitive motion trajectories. Behaviour classification performance was evaluated across 25 ROS-based simulation trials using metrics such as accuracy, precision, recall, and F1-score. Trials featured dynamic conditions, including varied obstacle layouts, proximity, speed, and sensory variables (e.g., AFTA, ADTA, AFTO). Escape behaviour was governed by fuzzy rules in FBDL, which activated high-weight escape responses under high perceived threat and fear, producing reactive motion through fusion with VFF vector fields.

To assess practical effectiveness, the framework was benchmarked against a traditional VFF controller [41, 42, 43], which, while effective in simple scenarios, suffers from limitations like local minima, oscillations, and lack of adaptability. Even enhanced variants such as behaviour-modulated VFF [34] fall short in terms of emotional modelling and decision transparency. The comparison, summarized in Table 3, used key performance indicators including task completion time, collision count, behaviour-switching latency, and escape classification accuracy. Results showed the fuzzy-VFF system outperformed the baseline across all metrics. Furthermore, Table 4 compares the proposed system with Subsumption Architecture, BDI Models, and Neuro-Fuzzy Systems [44, 45] emphasizing its unique integration of biological plausibility, emotional dynamics, and real-time adaptive control, effectively bridging reactive and deliberative strategies [46].

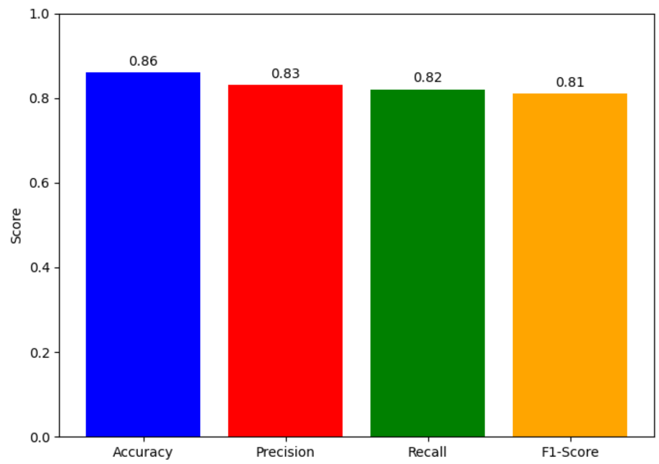

Figure 10. Hybrid Model Classification Metrics

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

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

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

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

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

Part 4: Conclusion, Future Work, and Publications

4.1. Conclusion

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

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

Concept: The model utilizes Fuzzy Behaviour Description Language to convert qualitative ethological insights into structured, interpretable fuzzy rules, enabling the modelling of emotional states such as fear, aggression, and escape.

Explanation and Proof: Animal behaviours are encoded through rule-based inference systems that respond to factors such as environmental familiarity, threat proximity, and prior experience. Simulated behavioural trajectories show that fuzzy controllers enable context-sensitive transitions, replicating biologically plausible emotional dynamics. This framework bridges ethology and robotics, offering real-time, adaptive, and interpretable emotional control suitable for therapeutic robotics and human-robot interaction.

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

Statement: *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, [Aaqib1- Aaqib5].*

Concept: The fuzzy state machine incorporates both latent and observable states (e.g., Fear, Attack, Escape, Immobility), with transitions governed by fuzzy logic rules informed by continuous sensor inputs and internal emotional appraisals.

Explanation and Proof: Developed in the Robot Operating System (ROS) and integrated with SLAM and LIDAR, the system dynamically evaluates threat and familiarity to trigger appropriate behaviour. Controlled experiments show accurate and lifelike transitions between states, verified using classification metrics such as precision, recall, and F1-score. The FSM ensures robustness, transparency, and scalability for emotionally informed control in applications like search-and-rescue and social robotics.

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

Statement: *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, [Aaqib1-Aaqib7]*

Concept: The framework combines VFF's with fuzzy emotion-based modulation, enabling robots to adapt movement strategies in response to internal emotional states like fear intensity. This integration allows biologically inspired, context-sensitive behaviour modulation based on factors such as threat distance, environmental familiarity, and escape path feasibility.

Explanation and Proof: Implemented in ROS with SLAM, LIDAR, and obstacle perception, the system adjusts navigational forces in real time e.g., high fear levels increase repulsive forces from nearby threats. Simulated scenarios demonstrate adaptive responses, such as escaping from multi-agent threats or exhibiting hesitant motion in unfamiliar terrain. The results validate the integration of affective reasoning with physical navigation, contributing to the development of emotionally and socially intelligent autonomous systems.

4.2 Future Work

This research opens several promising directions for advancing emotionally responsive robotics. *First*, extending the ethological model beyond fear and aggression to include behaviours such as nurturing, social bonding, and territoriality could enrich human-robot interaction (HRI) by enabling more complex social dynamics. Exploring behavioural parallels between humans, animals, and robots may also contribute to unified emotional frameworks that advance both robotics and behavioural science. *Second*, integrating machine learning techniques such as deep learning and reinforcement learning with fuzzy logic can enhance adaptability, allowing robots to learn from past experiences and perform effectively in uncertain environments. Hybrid architecture that combines symbolic reasoning with experiential learning could further broaden the capabilities of emotional robotics. *Third*, as robots increasingly display emotion-like behaviours, ethical and societal considerations must be addressed. Key concerns include emotional deception, user dependency, and moral agency; future work should focus on developing clear ethical guidelines to ensure emotionally intelligent robots act responsibly, particularly in sensitive applications. *Finally*, sentiment and behaviour analysis can be expanded through multimodal sensory integration (e.g., audio, vision, text), with advanced models that fuse these inputs alongside contextual reasoning. Such developments could improve emotional inference and enable richer, more natural interactions in domains such as caregiving, therapy, and collaborative robotics.

4.3 Author's Publications

Publications Related to Dissertation

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

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

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

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

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

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

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

Other Publications

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

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

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

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

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

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

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

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

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

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

References

1. Lehner, P.N., 1998. Handbook of ethological methods. Cambridge University Press.
2. McFarland, D., Bösser, T. and Bosser, T., 1993. Intelligent behaviour in animals and robots. Mit Press.
3. Miklósi Á, Korondi P, Matellán V and Gácsi M (2017) Ethorobotics: A New Approach to Human-Robot Relationship. Front. Psychol. 8:958. doi: 10.3389/fpsyg.2017.00958.
4. Piller, I., Kovács, Sz.: Fuzzy Behaviour Description Language: A Declarative Language for Interpolative Behaviour Modeling. In: ACTA POLYTECHNICA HUNGARICA 16:9, 2019, pp.47-72.
5. Archer, J. "The organisation of aggression and fear in vertebrates; in Perspeaives in Ethology" - Vol. 2 (eds P.P.G. Bateson and P. Klopfer), Plenum Press, New York, 1976. pp. 231-298.
6. Abdai, Judit, and Ádám Miklósi, eds. An introduction to Ethorobotics: robotics and the study of animal behaviour. Taylor & Francis, 2024.
7. Vincze, Dávid, et al. "A novel application of the 3d virca environment: Modeling a standard ethological test of dog-human interactions." Acta Polytechnica Hungarica 9.1 (2012): 107-120.
8. Vincze, Dávid, et al. "Ethologically inspired human-robot interaction interfaces." Proceedings of the 2012 Joint International Conference on Human-Centered Computer Environments. 2012.
9. Huntingford, F. ed., 2012. The study of animal behaviour. Springer Science & Business Media.
10. Taylor, Charles, and Alva Noë. The explanation of behaviour. Routledge, 2021.
11. Bateson, Patrick, and Kevin N. Laland. "Tinbergen's four questions: an appreciation and an update." Trends in ecology & evolution 28.12 (2013): 712-718.
12. Mo, Hongwei, Qirong Tang, and Longlong Meng. "Behaviour-Based Fuzzy Control for Mobile Robot Navigation." Mathematical problems in engineering 2013.1 (2013): 561451.
13. Primova, H. A., D. T. Mukhamedieva, and L. Safarova. "Application of Algorithm of Fuzzy Rule Conclusions in Determination of Animal's Diseases." Journal of Physics: Conference Series. Vol. 2224. No. 1. IOP Publishing, 2022.
14. Sandeep, B. S., and P. Supriya. "Analysis of fuzzy rules for robot path planning." 2016 international conference on advances in computing, communications and informatics (ICACCI). IEEE, 2016.
15. Kovács, Szilveszter. "Interpolative fuzzy reasoning in behaviour-based control." Computational Intelligence, Theory and Applications: International Conference 8th Fuzzy Days in Dortmund, Germany, Sept. 29–Oct. 01, 2004 Proceedings. Springer Berlin Heidelberg, 2005.
16. Koubaa, Anis, ed. Robot Operating System (ROS). Vol. 1. Cham, Switzerland: Springer, 2017.
17. Macenski, Steven, et al. "Robot operating system 2: Design, architecture, and uses in the wild." Science robotics 7.66 (2022): eabm6074.
18. Piller, I.: EXPRAIL: https://github.com/piller-imre/exprail-python
19. Piller, I.: FRIBE: https://github.com/piller-imre/fribe-python

20. Maen Alzubi, Mohammad Almseidin, Lone Mohd Aaqib, Szilveszter Kovács. Fuzzy Rule Interpolation Toolbox for the GNU Open-Source OCTAVE. In František Jakab (Ed.), Proceedings of the 17th International Conference on Emerging eLearning Technologies and Applications (ICETA 2019), pp. 16–22. Piscataway, NJ, USA: IEEE, 2019.
21. Ronald C. Arkin. Behaviour-based robotics. MIT Press, 1998.
22. Siciliano, Bruno, and Oussama Khatib, eds. Springer handbook of robotics. Springer, 2016.
23. Vásconez, Juan Pablo, et al. "A Behaviour-Based Fuzzy Control System for Mobile Robot Navigation: Design and Assessment." International Conference on Advanced Research in Technologies, Information, Innovation and Sustainability. Cham: Springer Nature Switzerland, 2023.
24. Maghzaoui, Ahlem, Emna Aridhi, and Abdelkader Mami. "Fuzzy Control of Mobile Robot Speed for Safe and Adaptive Navigation." 2023 IEEE Third International Conference on Signal, Control and Communication (SCC). IEEE, 2023.
25. Michaud, François, and Monica Nicolescu. "Behaviour-based systems." Springer handbook of robotics (2016): 307-328.
26. Brooks, Rodney. "A robust layered control system for a mobile robot." IEEE journal on robotics and automation 2.1 (2003): 14-23.
27. Rao, Anand S., and Michael P. Georgeff. "BDI agents: From theory to practice." Icmas. Vol. 95. 1995.
28. Jang, Jyh-Shing Roger, Chuen-Tsai Sun, and Eiji Mizutani. "Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]." IEEE Transactions on automatic control 42.10 (1997): 1482-1484.
29. Chang, Hyunjin, and Taeseok Jin. "Command fusion based fuzzy controller design for moving obstacle avoidance of mobile robot." Future Information Communication Technology and Applications: ICFICE 2013 (2013): 905-913.
30. Oliveira, Leandro Daros, and Armando Alves Neto. "Comparative Analysis of Fuzzy Inference Systems Applications on Mobile Robot Navigation in Unknown Environments." 2023 Latin American Robotics Symposium (LARS), 2023 Brazilian Symposium on Robotics (SBR), and 2023 Workshop on Robotics in Education (WRE). IEEE, 2023.
31. Abduljabbar, Abduljabbar Khudhur, Yousif Al Mashhadany, and Sameer Algburi. "High-Performance of Mobile Robot Behaviour Based on Intelligent System." 2023 16th International Conference on Developments in eSystems Engineering (DeSE). IEEE, 2023.
32. Zadeh, Lotfi Asker. "Fuzzy sets as a basis for a theory of possibility." Fuzzy sets and systems 1.1 (1978): 3-28.
33. Vadakkepat, Prahlad, et al. "Fuzzy behaviour-based control of mobile robots." IEEE Transactions on Fuzzy Systems 12.4 (2004): 559-565.

34. Nia, D. Nakhaei, et al. "Virtual force field algorithm for a behaviour-based autonomous robot in unknown environments." Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering 225.1 (2011): 51-62.
35. Sun, Q., Guo, Y., Fu, R., Wang, C. and Yuan, W., 2020. Human-Like Obstacle Avoidance Trajectory Planning and Tracking Model for Autonomous Vehicles That Considers the Driver's Operation Characteristics. Sensors, 20(17), p.4821.
36. Benbouabdallah, Karim, and Zhu Qi-dan. "A fuzzy logic behaviour architecture controller for a mobile robot path planning in multi-obstacles environment." Research Journal of Applied Sciences, Engineering and Technology 5.14 (2013): 3835-3842.
37. Hong, Tang Sai, Danial Nakhaeinia, and Babak Karasfi. "Application of fuzzy logic in mobile robot navigation." Fuzzy Logic-Controls, Concepts, Theories and Applications (2012): 21-36.
38. Jeong, Youngwoo, et al. "The Design of Embedded Fuzzy Logic Controller for Autonomous Mobile Robots." 2023 20th International SoC Design Conference (ISOCC). IEEE, 2023.
39. Gul, F., Rahiman, W. and Nazli Alhady, S.S., 2019. A comprehensive study for robot navigation techniques. Cogent Engineering, 6(1), p.1632046.
40. Drew, Daniel S. "Multi-agent systems for search and rescue applications." Current Robotics Reports 2 (2021): 189-200.
41. Khatib, Oussama. "Real-time obstacle avoidance for manipulators and mobile robots." The international journal of robotics research 5.1 (1986): 90-98.
42. Ge, Shuzhi Sam, and Yun J. Cui. "Dynamic motion planning for mobile robots using potential field method." Autonomous robots 13.3 (2002): 207-222.
43. Gyawali, Pratik, and Praveen Kumar Agarwal. "Fuzzy behaviour based mobile robot navigation in static environment." 2018 IEEE Recent Advances in Intelligent Computational Systems (RAICS). IEEE, 2018.
44. Ni, Jianjun, et al. "An improved VFF approach for robot path planning in unknown and dynamic environments." Mathematical Problems in Engineering 2014.1 (2014): 461237.
45. Chong, Hui-Qing, Ah-Hwee Tan, and Gee-Wah Ng. "Integrated cognitive architectures: a survey." Artificial Intelligence Review 28.2 (2007): 103-130.
46. Nakhaeinia, Danial, et al. "A hybrid control architecture for autonomous mobile robot navigation in unknown dynamic environment." 2015 IEEE International Conference on Automation Science and Engineering (CASE). IEEE, 2015.