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# Ethologically Inspired Hybrid Fuzzy-Virtual Force Field Navigation in ROS: A Simulation-Based Study

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ABSTRACT

Robust and adaptive navigation in dynamic environments remains a central challenge in autonomous robotics. Traditional methods such as Virtual Force Field (VFF) navigation are prone to issues like local-minima traps and unstable trajectories in cluttered spaces. This paper presents a simulation-based, ethologically inspired hybrid navigation framework that integrates a Fuzzy Behaviour module with VFF-based motion planning within the Robot Operating System (ROS). The proposed controller encodes biologically inspired internal states such as fear and escape into fuzzy logic rules that modulate repulsive and attractive forces based on real-time sensor data. Unlike the conventional fuzzy-VFF systems, the model interprets environmental cues through emotional analogs to support more context-sensitive behavioural decisions. The fuzzy rules and membership functions are specified using the Fuzzy Behaviour Description Language (FBDL) and implemented with LIDAR sensing in dynamic ROS-Gazebo scenarios. The system was evaluated across 25 simulation trials with varying obstacle and agent configurations. Compared to a standard VFF baseline, the proposed approach achieved a 28.1% reduction in collisions, a 13.3% reduction in task completion time, a 7.5% improvement in behaviour switching latency, and a 14.7% increase in model accuracy. While the results demonstrate significant gains in adaptability and interpretability, the current study is limited to simulation-based validation. The future work will focus on hardware deployment, quantitative validation through statistical testing, and optimization of the fuzzy rule base via learning-based approaches.



## 1. Introduction

As autonomous robots increasingly move from controlled industrial settings into unstructured human environments, the need for robust, adaptive navigation systems has become more critical than ever. Mobile robots are now deployed in diverse domains such as logistics, healthcare, urban service delivery, and disaster response [1]–[3]. These environments present constantly changing obstacles and unpredictable agents (e.g., humans, vehicles), requiring robots not only to perceive and react in real time, but also to adapt their decision-making processes based on situational context. While advancements in robot perception and control frameworks particularly through middleware like the Robot Operating System (ROS) have significantly lowered the barrier for autonomous system development, effective real-time decision-making in dynamic and cluttered spaces remains an open research challenge [4]–[6].

One widely adopted approach for real-time local path planning is the Virtual Force Field (VFF) method. VFF simulates attractive forces pulling the robot toward a goal and repulsive forces pushing it away from obstacles. Although VFF offers a lightweight, reactive control scheme, it suffers from several well-known limitations: it can trap robots in local minima, produce oscillatory paths, and lacks adaptability to changing environmental semantics [7]–[9]. Numerous enhancements to VFF have been proposed, including the integration of fuzzy logic to handle uncertainty and nonlinear relationships between sensor data and behaviour. However, many of these fuzzy-VFF hybrids rely on predefined rules triggered solely by static metrics such as obstacle proximity or speed. These systems often lack the capacity to reason about context or dynamically shift behavioural priorities.

To address this limitation, we propose an ethologically inspired behaviour modulation framework. Ethology the scientific study of animal behaviour provides valuable insights into how biological organisms interpret sensory data, internal emotional states, and past experiences to make adaptive behavioural decisions in real-world settings [10]–[12]. Ethologically inspired robotics (Ethorobotics) aims to model such internal states, like fear or curiosity, to improve robot-environment interaction. In this study, we introduce a fuzzy logic-based architecture where sensor-derived environmental cues (e.g., sudden obstacle movement, unfamiliar surroundings, or threat density) are mapped to biologically inspired internal states. These fuzzy internal states are then used to weight competing behavioural modules such as goal pursuit, obstacle avoidance, and escape [13]–[15].

This approach differs significantly from conventional fuzzy-VFF systems. The traditional fuzzy controllers typically encode deterministic rules like ”IF obstacle is near THEN increase repulsion”. Our model, instead, infers abstract emotional states from sensor stimuli for example, combining spatial unfamiliarity with high obstacle motion to generate a fuzzy ”fear” value. This internal state is then used to modulate the influence of the repulsion vector relative to goal attraction or exploratory drive. In this way, the system introduces a context-aware layer of behavioural modulation that better reflects the complex decision-making processes observed in animals [16]–[19]

The proposed system is implemented in a ROS-based simulation framework utilizing the Gazebo and RViz environments [20], [21]. Fuzzy behaviour rules are defined using the Fuzzy Behaviour Description Language (FBDL), which enables modular, interpretable control logic. The architecture integrates input from LIDAR sensors and SLAM-based localization to generate internal states that dynamically adjust behaviour weights during vector fusion. Performance was validated through 25 simulation trials involving dynamic environments that included static and dynamic obstacles, moving threats (Robot 2), and unfamiliar terrain. The key performance metrics including task completion time, behaviour switching latency, and collision count were evaluated against a standard VFF baseline. The primary research contributions are as; First, we propose a novel fuzzy behaviour fusion architecture that integrates biologically inspired internal states (e.g., fear) to guide robot navigation in dynamic environments. Second, we demonstrate that ethologically inspired internal state modeling improves system performance over traditional fuzzy-VFF approaches by enabling adaptive behavioural prioritization. Third, we implement and validate this system within a complete ROS-based simulation stack, incorporating Gazebo, SLAM, LIDAR, and FBDL, thereby ensuring modularity, interpretability, and reproducibility. Lastly, empirical evaluations show a 28.1% reduction in collision rate, behaviour switching latency was 7.5% lower, and a 14.7% improvement in navigation efficiency compared to a baseline VFF system.

By blending biologically motivated reasoning with fuzzy control and modern robotics platforms, this study contributes to the development of interpretable, adaptive, and behaviourally rich autonomous navigation systems. Applications span domains where responsiveness to complex, evolving environments is crucial, including human-robot interaction, autonomous service robotics, and real-time exploration in unstructured environments [22]–[24].

## 2. Fuzzy Behaviour Fusion

In behaviour-based robotic control, behaviour fusion refers to the process of integrating multiple behavioural outputs into a single, coherent action that responds dynamically to both environmental stimuli and task-specific goals. This mechanism is essential in autonomous systems where competing objectives such as goal pursuit, obstacle avoidance, and threat response must be balanced simultaneously [25], [26]. It enables robots to navigate complex and dynamic environments with flexibility, robustness, and responsiveness.

The core of the proposed system is the Behaviour Coordination Module, which computes the fuzzy relevance weights of each component behaviour using a set of linguistic fuzzy rules. These fuzzy weights are derived from sensor-driven inputs processed via the Fuzzy Behaviour Description Language (FBDL) [27], [28]. The sensory input includes LIDAR-based proximity data, SLAM-generated spatial familiarity maps, and short-term temporal metrics (e.g., changes in obstacle speed or density).

Unlike traditional fuzzy-VFF systems that operate using direct mappings (e.g., "IF distance is < threshold THEN increase repulsion"), our approach introduces an intermediate layer of biologically inspired internal states. Specifically, we model **fear** an ethological analog derived from obstacle familiarity, density, and perceived motion as the key modulator of behavioural fusion. These internal states are computed using trapezoidal fuzzy membership functions over inputs such as obstacle density and novelty, enabling context-aware behaviour switching [29], [30].

The Fig. 1 visualizes this architecture that consists of three primary behaviours: *Target Following ($B_T$)* generates an attractive vector toward the navigation goal. *Obstacle Avoidance ($B_O$)* produces repulsive vectors to prevent collisions. *Escape ($B_E$)* triggers emergency evasive manoeuvres in high-threat conditions.

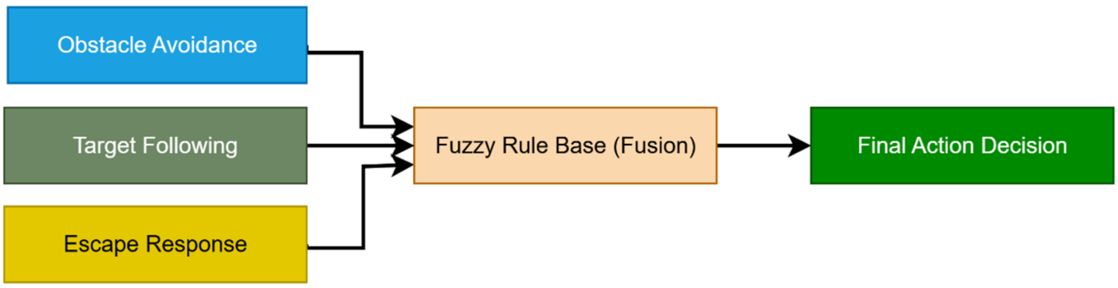


**Fig. 1.** Fuzzy behaviour fusion process: Internal states modulate the weights of directional outputs from component behaviours, producing context-adaptive navigation

Each behaviour outputs a directional recommendation $\vec{V}_i$ that is weighted according to the fuzzy-derived internal state of fear ($\mu_{\text{Fear}}$). The final motion vector is calculated using equation (1):

$$\vec{V}_{\text{final}} = w_T \cdot \vec{V}_T + w_O \cdot \vec{V}_O + w_E \cdot \vec{V}_E \tag{1}$$

Where the behavioural weights are defined as:

$$w_T = 1 - \mu_{\text{Fear}}, \quad w_O = \mu_{\text{Fear}}, \quad w_E = \sigma(\mu_{\text{Fear}} - 0.7)$$

Here, $\sigma$ denotes the sigmoid function, which softly activates the Escape behaviour when fear surpasses a threshold. This formulation captures ethologically inspired behaviour arbitration: under low fear, goal pursuit dominates; under high fear, the robot prioritizes avoidance and escape. The fuzzy decision engine uses a Fuzzy Rule Interpolation with FIVE FRI. Rules are defined in FBDL to model the relationship between environmental cues and behavioural priorities. For example: *IF obstacle_density is high AND obstacle_novelty is high THEN fear is high*

The fuzzy engine updates all behaviour weights in real-time at each simulation timestep, allowing the robot to dynamically adjust its strategy in response to environmental changes. This behaviour fusion mechanism enables smooth transitions between behaviours, avoiding abrupt switches that could destabilize navigation or create oscillatory motion. This fusion approach is biologically inspired. Animals exhibit complex behaviour arbitration, where internal states like fear mediate competing drives (e.g., escape). Our model mirrors this principle by continuously re-evaluating context to assign behavioural weights. This results in lifelike, adaptive navigation behaviour that balances risk, efficiency, and environmental change [31], [32]. By embedding fuzzy internal states into the fusion mechanism, this approach overcomes the rigidity of rule-based controllers and enables context-sensitive, real-time adaptation. It enhances the interpretability of decision-making, enables graceful handling of ambiguous or conflicting stimuli, and reduces oscillation in cluttered environments.

## 3. Virtual Force Field (VFF)

VFF navigation is a widely used technique in mobile robotics and autonomous systems, particularly for real-time obstacle avoidance and local path planning [33], [34]. The core concept models the robot's environment as a field of virtual forces: attractive forces pull the robot toward its goal, while repulsive forces push it away from nearby obstacles. At each timestep, the robot computes the resultant vector from these combined forces to determine its direction of motion. While VFF is widely appreciated for its computational efficiency and intuitive control structure, it exhibits notable limitations: susceptibility to local minima, oscillatory motion in tight spaces, and rigid behavior when multiple competing objectives arise [35], [36]. These challenges become more pronounced in dynamic environments involving unpredictable agents (e.g., moving humans or vehicles), where naive force balancing can lead to navigation deadlocks or unsafe paths.

To address VFF's limitations, we propose a hybrid approach that integrates VFF into a fuzzy behaviour-based control architecture. In this work, VFF is not used as a standalone navigation strategy. Instead, it is embedded within a fuzzy behaviour fusion framework, where it acts as the final vector synthesis engine. Behavioural outputs (e.g., from Escape, Target Pursuit, and Obstacle Avoidance modules) are converted into directional force vectors. These vectors are modulated by context-sensitive weights derived from fuzzy logic particularly based on the internal Fear state. For example, when the system detects a high-threat scenario (e.g., a fast-approaching obstacle), the fuzzy engine raises the weight of the Escape module. This increases the magnitude of the repulsive force vector in the VFF calculation, allowing the robot to divert rapidly from danger. In contrast, during low-threat conditions, the goal-seeking behaviour dominates, yielding a smoother and more direct trajectory. This dynamic weighting allows the VFF mechanism to adapt to context, addressing its classical rigidity. Applications include autonomous ground vehicles and aerial delivery systems, where real-time responsiveness and adaptability are essential [37]–[40].

The Fig. 2 demonstrates the fundamental concept of VFF navigation, in which a robot moves based on simulated force interactions within its environment. The Attractive forces draw the robot toward its destination, while repulsive forces steer it away from nearby obstacles. The combination of these opposing forces generates a resultant vector that dictates the robot's direction of travel. By continuously updating this vector, the robot can adjust its path in real time, allowing it to reach its target while effectively avoiding collisions and adapting to dynamic surroundings. The repulsive force exerted by an obstacle cell $(i, j)$ is modeled as in (2):

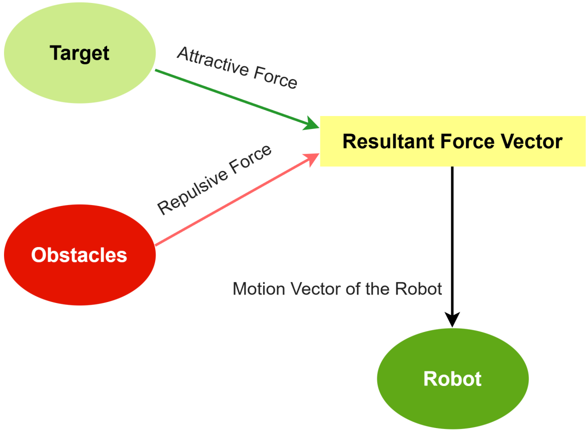


**Fig. 2.** Virtual force field navigation: attractive and repulsive forces combine to produce a net motion vector

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

Where $F_{cr}$ is the repulsive force constant (scaled by behaviour weight from fuzzy coordination). $d(i,j)$ is the Euclidean distance between the robot $(x_0, y_0)$ and grid cell $(x_i, y_i)$. $C(i,j)$ is the certainty that cell $(i,j)$ contains an obstacle.

This certainty level expresses the system's confidence that a specific cell contains an obstacle, guiding the robot in determining the influence of each cell's repulsive force on its path. A high certainty level suggests a strong likelihood of an obstacle, resulting in a greater repulsive force, whereas a low certainty level indicates a lower probability of an obstacle, producing a weaker repulsive effect. This force is undefined at $d = 0$; therefore, a minimum distance threshold $\delta$ is enforced to avoid singularities (typically $\delta = 0.05\,m$). The total repulsive force is the sum over all grid cells (3):

$$F_r = \sum_{i,j} F(i,j) \tag{3}$$

The attractive force toward the goal at $(x_g, y_g)$ is defined in (4) as:

$$F_a = F_a \left[ \frac{x_g - x_0}{d_g} \hat{x} + \frac{y_g - y_0}{d_g} \hat{y} \right] \tag{4}$$

Where $F_a$ is the attractive force constant and $d_g$ is the distance to the goal. The final motion vector is computed in (5) as:

$$F_{\text{net}} = \alpha \cdot F_a - \beta \cdot F_r \tag{5}$$

Here, $\alpha$ and $\beta$ are behaviour fusion coefficients derived from the fuzzy weights, updated in real-time as the internal state (e.g., Fear) changes. This modulation dynamically adjusts the robot's reactivity and goal orientation.

By embedding VFF within a fuzzy behaviour control architecture, the robot transitions from a purely reactive system to one capable of context-aware, emotionally modulated decision-making. This addresses the limitations of classical VFF such as local minima and rigid responsiveness and enables a more flexible navigation strategy suited for dynamic, cluttered environments [41], [42].

## 4. Implementation of Proposed Model

The proposed model integrates a fuzzy behaviour-based control system with VFF navigation to support adaptive, real-time decision-making in dynamic robotic environments. Drawing inspiration from biological systems [10], [43], [44], this architecture enables context-sensitive navigation and enhances the robot's ability to operate effectively in uncertain and rapidly changing conditions [45], [46]. The framework is structured around three interconnected modules. The *Behaviour Coordination* module uses fuzzy inference to analyze inputs such as obstacle density, proximity to potential threats, and environmental familiarity. Based on these factors, it assigns context-sensitive weights to behaviour components like goal pursuit, obstacle avoidance, and escape. These weights determine the relative importance of each behaviour component at any moment. Next, the *Component Behaviour* modules allows each behaviour to independently generate a motion vector aligned with its respective goal. These vectors are then passed to the *Behaviour Fusion* module, where the *VFF mechanism* combines them into a single movement directive. This fusion is based on attractive forces pulling the robot toward its goal and repulsive forces steering it away from threats or obstacles. Each force is scaled according to the fuzzy-derived behaviour weights, resulting in a balanced, responsive navigation decision.

In this framework VFF does not function as a standalone path planning method but operates as the underlying fusion mechanism. It calculates directional force vectors from real-time sensor data, such as LIDAR or depth cameras, and modulates them based on the fuzzy coordination outputs. For example, according to the Behaviour Coordination decisions, in environments perceived as risky or unfamiliar, the Escape behaviour receives a higher weight. This increases the repulsive influence in the motion vector, enabling the robot to adapt its path accordingly. This integration ensures that both low-level environmental constraints and high-level behavioural priorities are simultaneously addressed during motion planning [28], [42].

The fuzzy Behaviour Coordination is governed by a set of **If** [*conditions*] and **Then** *[actions]* statements that define relationships between observed environmental variables and behaviour priorities. These rules emulate biological decision-making processes and allow the system to make flexible, context-aware adjustments. Key input variables include Animal Familiarity Toward Place (AFTP), Familiarity Toward Another (AFTA), Animal Distance Toward Another (ADTA), and Escape Path Exists (EPE). For example, a rule might state [47]:
**IF** AFTP=*Low* **And** AFTA=*Low* **And** ADTA=*Low* **And** EPE=*High* **Then** ESCAPE=*High*

Here antecedent variables are AFTP, AFTA, ADTA, EPE. The consequent variable is ESCAPE. This rule does not trigger an immediate action but instead increases the influence of the Escape behaviour during fusion. This approach supports gradual behavioural transitions rather than binary switches, resulting in smoother navigation responses. Once the behaviour vectors are scaled by their relevance weights, the VFF fusion module calculates the final motion vector by summing the attractive and repulsive components. This process allows the robot to dynamically resolve behavioural conflicts such as choosing between goal pursuit and threat avoidance based on current environmental context. The result is an agent capable of lifelike, adaptive navigation strategies.

To demonstrate the proposed approach, an ethologically inspired Escape behaviour was implemented using fuzzy rule bases defined with the Fuzzy Behaviour Description Language (FBDL) [48]. The model emphasizes the identification of key internal states, such as fear or escape, and external observations, like familiarity with surroundings or availability of escape paths. These variables guide the Behaviour Coordination module in real time, enabling the robot to simulate animal-like adaptive responses. By combining fuzzy reasoning with VFF-based motion fusion, the system captures the complexity of biological navigation and enhances robotic autonomy in dynamic environments. See more details of the fuzzy Behaviour Coordination implementation of the Archer's "The Organization of Aggression and Fear in Vertebrates" [43], [45] ethological model in [47].

**State Variables:** These represent the current state or condition of the system. The escape behaviour fuzzy model includes two state variables: "Escape" and "Fear." "Escape" is linked to specific behavioural components, while "Fear" is a hidden state variable (i.e. this state variable has no directly

linked behavioural component).
*Fear:* A complex reaction involving physiological, behavioural, and emotional responses to stimuli. When an animal experiences extreme fear, it may exhibit changes in body posture and physical activity, such as crouching, pulling ears back, widening eyes, and tucking the tail. In the model, fear influences other state variables but cannot be observed directly.
*Escape:* Any action intended to distance the animal from a threat. Animals display escape behaviour when their lives are in danger, such as rapidly moving away from a perceived threat.
**Observations:** These are the situations in which the animal is found, influencing the state variables.
*Animal Familiarity Towards Place (AFTP)* the degree of familiarity an animal has with a location. Fear behaviour often occurs in unfamiliar environments.
*Animal Familiarity Towards Another Animal (AFTA)* the level of familiarity one animal has with another. Fear can arise when an unfamiliar animal enters a known territory.
*Animal Distance Towards Another Animal (ADTA)* is the distance between one animal and another, affecting the likelihood of fear or aggression.
*Animal Familiarity Towards Object (AFTO)* is the degree of familiarity with a specific object. An unfamiliar object in a known territory can trigger fear, aggression, or escape.
*Animal Distance Towards Object (ADTO)* The distance between an animal and an object, with unfamiliar objects potentially causing fear or aggression.
*Escape Path Exists (EPE)* The availability of an escape route. If an escape path is blocked, the animal may exhibit aggressive behaviour despite showing fear.

Understanding these state variables and observations is crucial to modeling how animals respond to environmental and social stimuli, which is an essential foundation for developing adaptive and intelligent robotic systems [10], [11], [47], [49], [50]. The proposed framework leverages this understanding to enable robots to mimic animal-like behaviours and pursue context-sensitive goals such as avoiding threats, tracking targets, or escaping confined spaces based on real-time environmental cues. These responses are governed by fuzzy rules, which allow the system to assign greater weight to behaviours like Escape when unfamiliar objects or agents are detected. Consequently, the repulsive forces in the fusion process are intensified, prompting rapid and adaptive reactions that closely mirror the survival strategies observed in animals.

FBDL [48] provides a structured framework to define input and state variables, including the terms used (e.g., ”Low” or ”High”) and the rules that dictate behavioural responses. For example, when evaluating ”Animal Familiarity with Another Animal” (AFTA) with possible values of ”Low” or ”High,” the FBDL code might look like this:

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

The fuzzy rule base and corresponding FBDL definitions are designed to address a wide range of behaviourally relevant scenarios such as: (i) The degree of familiarity an animal has with a particular location, object, or other animal. (ii) Proximity of an approaching object or agent. (iii) Appearance of a new object or animal within a familiar territory. (iv) Animal entering an unfamiliar environment, often triggering a fear response. (v) Presence of a familiar object in an unfamiliar setting. These scenarios inform the construction of fuzzy rules that govern key behaviours such as ”Fear” and ”Escape”, enabling the robotic system to respond in a manner consistent with ethologically inspired models. The fuzzy logic rules supporting these behaviours are outlined in the following sections.
In fuzzy rule-base format the fuzzy rules of **FEAR** are the following [47]:
**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*

Here, AFTP, AFTA, ADTA, AFTO, ADTO, and EPE are the *antecedent universes*, while FEAR is the *consequent universe*. The terms *Low* and *High* represent fuzzy linguistic values within their respective universes.

In fuzzy rule-base format the fuzzy rules of **Escape** are the following [47]:
**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*.

Here, AFTP, AFTA, ADTA, AFTO, ADTO, EPE, and FEAR are the *antecedent universes*, while ESCAPE is the *consequent universe*. The linguistic terms *Low* and *High* denote the fuzzy membership levels within these universes.

The same **ESCAPE** rule base in FBDL format can be represented as:
**Rule** *High* **when** EPE=*High* **and** FEAR=*High* **end**
**Rule** *High* **when** AFTA=*Low* **and** AFTP=*Low* **and** EPE=*High* **and** AFTO=*Low* **end**
**Rule** *Low* **when** FEAR=*Low* **and** EPE=*Low* **end**
**Rule** *Low* **when** AFTA=*High* **and** AFTP=*High* **and** ADTA=*High* **and** AFTO=*High* **and** ADTO=*High* **end**

### 4.1. Trajectory Example

The Fig. 3 illustrates a trajectory simulation of ethologically inspired escape behaviour, implemented through a hybrid control architecture that integrates VFF navigation with fuzzy behaviour control. This system enables real-time trajectory adaptation by combining fuzzy logic-based decision-making with virtual force-based motion planning. The scenario involves two autonomous mobile agents Robot_1 (the navigating robot) and Robot_2 (a moving obstacle or perceived threat) alongside both static and dynamic environmental obstacles.

In this example the Robot_1 is the primary actor and is tasked with reaching a target location at coordinates $(5.5, 5.5)$. Its path is influenced by the dynamic motion of Robot_2 and the presence of other obstacles, both designed to evaluate Robot_1 adaptive navigation capability. The robot's internal state, especially the level of fear, is visualized through the color of the trajectory path: blue indicates low fear (calm navigation), and red indicates high fear (active escape behavior).

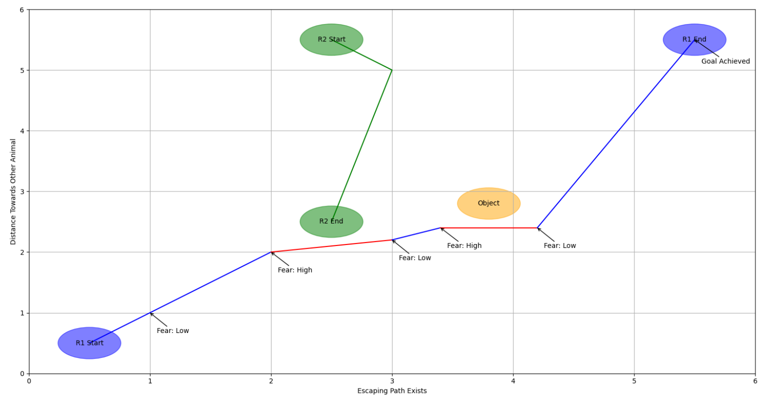


**Fig. 3.** Trajectory representation of hybrid model: robot_1 moving from initial to goal location

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Robot_1 begins its journey from the origin point $(0, 0)$ with a low fear level, indicated by a blue trajectory. As it moves toward its target at $(5.5, 5.5)$, it encounters Robot_2, which gradually obstructs its path. When Robot_2 comes close, the proximity between the two agents decreases (ADTA=Low). The fuzzy coordination system evaluates proximity (ADTA = Low), low familiarity with the other agent (AFTA = Low), and the availability of an escape route (EPE = High). Based on these sensory cues, fuzzy rules such as: **IF** AFTA=*Low* **AND** ADTA=*Low* **AND** EPE=*High* **THEN** ESCAPE=*High* are triggered, elevating the weight of the Escape behavior in the Behaviour Fusion module. This causes the VFF system to amplify repulsive forces and reduce goal-directed attraction, initiating an evasive maneuver. The trajectory's shift from blue to red reflects this real-time internal state modulation. The Repulsive and attractive forces influencing the robot's movement are computed using the following (6) and (7):

$$X_{cr} = -F_{cr}\left(\frac{X_i - X_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_0)^2}}\right), \quad Y_{cr} = -F_{cr}\left(\frac{Y_i - Y_0}{\sqrt{(X_i - X_0)^2 + (Y_i - Y_0)^2}}\right) \tag{6}$$

Where $X_{cr}$ and $Y_{cr}$ are the $x$ and $y$ components of the repulsive force, respectively; $F_{cr}$ is the repelling force constant; $(x_0, y_0)$ represents the current coordinates of Robot_1; and $(x_i, y_i)$ represents the coordinates of Robot_2 or an obstacle.

$$X_{ca} = F_a\left(\frac{H_x - X_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}}\right), \quad Y_{ca} = F_a\left(\frac{H_y - Y_0}{\sqrt{(H_x - X_0)^2 + (H_y - Y_0)^2}}\right) \tag{7}$$

Here, $X_{ca}$ and $Y_{ca}$ are the $x$ and $y$ components of the attractive force from the goal location toward Robot_1. $H_x$ and $H_y$ denote the goal position along the $X$ and $Y$ axes, respectively, and $F_a$ represents the gain of the attractive force

These components are vectorially summed based on fuzzy-weighted behavior fusion to determine the final motion vector. After escaping from Robot_2, Robot_1 increases its distance, which results in a reevaluation of its internal state. As fear levels drop, the weight of the Escape behavior is reduced, and attraction toward the goal becomes dominant again. This is seen in the trajectory shifting back to blue, indicating resumption of goal-directed navigation. This dynamic shift illustrates the real-time adaptability of the fuzzy coordination module, which continuously updates behavioural priorities based on changing environmental stimuli.

Later, Robot_1 encounters an unfamiliar object obstructing its route. This triggers another rise in Fear as the system detects low familiarity (AFTO=Low), close proximity (ADTO=Low), and an available escape path (EPE=High). These inputs again result in a High Escape output, leading to increased repulsive influence in the VFF layer. Robot_1 performs another avoidance maneuver, with the red trajectory indicating elevated fear and reactive escape. After successfully navigating around the obstacle, the fuzzy behaviour coordination module lowers the weight of the Escape behaviour. The system reverts to a calmer internal state, and the trajectory returns to blue, marking the final phase of movement toward the goal. The color-coded path visually represents the robot's internal behavioural modulation: blue denotes calm, goal-seeking behaviour (low fear), red indicates escape-driven avoidance (high fear), and transitions reflect real-time modulation of control priorities.

This trajectory representation highlights the effectiveness of the proposed fuzzy-VFF hybrid control architecture. Fuzzy logic interprets environmental context and assigns behaviour weights, while the VFF method fuses these behaviours into a resultant motion vector. Together, they enable the robot to exhibit ethologically inspired escape responses and maintain intelligent, adaptive navigation in uncertain, multi-agent environments. The graded transitions in behaviour demonstrate the system's ability to mimic animal-like reactivity, confirming its viability for real-world applications involving complex, dynamic interactions.

The Fig. 4 presents the basic flowchart of the prposed system and the Table 1 summarizes the key differences between traditional VFF navigation and the proposed fuzzy-VFF hybrid system, clearly illustrating the added value of our approach in terms of emotional modeling, adaptability, and explainability.

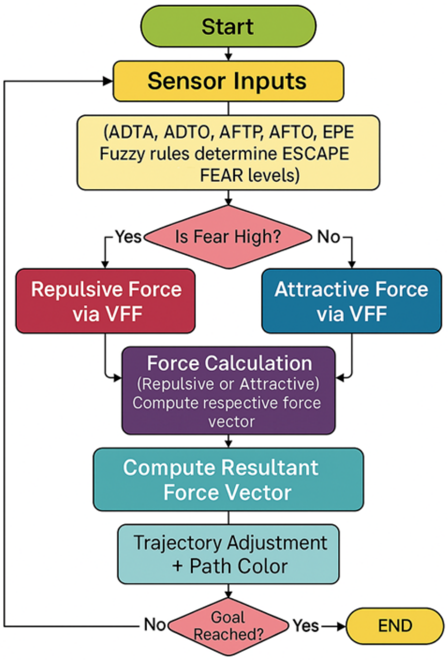


**Fig. 4.** Flowchart of the proposed model. Sensor inputs are interpreted via fuzzy logic to assess emotional states (e.g., Fear), which then guide the vector force selection through VFF calculations

**Table 1.** Comparison of traditional VFF vs. proposed Fuzzy-VFF hybrid

| Feature | Traditional VFF | Proposed Hybrid Fuzzy-VFF |
|---|---|---|
| Behaviour Fusion | Vector sum of attractive and repulsive forces | Weighted fusion via fuzzy inference and VFF |
| Context Awareness | None | High (via internal states like Fear/Escape) |
| Emotional Modeling | Not supported | Ethologically inspired |
| Decision Logic | Deterministic | Rule-based fuzzy reasoning |
| Adaptability to Dynamic Agents | Limited | Real-time adaptive behaviour selection |
| Trajectory Smoothness | Prone to oscillations and local minima | Smoothed via behaviour modulation |
| Explainability | Low | High via FBDL rule base |

### 4.2. ROS Simulation

To validate the effectiveness of the proposed fuzzy-VFF hybrid control system, simulation experiments were carried out within the Robot Operating System (ROS) framework [51]–[54]. This environment enables seamless integration of perception, mapping, and motion planning components, which are crucial for deploying intelligent mobile robots in dynamic environments. The simulation was demonstarted using key ROS tools such as: *RViz* used to visualize the robot's real-time trajectory, sensor data, and behaviour transitions. *Gazebo* a physics-based 3D simulator for testing robot interactions with static and dynamic elements, such as walls, objects, and other agents. *Light Detection and Ranging* (LIDAR) provided high-resolution environmental perception for obstacle detection. *Simultaneous Localization and Mapping* (SLAM) enabled real-time mapping and localization. SLAM enables Robot_1 to construct and continuously update a map of the environment while localizing itself within it. This spatial data is crucial for both behaviour coordination and VFF vector computation. In escape scenarios, SLAM output supports the fuzzy system in evaluating threat proximity, fear levels, and escape path availability, while simultaneously informing the VFF module for repulsive and attractive force generation.

The Fig. 5 to Fig. 9 present a visual sequence demonstrating the robot's adaptive behaviour in a dynamic environment. Each figure shows synchronized views from Gazebo (right) and RViz (left), providing both physical execution and sensor-based reasoning perspectives. The simulation scenario involved two mobile robots, Robot_1 (the primary navigating agent) and Robot_2 (a potential threat), operating within a bounded environment populated with static and dynamic obstacles. Robot_1 was assigned a target navigation goal and had to adapt its trajectory in real-time to avoid collisions using the proposed fuzzy-VFF control logic, as described in the Section 4.1. In Fig. 5 both robots begin at predefined starting positions (different coordinates). Robot_1 initiates movement toward the target Fig. 6, while Robot_2 begins to explore the environment, creating the potential for interaction.

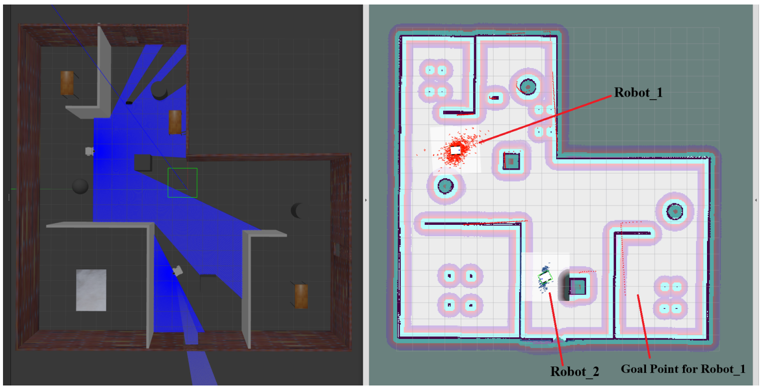


**Fig. 5.** Initial configuration: robot_1 and robot_2 at their starting positions within the simulation environment

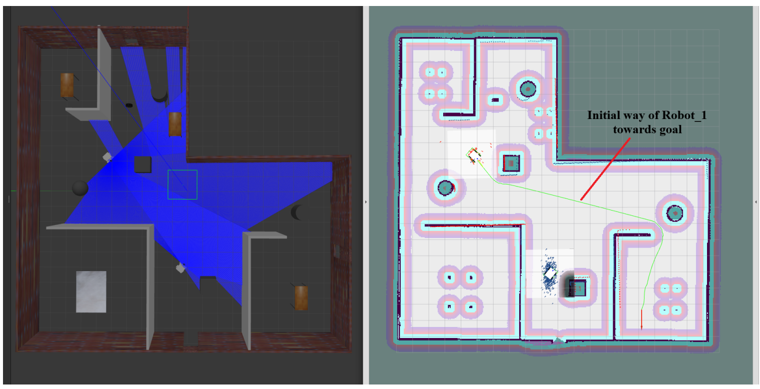


**Fig. 6.** Navigation initiation: robot_1 begins moving toward the goal location using the fuzzy-VFF hybrid control

In Fig. 7, Robot_1 detects Robot_2 approaching using LIDAR. The hybrid model operates through three core modules. The *Behaviour Components* generate motion vectors for behaviours such as goal pursuit or escape, based on environmental evaluations. The *Behaviour Coordination* module assigns relevance weights to these behaviours by processing inputs such as fear level, familiarity, and obstacle proximity. Finally, *Behaviour Fusion (VFF)* combines the weighted behaviours into a single motion directive by computing attractive forces toward the goal and repulsive forces from obstacles. As shown in Fig. 7, the fuzzy system interprets the interaction as threatening due to low proximity (ADTA), low familiarity (AFTA), and the presence of escape path (EPE). Consequently, the Escape behaviour weight is increased, leading VFF to emphasize repulsive forces and generate an evasive motion.

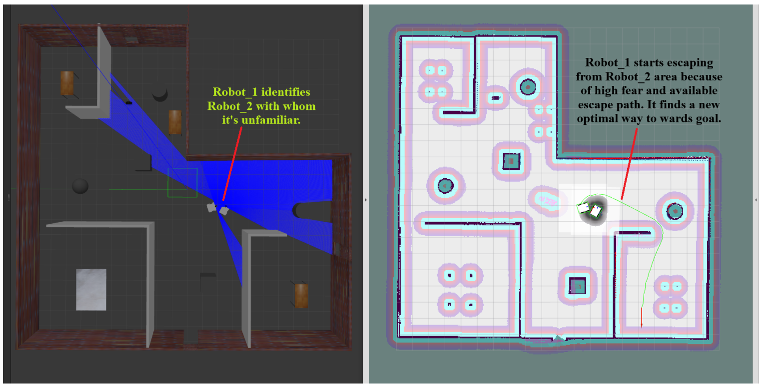


**Fig. 7.** Threat detection: robot_1 identifies robot_2 as a threat and initiates escape behaviour based on fuzzy reasoning

After successfully evading from Robot_2, Robot_1 encounters a new unfamiliar object as shown in Fig. 8. As the distance gets closer, the fuzzy system again evaluates the situation: unfamiliarity (AFTO=Low), close distance (ADTO=Low), and a valid escape path (EPE=High) trigger another Escape behaviour. VFF dynamically recalculates the repulsive vector, pushing Robot_1 away from the object. Once the object is sufficiently distant, the fuzzy controller de-emphasizes Escape and reactivates Goal Pursuit by strengthening the attractive force.

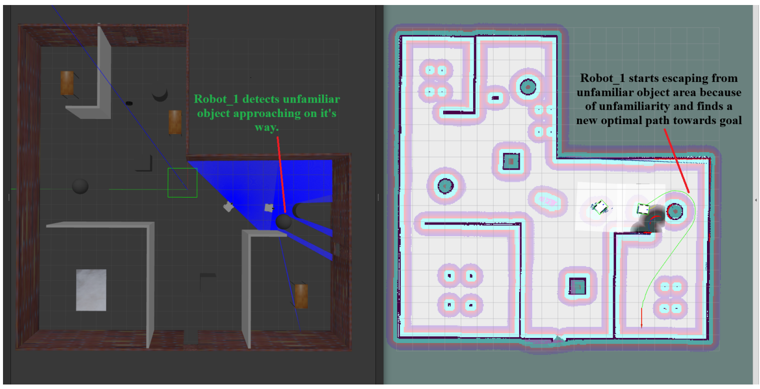


**Fig. 8.** Obstacle avoidance: robot_1 encounters an unfamiliar static object and adapts its path using escape logic

The Fig. 9 concludes the simulation, showing Robot_1 successfully reaching its goal after dynamically avoiding both Robot_2 and the unidentified object. This sequence demonstrates the system's robustness in responding to real-time, multi-agent, and obstacle-rich environments. This simulation confirms that the hybrid model not only ensures safe navigation but also exhibits lifelike behavioural responses by integrating biologically inspired fear and escape mechanisms, highlighting its potential for real-world autonomous navigation in complex and uncertain domains.

To address the **VFF Local Minima** scenario, we have specially designed a simulation in a constrained environment where Robot encounters unexpected, dynamically introduced blockages. These scenarios mimic classical local minima traps, a well-known limitations of conventional VFF controllers. The experiment was implemented using the ROS tools simulation framework, Gazebo-RViz integrated with LIDAR and SLAM for real-time perception, localization, and mapping [55]–[58]. The Fig. 10 to Fig. 14 present a sequence of synchronized visualizations from RViz (left), which

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displays the SLAM-generated occupancy grid and navigation trajectory, and Gazebo (right), showing the physical robot and environment layout. Together, they demonstrate the robot's adaptive behavior in response to dynamically evolving conditions.

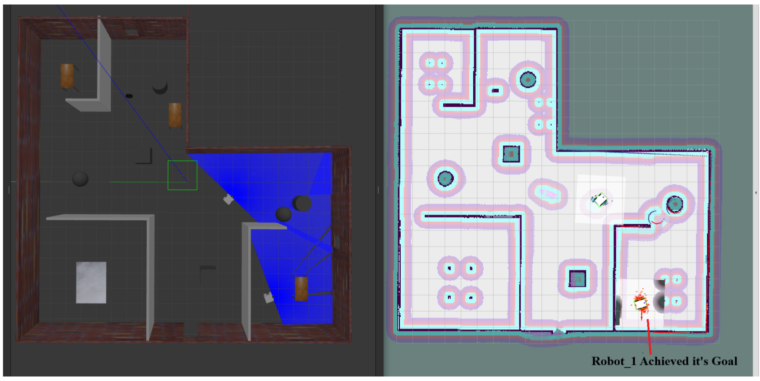


**Fig. 9.** Goal achievement: robot_1 successfully reaches the goal after adaptive navigation through threats and obstacles

The Fig. 10 presents the iniatial position of Robot in a simulation. In Fig. 11, Robot initiates navigation toward a predefined goal location. A trajectory line illustrates the intended path, and the environment includes static obstacles in a semi-structured.

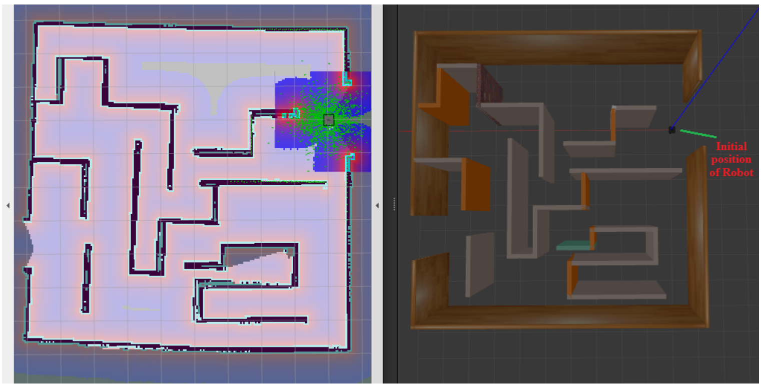


**Fig. 10.** Initial positions of robot in a predefined simulation environment

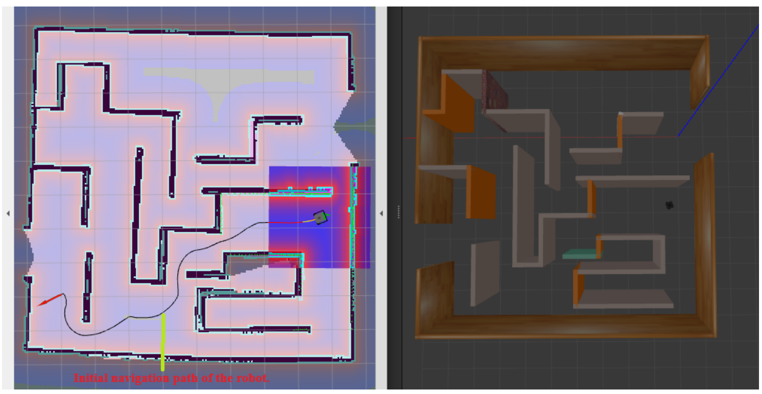


**Fig. 11.** Robot begins its trajectory toward the goal. The planned direction is shown as a line from the start to the goal position.

In Fig. 12, an unexpected obstacle is introduced along the planned path, simulating a local minima trap. Traditional VFF methods typically struggle here due to balanced repulsive forces, leading to robot stagnation. However, in our proposed model, the fuzzy coordination module interprets the situation using inputs such as low distance to threat (ADTO), low familiarity (AFTO), and the availability of an escape path (EPE). As detailed in Section 4.1, this increases the weight of the Escape behavior, prompting the VFF controller to emphasize repulsion and redirect the robot along an alternative route.

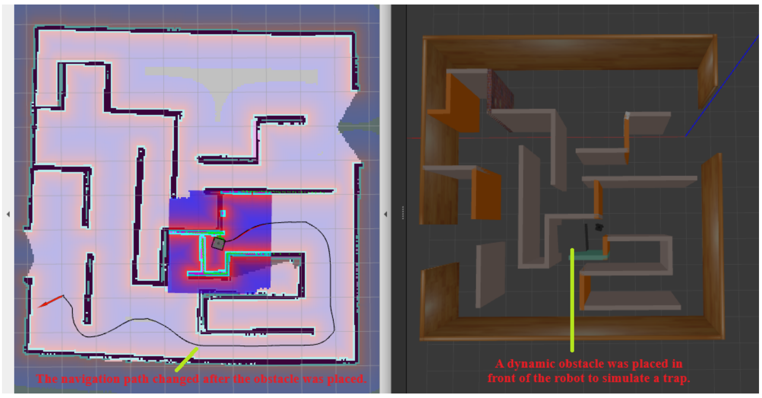


**Fig. 12.** A dynamic obstacle is introduced mid-path to simulate a local minima trap. The fuzzy system triggers an Escape response based on reduced proximity and unfamiliarity, causing deviation from the original path

As Robot reaches near the goal in Fig. 13, a second dynamic obstacle is introduced, blocking the path. The robot reassesses the situation via fuzzy logic and unlike standard VFF systems avoids getting trapped by quickly reorienting and continuing its progress.

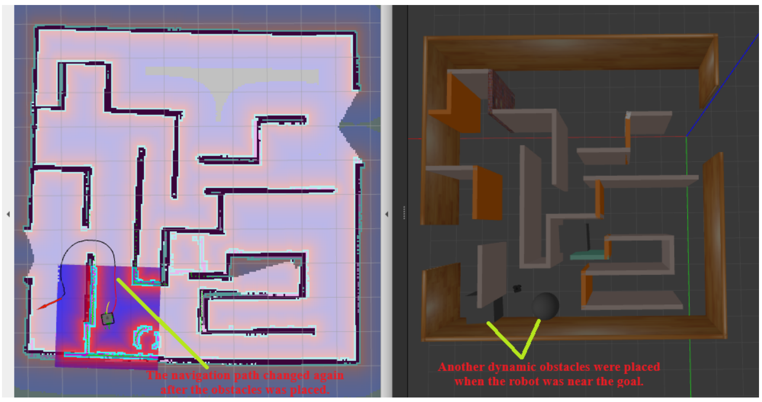


**Fig. 13.** Dynamic obstruction near the goal triggers rerouting via fuzzy Escape behaviour

Finally the Fig. 14 illustrates that Robot successfully reaches its goal while avoiding both static and dynamic obstructions. This scenario confirms the efficacy of the proposed hybrid model in resolving local minima issues through the fusion of emotion-inspired fuzzy reasoning with reactive VFF control.

## 5. Result

This section presents a detailed evaluation of the proposed hybrid navigation system that integrates VFF motion planning with a fuzzy behaviour coordination mechanism inspired by ethology. The objective is to assess the system's capacity to make context-sensitive, adaptive decisions in dynamic environments. To evaluate behavioural accuracy, we conducted 25 independent ROS-Gazebo simulations in varied dynamic environments that included static and dynamic obstacles, moving threats (Robot_2), and unfamiliar terrain. The fuzzy inference system dynamically adjusted internal states such as *Fear* and selected behaviours (e.g., *Escape* or *Goal Pursuit*) based on sensor-derived fuzzy variables: AFTA, ADTA, and AFTO, EPE.

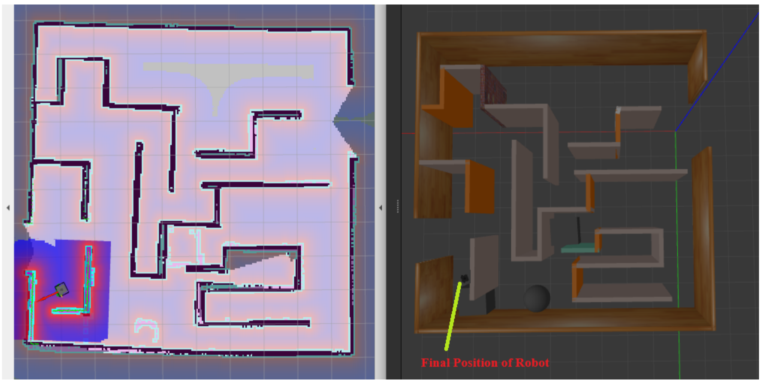


**Fig. 14.** Robot successfully reaches the goal by avoiding static and dynamic threats

The Fig. 15 shows the classification metrics of the of the proposed hybrid model. We computed standard performance metrics **accuracy, precision, recall, and F1-score** using labelled behavioural transitions observed during simulation. The system achieved a classification accuracy of **86%**, demonstrating its ability to effectively distinguish between safe and threatening contexts, and to activate appropriate behaviours accordingly.

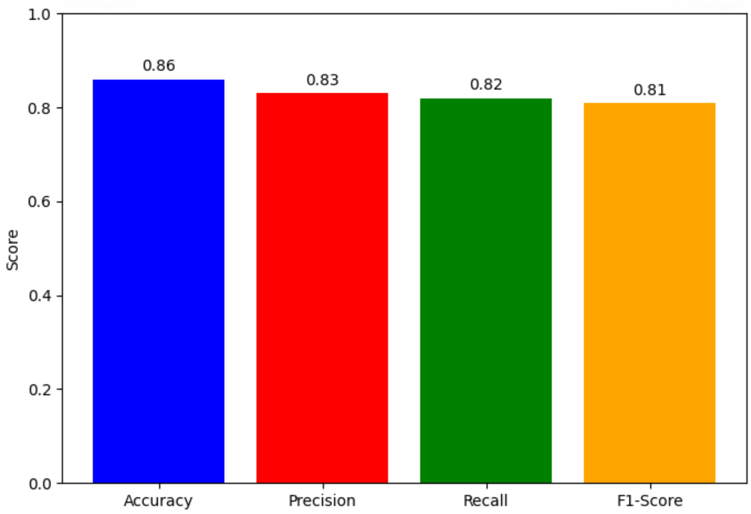


**Fig. 15.** Classification metrics for fuzzy behaviour coordination module in dynamic scenarios

To highlight the practical advantages of the system, we conducted a comparative benchmarking study against a baseline VFF reactive controller, following established canonical models [37], [59]–[61]. Conventional VFF methods rely on fixed attractive and repulsive force equations and are prone to challenges such as local minima, oscillatory trajectories, and limited adaptability in complex environments. While variants like behaviour-coordinated VFF [33]–[35], [42] have improved responsiveness, they still lack mechanisms for emotional modeling, contextual reasoning, and interpretability in behaviour fusion. As shown in Table 2, our comparative evaluation was based on key performance indicators: *Task Completion Time* is the time taken to reach the goal while avoiding hazards; *Number* *of Collisions* presents the number of collisions with dynamic-static entities; *Behaviour Switching Latency* is a delay between a triggering condition and behaviour activation; and *Classification Accuracy* is the correct prediction of appropriate behaviour. The proposed fuzzy-VFF hybrid system significantly outperformed the baseline across all metrics.

**Table 2.** Comparison between proposed model and baseline VFF reactive navigation

| Metric | Fuzzy-VFF Hybrid | VFF 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 |
| Classification Accuracy | 0.86 | 0.75 |

The Key findings are as: *Task Completion Time* reduced by 13.3%, due to smoother transition planning and proactive behaviours; *Collision Rate* dropped by 28.1%, showing enhanced safety in unpredictable environments; *Behaviour Switching Latency* is 7.5% lower, reflecting faster internal state evaluation; and *Escape Model Accuracy* is around 14.7% higher than the baseline, showcasing improved emotional reactivity.

To situate the proposed framework within the broader robotics literature, we compared it against three prominent behaviour-based navigation paradigms: *Subsumption Architecture*, *Belief-Desire-Intention (BDI) Models*, and *Neuro-Fuzzy Systems* [62]–[65]. The Table 3 outlines the conceptual differences across several critical dimensions, including interpretability, emotional modeling, real-time adaptability, and obstacle navigation robustness.

**Table 3.** Comparison of traditional navigation paradigms vs proposed system

| Aspect | Subsumption Architecture | BDI Models | Neuro-Fuzzy Systems | Proposed-Model (VFF+FS) |
|---|---|---|---|---|
| Behaviour Coordination | Hierarchical suppression | Symbolic reasoning | Learned rules, opaque | Rule-based system, 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 |

## 6. Conclusion

This paper has presented a biologically inspired hybrid navigation framework that integrates a Fuzzy Behaviour Coordination module with Virtual Force Field based motion planning to enable adaptive, real-time decision-making in complex, dynamic environments. The system, developed and tested within a ROS Gazebo simulation environment, incorporates ethological constructs such as fear and escape, which are modelled through a fuzzy inference system using sensor-based inputs including proximity, familiarity, and threat estimation. These internal states influence the fusion of repulsive and attractive forces in the VFF layer, enabling smooth, emotionally grounded trajectory adjustments. Compared with a baseline VFF controller, the proposed hybrid model achieved a 13.3% reduction in task completion time (43.6 s vs. 50.3 s), a 28.1% decrease in collisions (2.3 vs. 3.2), a 7.5% improvement in behaviour switching latency (370 ms vs. 400 ms), and a 14.7% improvement in escape behaviour model accuracy (86% vs. 75%). Furthermore, conceptual comparison with Subsumption, BDI, and Neuro-Fuzzy systems underscores the novelty of our approach in combining explainable reasoning, emotional modelling, and reactive adaptability. The results validate the effectiveness and originality of the proposed system in addressing limitations of traditional navigation frameworks, making it highly suitable for real-world applications in logistics, service robotics, and human robot interaction. However, the current work is limited to simulation-based validation. Future work will focus on real-world implementation, quantitative validation through statistical testing, and optimization of the fuzzy rule sets via learning-based approaches. Through this hybrid framework, we take a step toward bridging reactive and deliberative control strategies for more resilient and context-aware autonomous systems.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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