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DEVELOPMENT OF A DYNAMIC ONTOLOGY-BASED FRAMEWORK FOR ENHANCING THE INTELLIGENCE AND AUTONOMY OF ROBOTIC SYSTEMS

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Abstract

In recent years, intelligent agents driven by ontologies have shown significant promise in learning from their experiences and adapting to dynamic environments. These agents have been successfully applied to a variety of domains, including autonomous systems, robotics, and decision support systems, where their ability to process and adapt to changing circumstances is crucial. However, despite their potential, these agents often encounter significant challenges when confronted with unpredictable or hostile conditions, such as high uncertainty, evolving adversarial behaviors, or environmental disturbances. In such scenarios, traditional models may struggle to maintain effective learning and decision-making, leading to suboptimal performance and failure to achieve desired outcomes. This limitation arises from the inability of many existing models to fully account for anomalies or unexpected changes that deviate from anticipated patterns. As a result, the agents' capacity for robust decision-making and adaptability is compromised, hindering their performance in real-world applications. Addressing these challenges requires models that are not only capable of learning from experience but also flexible enough to deal with unexpected events and changes in the environment. To overcome these limitations, this thesis introduces a novel dynamic, ontology-driven agent model that emphasizes continuous learning from past experiences. The model integrates an adaptive reasoning framework capable of adjusting its strategies and planning processes in response to new, unforeseen challenges. By leveraging the rich contextual information embedded in ontologies, the proposed agent model can enhance its action planning and reasoning abilities, enabling it to identify and adapt to anomalies more effectively. Furthermore, the model is designed to improve its adaptability by dynamically updating its ontological knowledge base based on real-time data, ensuring that it remains resilient in hostile and unpredictable environments. This research seeks to advance the field of intelligent agents by proposing a more robust and adaptive framework that not only learns from past experiences but also evolves and adjusts its strategies in response to novel and challenging conditions. The expected outcome is a highly adaptable agent model capable of improving decision-making, planning, and performance in dynamic, uncertain, and adversarial environments, thus expanding the potential applications of intelligent agents across various complex domains.

INTRODUCTION

The idea of robots originated in 1921 with the play *Rossum's Universal Robots*, which introduced machines resembling humans. Since then, robotics and artificial intelligence (AI) have evolved rapidly, resulting in intelligent systems that support various human activities. AI-driven robots are now deployed across multiple sectors, including manufacturing, healthcare, security, and domestic environments. This evolution has led to the development of intelligent agents—autonomous systems that interact with their environment to achieve specific goals. According to Wooldridge, an intelligent agent is a computational entity capable of making autonomous decisions based on environmental input. Such agents are characterized by various attributes: autonomy, deliberation, reactivity, proactiveness, flexibility, robustness, social behavior, rationality, and the ability to learn.

- **Autonomy** allows agents to operate independently without constant supervision.
- **Deliberation** enables logical planning and decision-making.
- **Reactivity and Proactivity** allow agents to respond to changes and act purposefully.
- **Social capabilities** enable interaction with other agents and humans.
- **Learning** ensures adaptability through experience.

Agents operate in either **static** or **dynamic** environments. In static settings, where conditions remain constant, agents often perform repetitive tasks without the need for complex decision-making. However, dynamic environments require agents to adapt to unpredictable conditions and continuously evolving tasks. In such contexts, agents must go beyond fixed rule sets and learn from ongoing interactions.

Despite advancements, many existing agents rely heavily on predefined rules and are unable to modify or extend their knowledge effectively. They often fail in situations where no prior experience or instruction exists.

.1. Problem Statement

Existing ontology-based agents are often designed for static environments and rely on fixed rules, which limits their performance in complex and evolving scenarios. These agents are typically incapable of updating or generating new rules autonomously. This thesis aims to address these shortcomings by proposing a dynamic ontology-based agent model that can:

Adapt to new, unseen situations.

Learn from both environment and experience.

Generate or refine rules as needed for problem-solving.

Ontology provides a structured framework for representing knowledge, facilitating reasoning, and supporting semantic interoperability. It organizes domain-specific knowledge into classes, relationships, instances, axioms, and rules. Ontology enables agents to retrieve, share, and reason about knowledge more effectively.

The following functions highlight the importance of ontology in intelligent systems

. **Specification**: Defines domain-specific concepts and their interrelations.

. **Information Access**: Enables agents and humans to retrieve relevant knowledge semantically.

. **Semantic Search**: Improves information retrieval through contextual understanding.

4. **Knowledge Reuse**: Allows agents to build upon existing knowledge bases.
5. **Modeling**: Represents internal and external elements relevant to the domain.
6. **Dynamic Adaptation**: Supports evolving knowledge in dynamic environments.

However, existing ontology-driven systems are often limited in their adaptability. They struggle to distinguish between procedural and declarative knowledge or to integrate new experiences with existing data effectively.

The contribution of this work as follows:

To overcome these limitations, this research introduces a **Dynamic Ontology-Based Agent Model**. The model enhances learning and reasoning by enabling agents to:

Integrate new experiences into existing ontologies.

Create new rules dynamically when predefined ones are insufficient.

Generalize from previous experiences to handle unfamiliar scenarios.

For example, if an agent is tasked with digging soil but lacks the appropriate tool, it can use past knowledge to identify a substitute (e.g., using a spoon instead of a shovel) by analyzing properties and relationships in its knowledge base.

2. Related work

The Open Robots Ontology (ORO) framework provides a symbolic approach to knowledge representation, enabling intelligent agents to perform reasoning, categorize information, and apply common-sense understanding. As highlighted in ORO design, effective decision-making in complex environments requires agents to access and utilize prior knowledge. This stored knowledge serves as the foundation for extracting relevant rules and principles tailored to specific situations. ORO excels in integrating diverse types of data including visual inputs, logical reasoning, and human-like common-sense knowledge into a unified symbolic representation. It employs a blackboard architecture, allowing the system to infer knowledge by referencing memory. All knowledge is represented using RDF triples, managed through the Jena framework, while Pellet is used as the reasoning engine to support data categorization.

Communication is handled using the ASCII protocol over TCP, selected for its broad compatibility, ease of debugging, and accessibility using standard tools. When the agent encounters an unfamiliar object, it initiates a questioning process to gather contextual information. Based on these interactions, the agent constructs a conceptual model of the new object and updates its knowledge base by incorporating newly derived facts and rules. However, a key limitation of ORO lies in its relatively static approach to conceptualization. While it effectively manages and reasons over consistent information, it does not dynamically adapt its object categorization or ontology structure in real-time, limiting its flexibility in rapidly changing environments.

The Ontology-Based Multi-Layered Robot Knowledge Framework (OMRKF) is designed to facilitate structured knowledge representation, particularly for effective interaction between robots and humans. This architecture organizes knowledge into four primary domains: activity, perception, model, and context. Each of these domains is structured into three interrelated levels, and each level incorporates three layers of ontologies: the meta ontology layer, the schema ontology layer, and the instance ontology layer. The system supports logical reasoning through the use of well-defined axioms and two types of rule structures: unidirectional rules, which operate within a single knowledge domain, and bidirectional rules, which facilitate reasoning across multiple knowledge domains. The knowledge representation and reasoning mechanisms in OMRKF are implemented using Prolog, enabling rule-based inference. A key feature of OMRKF is its focus on knowledge reusability and shareability, which enhances its utility across various tasks. The use of Horn clauses aids in logical inference, allowing the agent to deduce hidden or implicit information from its environment. While the symbolic structure of OMRKF proves effective for straightforward and clearly defined tasks, its performance tends to decline when applied to complex or dynamic problem scenarios, where more flexible and adaptive reasoning is required.

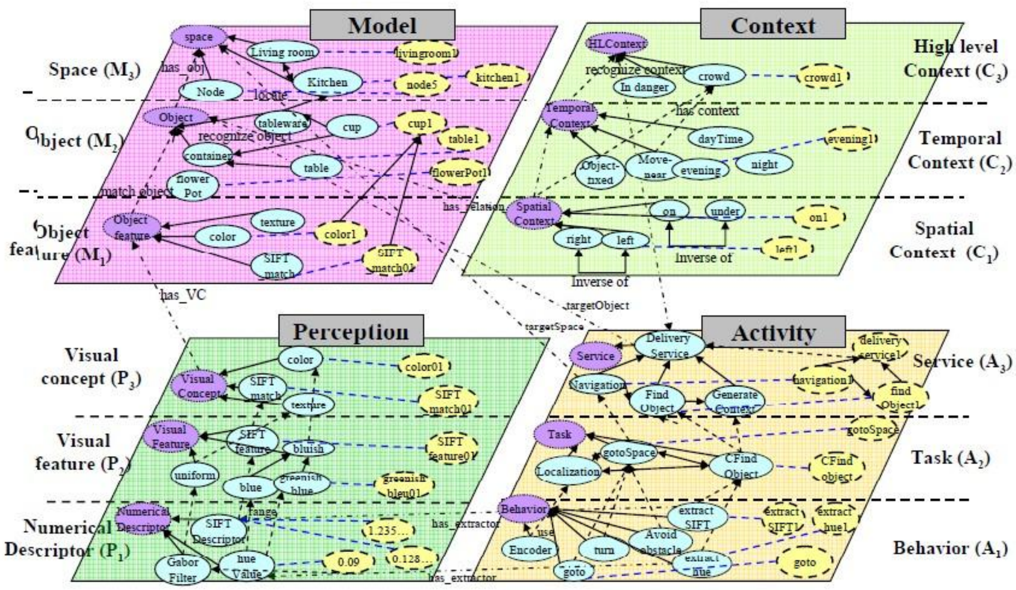

Figure 1: Ontology Base Multi Layered Robot Knowledge (21)

The OUR-K framework, introduced by Gi Hyun Lim, addresses several challenges commonly encountered by ontological agents, particularly when dealing with complex tasks. One of its key strengths lies in its ability to process and identify partially observable objects, enabling it to operate effectively even in environments where complete data is not available.

This framework integrates both low-level sensory data and high-level semantic knowledge, creating a unified structure where information is semantically interconnected. The framework's knowledge model is built on five distinct knowledge classes, which facilitate the interaction between abstract (high-level) and concrete (low-level) data.

The reasoning process in OUR-K is divided into two major components:

Knowledge Description – This focuses on organizing and detailing the five knowledge classes, supporting the integration of various data layers.

Knowledge Association – This involves applying logical inference and reasoning rules, including both unidirectional and bidirectional rules, to establish meaningful connections between concepts.

The framework relies on a combination of techniques:

Bayesian reasoning to interpret and infer information about partially observable variables. Logical inferences to establish relationships among properties and classes. Heuristic methods to identify unknown objects based on existing knowledge. The ontology used in OUR-K is built upon the Karlsruhe Ontology (KAON) platform. This foundation supports advanced reasoning, particularly in tasks involving temporal and spatial data, improving the performance of systems like T-ROT and CIR. Despite its strengths, one limitation of OUR-K is that it lacks the ability to autonomously generate new knowledge when encountering completely unfamiliar objects. While it can complete tasks using partial data, it depends heavily on existing knowledge and cannot formulate new facts without prior information.

Feature	ORO (19)	OMRKF (37)	OUR-K (23)	RACE (37)	CORA (28)	OPEN-EASE (18)	KNOWROB (16)	RAPP (38)
Previous Experience	Yes	Yes (object recognition & space classification)	Yes	Yes (conceptualization & plan adaption)	Yes	Yes (memorized experiences)	Yes	Yes
Integration of Low- and High-Level Data	Not specified	Yes	Yes	Yes	Not specified	Not specified	Yes (categorization & classification)	Partially
Knowledge Sharing	Not specified	Yes (common concepts, facts, functions)	Yes	Not specified	Yes	Yes	Not specified	Yes (experience sharing via cloud)
Improvement of Rules & Constraints	No (does not support inconsistency)	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified
Extending New Knowledge	Yes	Not specified	Not specified	Partially (needs supervision)	Not specified	Yes	Not specified	Yes

Complex Task Execution	Not specified	No (limited to simple tasks)	Not specified	Partially (requires supervision)	Not specified	Yes	Yes (intentional and extensional models)	Yes
Ontology Suggests Alternative Solutions	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified

3. Method and materials

The proposed model (31) is designed around dynamic constraints, enabling it to continuously improve and adapt its rules through environmental learning. Unlike earlier frameworks such as RACE (37), OUR-K (23), OMRKF (21), and ORO (19), which rely on static constraints and are unable to modify or enhance their rules or propose alternative solutions, this model can update its constraints and apply them to various problem scenarios. This ontological framework learns from experience and collectively infers dynamic actions based on its knowledge base. It also stores newly generated rules and their attributes for future use. As a result, it can handle situations that were not encountered before and function effectively in new environments. Much like humans, whose understanding of their surroundings, spatial relationships, objects, and contexts expands over time, this model continuously enriches its knowledge. The core objective is to develop an autonomous agent capable of learning from its environment, updating existing rules, creating new ones, and applying these rules across diverse situations. Rather than operating solely on predefined rules, this agent draws from prior experiences and extracts relevant knowledge from its knowledge base to navigate novel challenges.

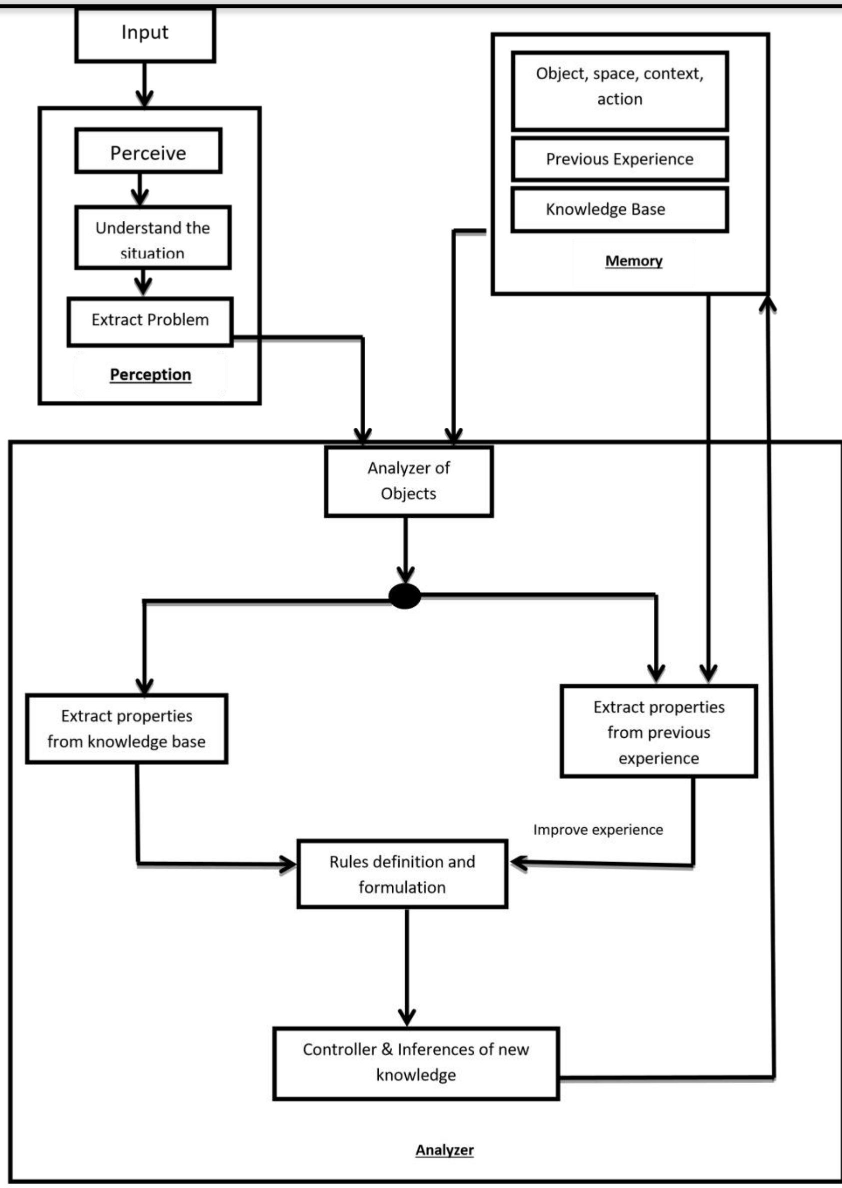

Figure 2: Proposed Model

The proposed model is built on a layered framework, consisting of three key modules:

- Perception
- Memory
- Analyzer

3.1.1. Perception

The Perception module is the first step in the model. Initially, the agent receives input either from its environment or through a human interface. Upon receiving this input, the agent processes and perceives it. For example, when a game starts, the bird identifies its surroundings and the objects within the environment. After perceiving the input, the agent enters the phase of understanding the problem at hand. As the bird moves in the game, it begins to encounter various objects. The agent then starts to extract problem-relevant information, distinguishing between different objects such as obstacles and food points

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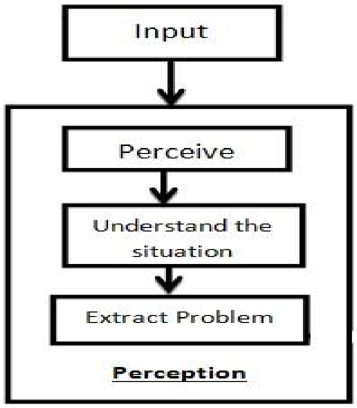

Figure 3: Perception layer of Proposed Model

3.1.2. Memory

The Memory module is the second layer in the proposed model. It functions similarly to the preconscious state of the bird, supporting its activities and decision-making processes. Memory primarily involves the description and association of knowledge (28). Knowledge representation outlines the various objects in the environment, while knowledge association establishes the relationships between these objects. Memory consists of the following layers: Object, Space, Context, Action, Previous Experience, and Knowledge Base.

3.1.2.1. Object, Space, Context, Action

This layer stores information about the objects in the environment, such as the bird itself, types of obstacles, and the consequences of interactions with these objects. It includes details like what happens when the bird collides with a hurdle, how it affects the score, and the impact of food points when the bird consumes them. Additionally, it encompasses the space (the background and environment the agent operates within), context (the situational setup), and actions (the possible moves the bird can make).

3.1.2.2. Previous Experiences

This layer stores the actions previously taken by the bird in the environment. It includes past actions, along with the bird's learning about the objects, space, and their respective attributes. This knowledge helps shape the bird's behavior and operational patterns. When the bird encounters a problem situation, it refers to the previous experiences to find relevant solutions. If a matching solution is found, the bird selects the appropriate behavior and working pattern from the previous experiences.

3.1.2.3. Knowledge Base

The Knowledge Base layer holds general concepts and common knowledge about the objects and the environment. It includes a comprehensive understanding of the properties of various objects.

If a solution is not found in the previous experiences, the system can retrieve a solution from the knowledge base.

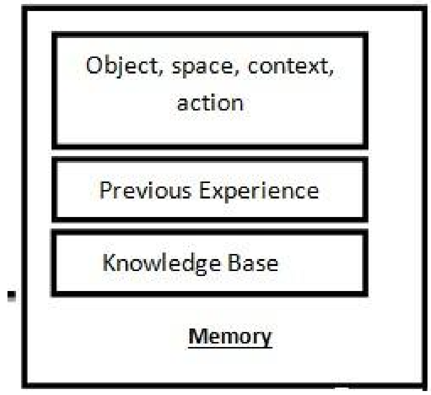

Figure 4: Memory Layer of Proposed Model

3.1.3. Analyzer

Once problems are extracted and analyzed, they are passed to the Analyzer, which is the third module of this framework. If relevant previous experiences exist, the system retrieves applicable rules from them. In cases where no prior experiences are available, it evaluates the problem by analyzing the properties using knowledge descriptions and associations. The Analyzer is responsible for formulating new rules and constraints, drawing both from previous experiences and from its own analysis. A key feature of this model is its ability to improve and refine existing rules. The system can infer various types of rules and select the most appropriate ones based on the current environment. After determining the suitable rule, the agent applies it and stores the new information in its repository of previous experiences. By considering factors such as objects, space, context, actions, past experiences, and the knowledge base, the agent is equipped to solve a wide range of dynamic problems. This continuous learning process helps the agent enhance its knowledge and improve its understanding of the environment. When necessary, the agent can also generate new constraints from the knowledge base.

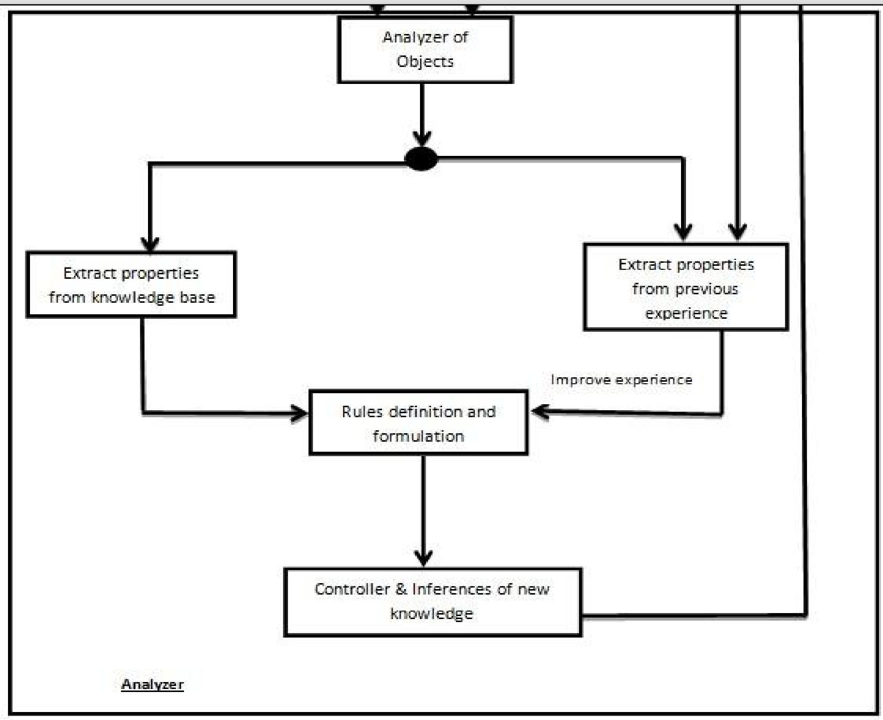

Figure 5: Analyzer of Proposed Model

When the agent receives input from its environment and is assigned a task, it first attempts to extract the problem. If the problem cannot be identified, it returns to the starting phase. However, if the problem is detected, the agent then analyzes the objects based on the "object, space, context, actions" data from the memory layer. After analyzing the task, the **Previous Experience** module checks if the agent has encountered and solved a similar problem in the past. If matching experiences are found, the agent bases its actions on these predefined solutions.

If no similar problem exists in the past, the agent extracts relevant object properties and knowledge from the **Knowledge Base** section of the memory layer. Subsequently, the agent defines and formulates new rules. During this step, existing rules may also be improved. Once the rules are defined, the most appropriate rule is selected, and an action plan is created for the required task. Finally, the new inferences, rules, and experiences are stored in the memory layer, and the task is completed.

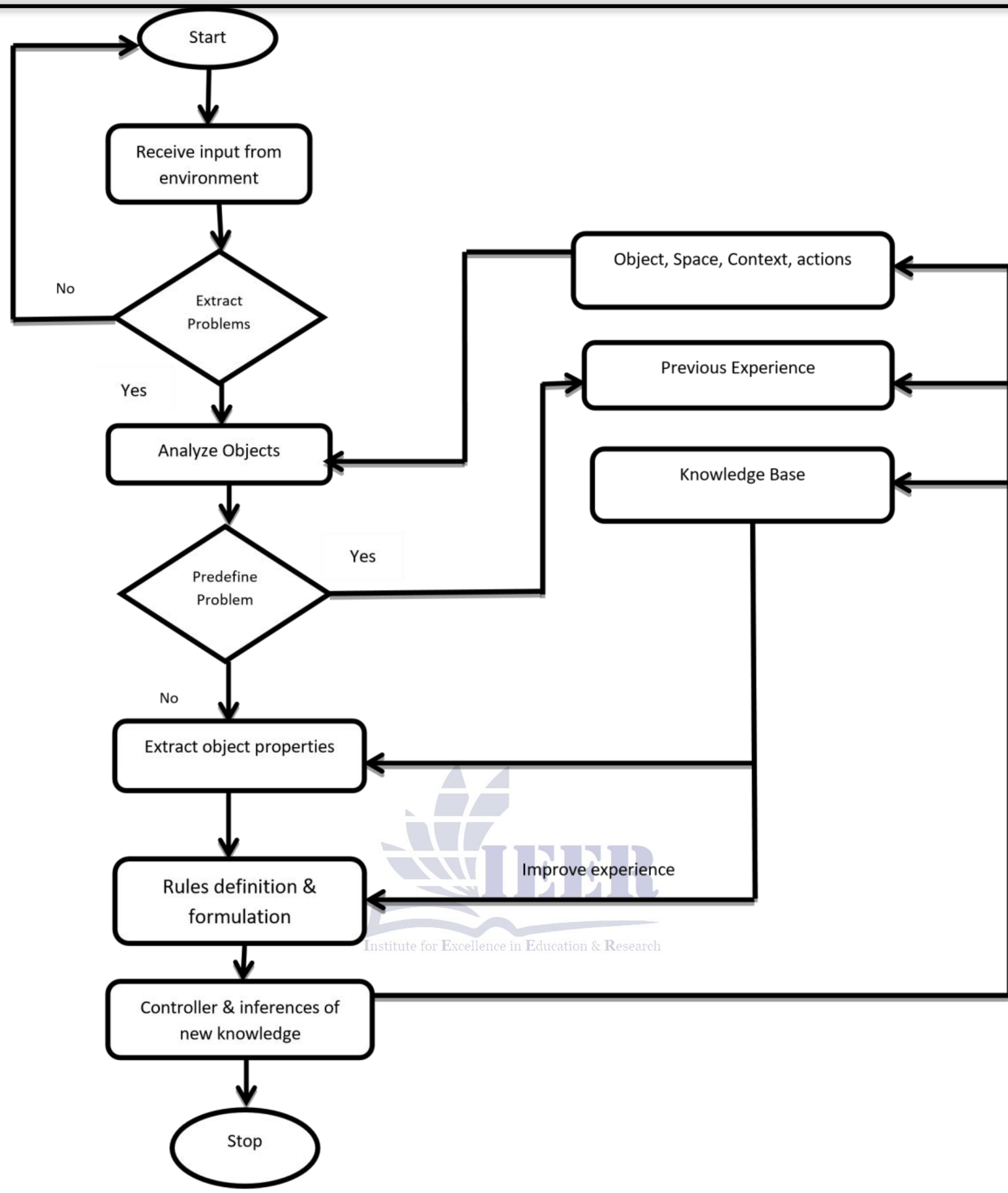

Figure 6: Data flow diagram of Proposed model

4. Implementation and result

As outlined in Section 3.4, the model consists of three primary modules: Perception, Memory, and Analyzer. The **Perception** module initially receives input from the environment, understands the situation, and extracts the problem (as discussed in Section 3.4.1). These problems are then analyzed in the **Analyzer** module, which either retrieves properties from the **Knowledge Base** (apart of the memory module, described in Section 3.4) or draws upon previous experiences (also part of the memory module). If applicable action rules already exist in previous experiences, they are extracted and applied. If not, the rules are evaluated from the knowledge base. Once the rules are defined, either based on previous experiences or the knowledge base, the most suitable rule is selected to form an action plan, as detailed in Section 3.4

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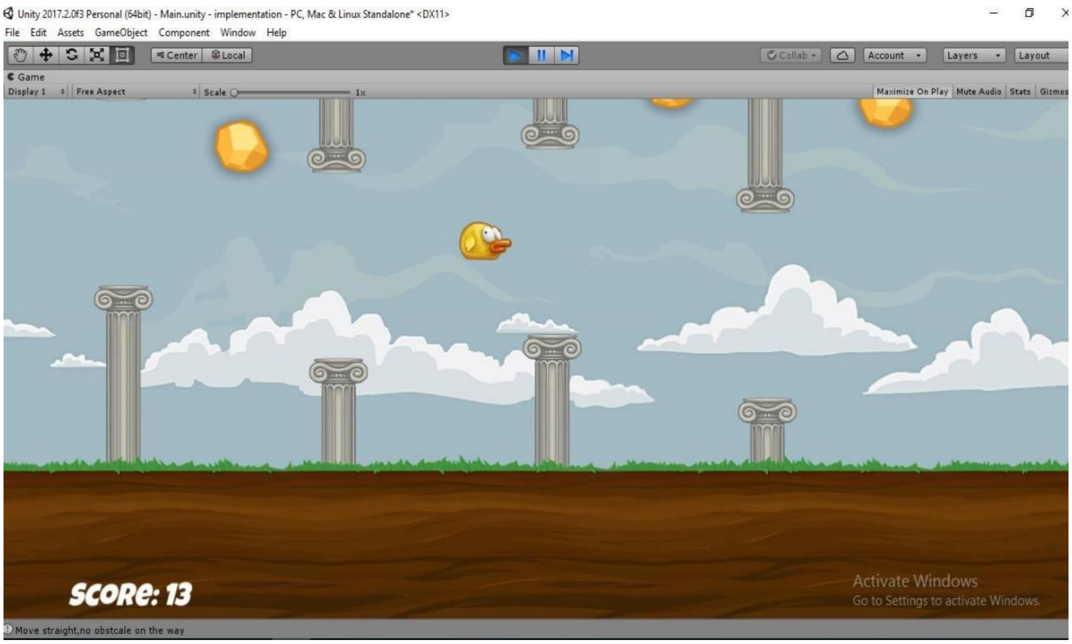

Figure 7: Simulation

The image in **Figure 8** represents the simulation of our architecture, implemented as a Flappy Bird game. The screen displays the main game board, where a yellow bird moves at a set speed. At the bottom left of the screen, the score is shown. The score increases by one when the bird successfully passes through an obstacle, and by five when it collects a food item. Two pairs of columns are displayed at regular intervals, with their positions being dynamic and random. The yellow ball represents the food item. The game begins when the play button is pressed, allowing the computer to start the game.

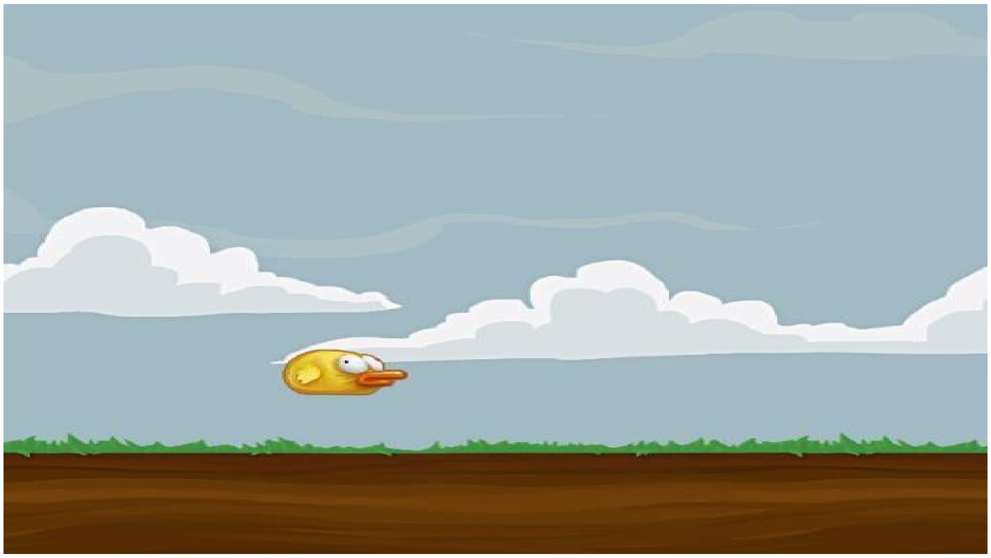

Figure 8: No obstacle view

When the bird (agent) begins to move, it first perceives its environment through the **Perception** module. For instance, it recognizes that obstacles are harmful if the bird collides with one, it will be destroyed, while collecting food items increases its score. **Figure 9** above shows a scenario where there are no obstacles. After performing an ontological analysis, **Figure 9** highlights the area that results from this analysis, indicating that the bird can move straight without taking any action. Initially, the bird perceives its surroundings and the problem at hand, with all this information being drawn from the **Memory** module. The **Analyzer** then evaluates the situation, confirming that there are no obstacles or food items ahead of the bird. Since no relevant rule exists in previous experiences, the agent extracts actions from the knowledge base. In this case, the agent selects and implements the action "Move straight, no obstacle ahead," based on the data from the knowledge base

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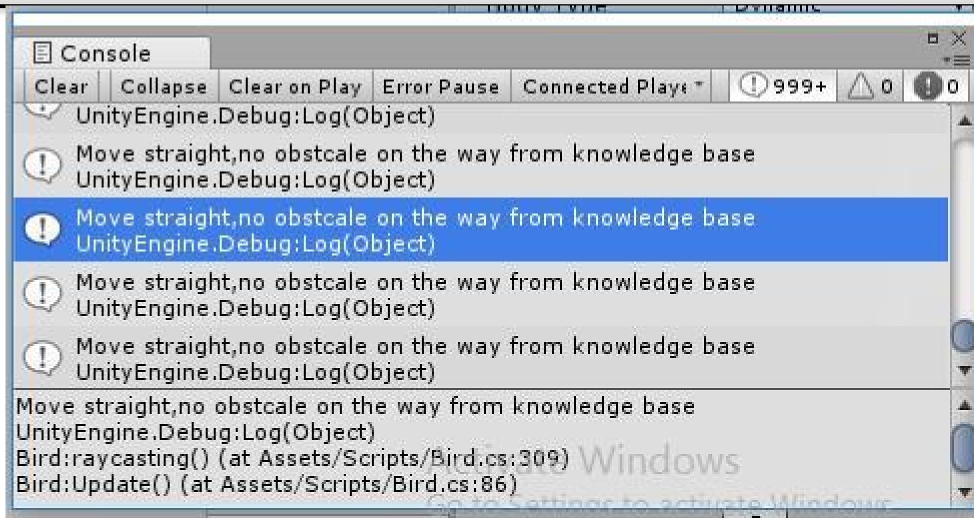


Figure 9: Ontological Analysis

In **Figure 10** below, the bird perceives an obstacle in its path. This problem is sent to the **Analyzer** module, where properties are extracted either from the knowledge base or from previous experiences stored in the memory module. Various rules are evaluated, and the controller selects the most appropriate rule from the memory for the current situation.

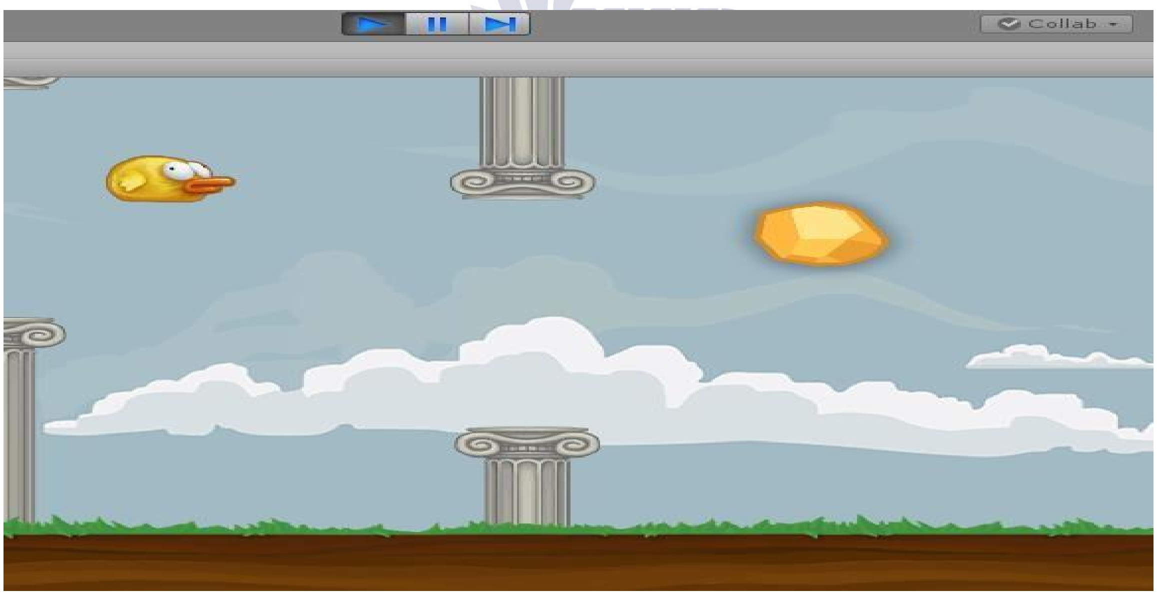
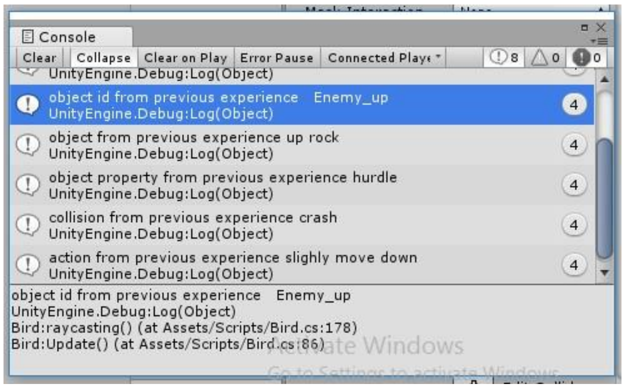
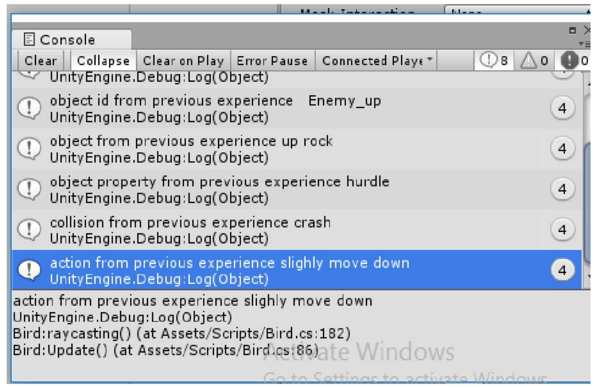


Figure 10: Up obstacle view

In **Figure 11** above, the bird perceives an obstacle ahead. The system extracts different rules from both the knowledge base and previous experiences. It then performs an ontological analysis of the situation. In **Figure 11A**, the highlighted area on the left side shows the problem statement and the ontological analysis, which is identified as "Enemy Up." After analyzing the situation, the most appropriate action is chosen from the memory.

Once the objects and the problem are analyzed, the system checks previous experiences for similar situations. A list of rules is available in the previous experiences, and one such rule aligns with the current problem, as shown in **Figure 11B**. However, the controller selects the most suitable rule for this scenario, and an ontological decision is made. As illustrated in the highlighted area of **Figure 11B** on the right, the chosen action is to "slightly move down."





ure 11A: Ontological Analysis Figure 11B: Ontological decision making

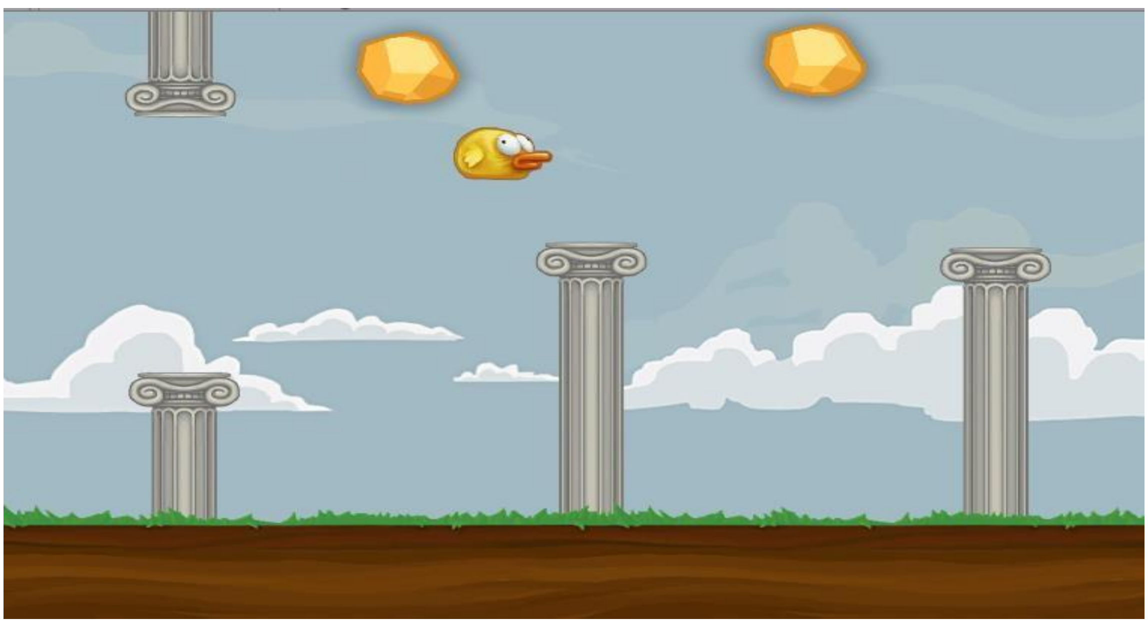


Figure12: After decision making

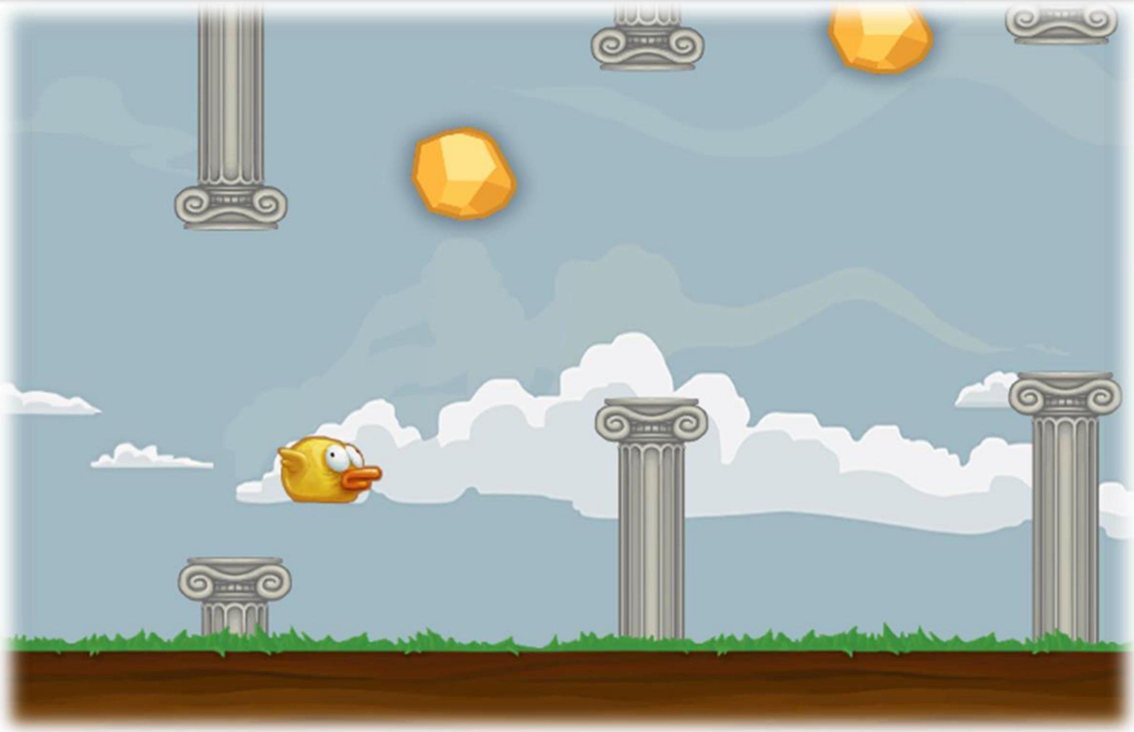


Figure 13: Down obstacle view

In **Figure 14** above, the bird detects an obstacle in front of it. The highlighted area in **Figure 15** below indicates the problem statement, which is "Enemy down." After performing an ontological analysis of the situation, the most appropriate action is chosen from the knowledge base.

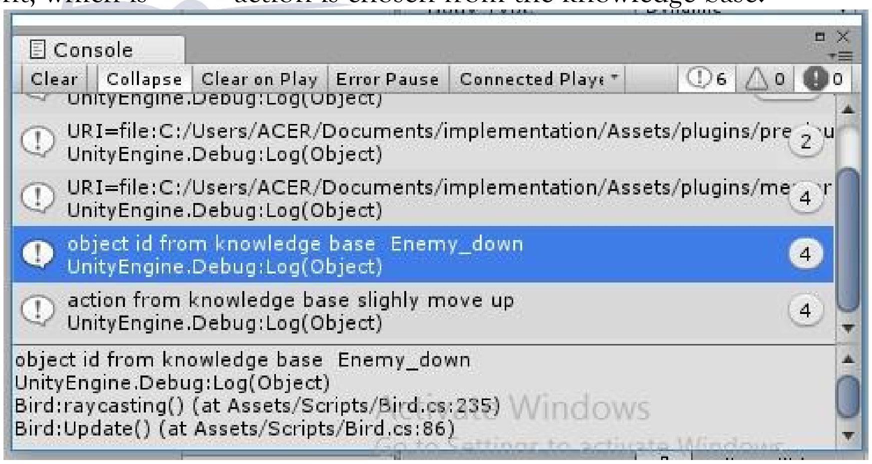


Figure 14: Ontological Analysis

After analyzing the objects and the problem, various rules are retrieved either from the knowledge base or from previous experiences. Since no relevant rule exists in the previous experiences, rules are extracted from the knowledge base. A list of potential rules is then generated, but the controller selects the most appropriate one for the given situation. As shown in the highlighted area in **Figure 15**, the chosen action is "slightly move up," and the ontological decision is reflected in **Figure 16**.

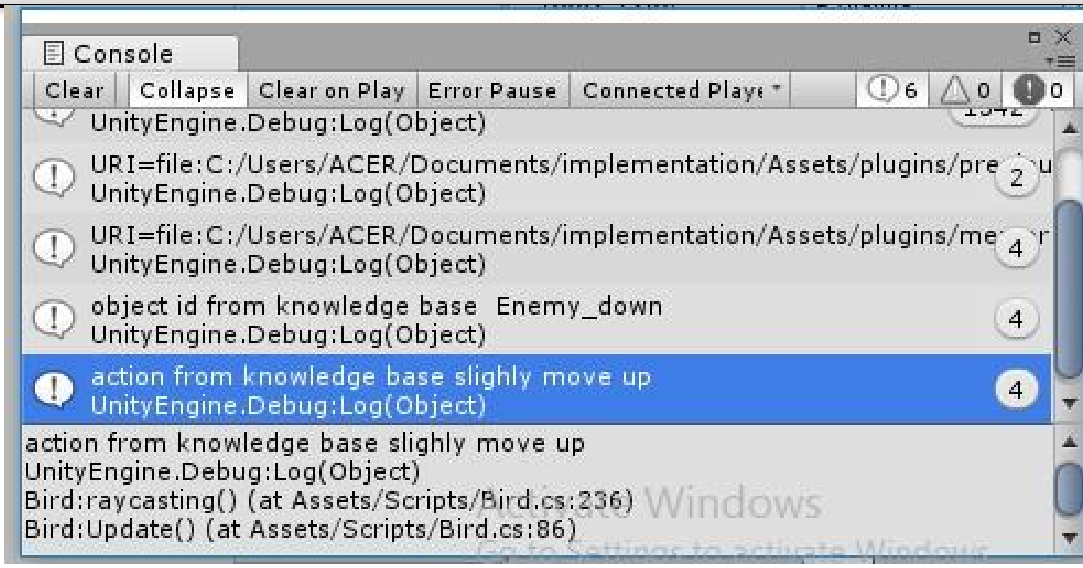


Figure 15: Ontological decision making

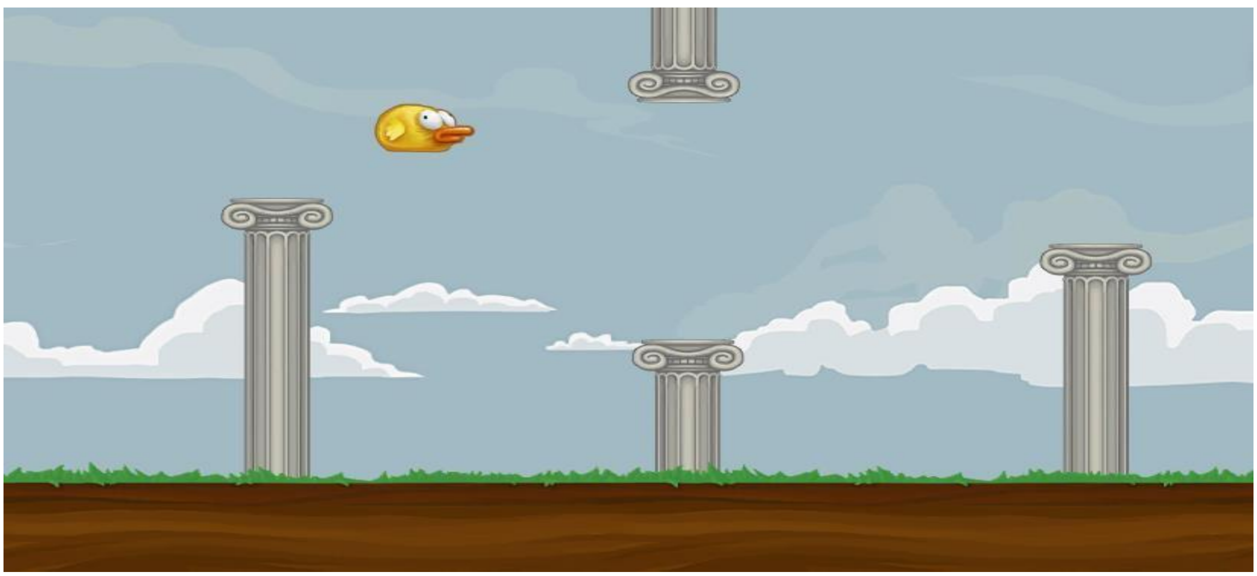


Figure 16: After decision making

Figure 17: Food item view

In **Figure 18** above, the bird detects a food item ahead. First, the bird identifies the type of object whether it's an obstacle or a food item. From its memory, the bird recognizes that it is a "food item." The previous experience contains a rule for handling such situations when a food item appears in front of the bird. The system then extracts the relevant information from the **Perception** module to address the situation.

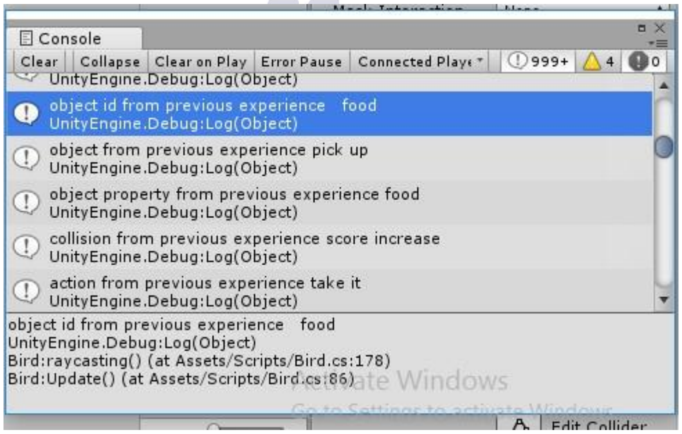


Figure 18: Ontological Analysis

In the highlighted area of **Figure 19** above, the problem statement "food item" is identified. After performing an ontological analysis of the situation, the most appropriate action is chosen based on previous experiences.

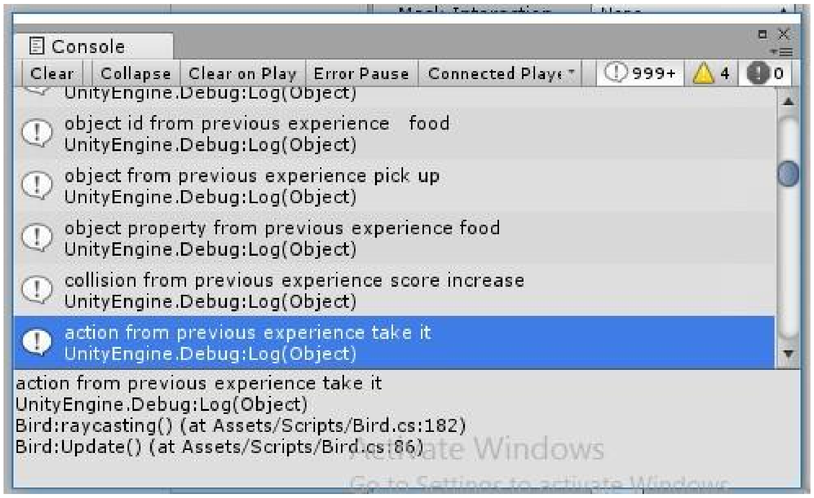


Figure 19: Ontological decision making

After analyzing the objects and the problem, various rules are retrieved from both the knowledge base and previous experiences. A list of potential rules is then generated, but the controller selects the most appropriate rule for the current situation. As seen in the highlighted area of **Figure 20**, the chosen action is "take it." **Figure 21** below shows the outcome after the decision is made.

Figure 20: After decision making

The results demonstrate that the proposed model can function in heterogeneous environments and dynamically extract rules. While the models discussed in the literature review section (from 2.1 to 2.9) such as ORO (19), OUR-K (23), RACE (37), KNOW ROB (16), OPEN-EASE (18), and CORA (28) are also based on ontology and have capabilities to adapt accordingly, they have a significant limitation: they cannot extract rules dynamically.

Although these frameworks (ORO, OUR-K, RACE, KNOW ROB, OPEN-EASE, CORA) also rely on previous experiences, the proposed model goes a step further. It can learn not only from past experiences but also from the knowledge base. If a solution to a problem exists in the agent's previous experiences, rules are extracted from there. However, if no relevant solution is found in the past experiences, the agent retrieves the solution from the knowledge base. In contrast, the models mentioned earlier are solely based on previous experiences and do not incorporate a knowledge base.

5. Conclusion & Future work

Autonomous agents that lack an ontological framework and the ability to learn from past experiences often struggle to select the best course of action and make decisions. Agents relying only on past experiences can face issues and anomalies, leading to incorrect responses and an inability to address new or unforeseen problems. Therefore, a dynamic ontological model is essential. An agent equipped with a dynamic ontological model has the ability to adapt its rules based on its environment and offer multiple suitable solutions to different situations. The models reviewed in Section 2 of the literature do not have features such as learning from past experiences, knowledge sharing, improving rules and constraints, or executing complex tasks. Thus, the dynamic ontological model should include the ability to learn from past experiences, enhance rules and constraints, and handle complex tasks. The proposed layered model consists of three modules.

The agent perceives the problem and situation through the **Perception Module**, stores past experiences and knowledge in the **Memory Module**, and processes the information using the **Analyzer Module**. The Analyzer evaluates objects, extracts properties from both the knowledge base and previous experiences, selects the most appropriate rules, and makes ontological decisions, as detailed in Section 3.4.

In the future, the goal is to integrate common sense reasoning and metacognition into this architecture to enhance its flexibility and robustness in dynamic environments. This would require modifications to the Perception and Analyzer modules, enabling the architecture to perform actions effectively across different environments. Additionally, this model could be implemented in various contemporary robotic architectures to ensure dynamic ontological functionality.

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