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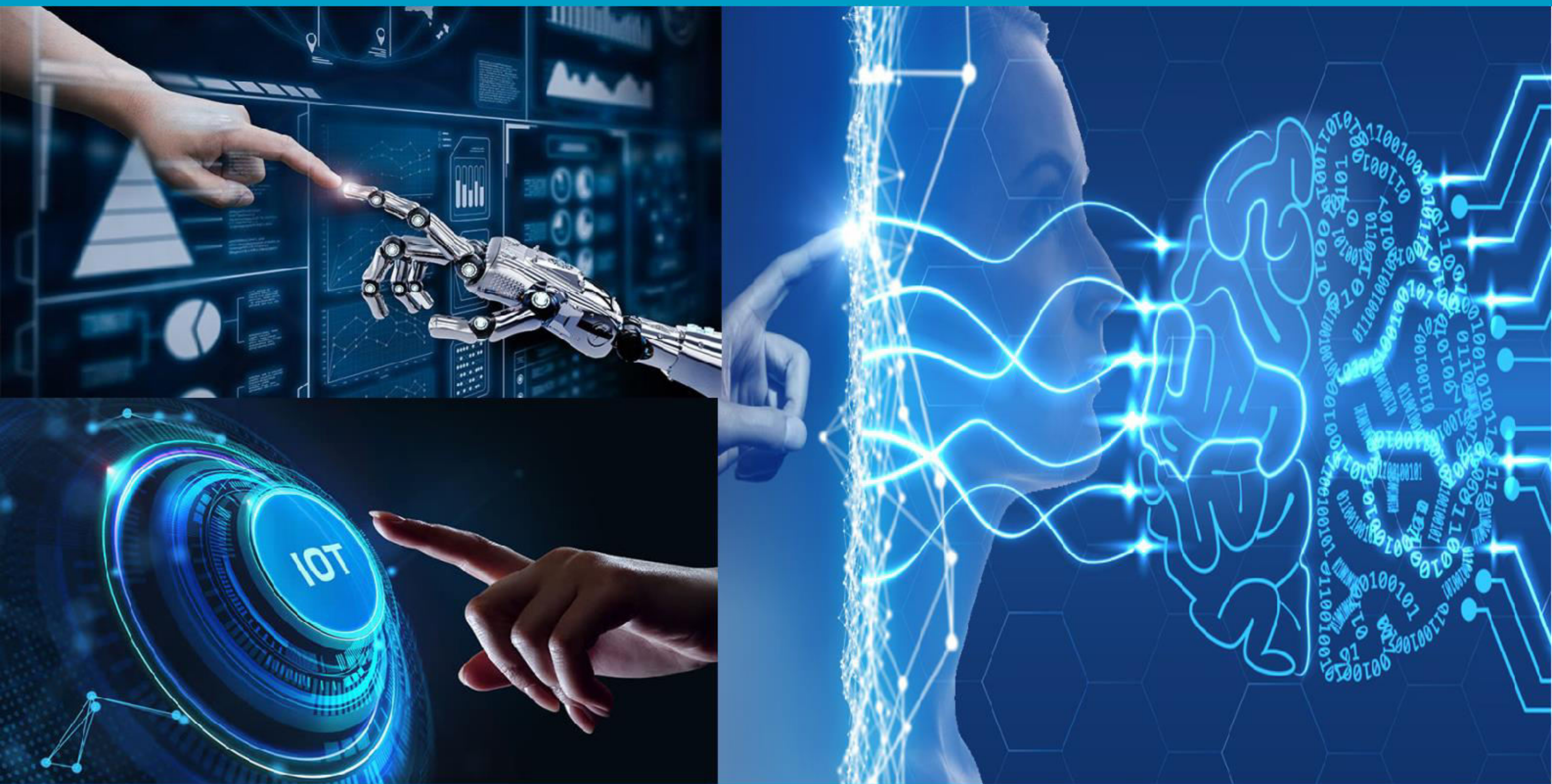

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Simulating Optimal Ant Navigation along the John Muir Trail via Genetic Algorithms

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ABSTRACT: This paper presents a novel approach for the efficient path traversal of the John Murli Trail (JMT) by simulating ant-like behaviour through a hybrid framework combining Finite State Machines (FSMs) and Genetic Algorithms (GAs). The trail is first represented in a structured format suitable for agent navigation, followed by simulation of artificial ant movement to explore potential routes. Optimization techniques refine these paths to minimize traversal time and energy consumption. State-based navigation enables the artificial ants to make context-aware decisions at each trail segment, enhancing adaptability to varying trail conditions. The FSM governs the decision-making logic of each ant, controlling transitions between exploration, exploitation, and return states. To evolve efficient pathfinding strategies, a GA is employed where paths are encoded as chromosomes. The algorithm includes population initialization, fitness evaluation based on path length and efficiency, and evolutionary operations such as selection, crossover, and mutation. Termination criteria are defined by a convergence threshold or maximum generations. Finally, FSM and GA are integrated to create a self-improving navigation system that learns optimal traversal strategies over time. Experimental results demonstrate that the proposed method significantly improves path efficiency and robustness, making it highly suitable for real-time trail navigation applications in both virtual and physical environments.

KEYWORDS: Route Optimization, Chromosome Encoding, Adaptive Navigation

I. INTRODUCTION

Finding the best way through a given environment is the goal of efficient path traversal, which is still a basic problem in robotics, simulation, and geographical exploration systems. Due to its varied path layouts and challenging topography, the John Murli Trail poses special difficulties for intelligent traversal systems and autonomous navigation. According to [1], traditional pathfinding techniques like Dijkstra's algorithm and A* search are frequently constrained by their deterministic character and inability to adapt to dynamic or unstructured situations. Biologically inspired methods, especially those based on ant foraging behavior, have become increasingly popular in study and practice to overcome these constraints.

Ant Colony Optimization (ACO) and artificial ant simulations emulate the decentralized, pheromone-driven behavior of real ants to explore multiple paths simultaneously and converge on optimal solutions over time [2]. Building on this foundation, our approach employs artificial ants whose decisions are regulated by a Finite State Machine (FSM). The FSM enables state-based transitions that control the artificial ant's behavior, such as path selection, obstacle avoidance, and goal reorientation, enhancing responsiveness to environmental changes [3].

However, while FSMs are effective at modeling reactive behaviors, they may lack the global optimization capability required for complex trail traversal. To bridge this gap, we incorporate a Genetic Algorithm (GA), an evolutionary method known for solving high-dimensional and multi-modal optimization problems [4]. GAs utilizes biologically inspired operations—such as selection, crossover, and mutation—to iteratively evolve better solutions from a population of candidate paths. By integrating FSM with GA, we create a hybrid system where local decision-making is complemented by global optimization, resulting in a self-adaptive and highly efficient path traversal framework.

This paper details the simulation of ant movement across the John Murli Trail, representation of trail structure, optimization strategies, and the synergistic integration of FSM and GA. The proposed method is not only capable of discovering efficient paths but also dynamically adapting to the trail's complexity, providing significant improvements over conventional approaches in both static and changing environments.

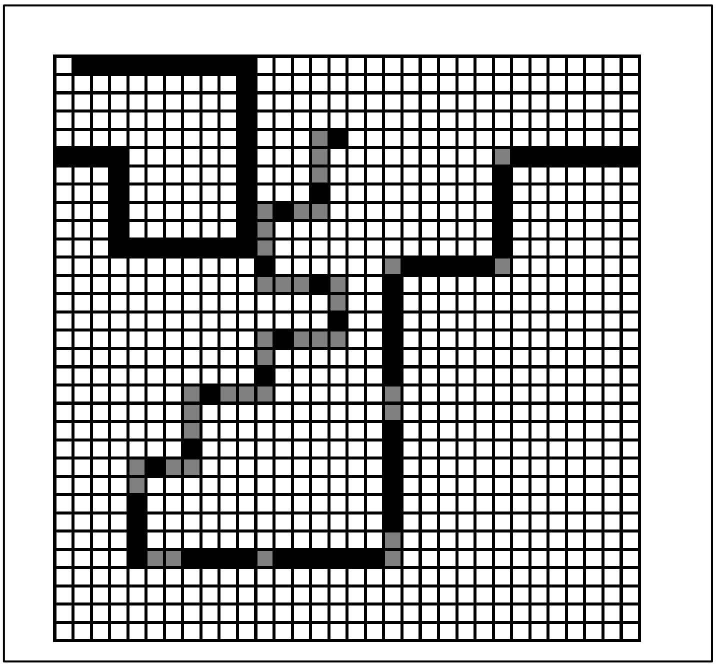

Figure 1: An instance of JMT

Research Background:

Efficient path traversal is a critical area of study in fields such as autonomous robotics, geographic information systems (GIS), and intelligent agent simulation. The challenge lies in identifying the most effective route through complex, often dynamic environments while balancing factors such as distance, energy consumption, and obstacle avoidance. Nature-inspired computing has emerged as a powerful paradigm to address these challenges, particularly through the modeling of swarm intelligence and evolutionary processes.

Ant Colony Optimization (ACO) is a popular bio-inspired technique that emulates the collective foraging behavior of ants, which communicate the best routes to food sources using pheromone trails. Because of its decentralized decision-making and capacity to locate near-optimal solutions in intricate search environments, ACO has been effectively used in robotic navigation, routing, and logistics [5]. Artificial ants are well-suited for pathfinding in unstructured contexts because they mimic this behavior utilizing probabilistic state transitions and local knowledge.

The classical control architecture known as Finite State Machines (FSMs) uses discrete states and transitions to represent agent behavior. FSMs offer a modular approach to encoding task-specific behaviors in robotic navigation, including backtracking, course correction, and goal-seeking [6]. Although FSMs provide real-time responsiveness, they might not be able to learn from previous traversal experiences or adjust to non-deterministic settings when employed alone. As autonomous systems become more prominent in fields such as environmental monitoring, search and rescue, and robotic exploration, efficient path planning methods are essential for navigating unpredictable and rugged terrains like the John Murli Trail. Traditional deterministic methods often struggle with real-world uncertainties, making bio-inspired and adaptive approaches more favorable [9-10].

Genetic Algorithms (GAs) add learning and optimization capabilities to FSMs to enhance their reactivity. GAs use biologically inspired operators such as crossover, mutation, and selection to evolve candidate solutions over generations [4]. They work particularly well in big, nonlinear search areas where it is impossible to find analytical solutions. Robot motion planning, labyrinth solution, and dynamic path optimization in terrain navigation are some of the applications of GAs in path planning [7-8]. Hybrid models that combine FSMs and GAs to take use of both global optimization and reactive control have been the focus of recent developments. While GAs develop high-level path strategies, FSMs manage low-level decision-making, enabling artificial agents to adjust over time and perform better under a variety of trail conditions. In applications involving the exploration of challenging terrain, such as the John Murli Trail, this hybridization enhances navigation systems' scalability, adaptability, and resilience. By combining the natural efficiency of artificial ants, the behavioral control of FSMs, and the adaptive learning power of GAs, the proposed approach aligns with current trends in intelligent path traversal systems and represents a step forward in autonomous trail exploration technologies.

II. PROPOSED MODEL

We have designed an optimal pathfinding strategy for an artificial ant agent to maximize food collection from start to end of trail. There are some constraints too like: Limited moves, presence of obstacles, terrain variations.

1. **Environment Representation:** Generate a grid-based map which divide the trail into grid cells. Each cell has attributes like Food quantity, Terrain type, Elevation etc.

2. **Finite State Machine (FSM) for Ant Navigation:** Define FSM Components like Ant's status in response to environment like Idle, Move Forward, Turn Left, turn right, climb, avoid obstacle, collect food. Events (E) like Food detected, obstacle detected, terrain change, elevation change, step limit reached and no path available. Transitions (T) like Idle → Move Forward on Food detection, Move forward → Collect food on arrival at food, Move forward → Avoid obstacle on obstacle detected, Avoid obstacle → Turn left or Turn right. The ant agent transitions between states based on environmental triggers.

3. **Ant Colony Optimization (ACO) for Path Optimization:**

   3.1. **Initialize Pheromone Matrix:** Grid edges (possible moves) are assigned initial pheromone values. Ants deposit pheromones proportional to food collected and efficiency of the path.

   3.2. **Ant Simulation:** Each ant starts at origin and navigates using FSM. Chooses next move using probabilistic rule based on:

$$P_{ij} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\alpha}}{\sum_k [\tau_{ik}]^{\alpha}\, \eta_{ik}{}^{\beta}} \quad (1)$$

   Where, τ_{ij} is the pheromone level on edge ij. The η_{ij} is the heuristic value. α and β are weights.

   3.3. **Pheromone Update:** After all ants finish, pheromone is updated.

$$\boldsymbol{\tau_{ij} = (1-\rho).\tau_{ij} + \sum \Delta\tau_{ij}} \quad (2)$$

   Where, ρ is the evaporation rate**.**

4. **Canonical Genetic Algorithm (GA) for Global Optimization:**

   4.1. **Chromosome Encoding:** Each chromosome represents a sequence of moves (FSM transitions). For example: [F, F, L, F, R, C, F] where, (F = Forward, L = Left, R = Right, C = Climb).
   4.2. **Initial Population:** Generate random valid move sequences (based on trail limits).
   4.3. **Fitness Evaluation:** Each path is simulated with Fitness = Total_Food_Collected – Penalty for Obstacles – Energy for Climbing.
   4.4. **Selection (Roulette Wheel): Selection probability $\mathbf{P_i = \frac{f_i}{\sum f_j}}$.** Fitter individuals have higher chance of selection.
   4.5. **Crossover:** One-point or two-point crossover to combine parent chromosomes to generate offspring.
   4.6. **Mutation:** Randomly flip or insert a movement (e.g., mutate F to R) and maintains diversity.
   4.7. **Termination Criteria:** Stop when max generations reached, no significant improvement or optimal path found.
5. **Integration of FSM, ACO, and GA:** In this integration FSM Defines how ants interact with environment, ACO optimizes pheromone-guided path discovery and GA globally optimizes navigation strategy using FSM transitions. Figure 2 shows the basic steps involved in this method.

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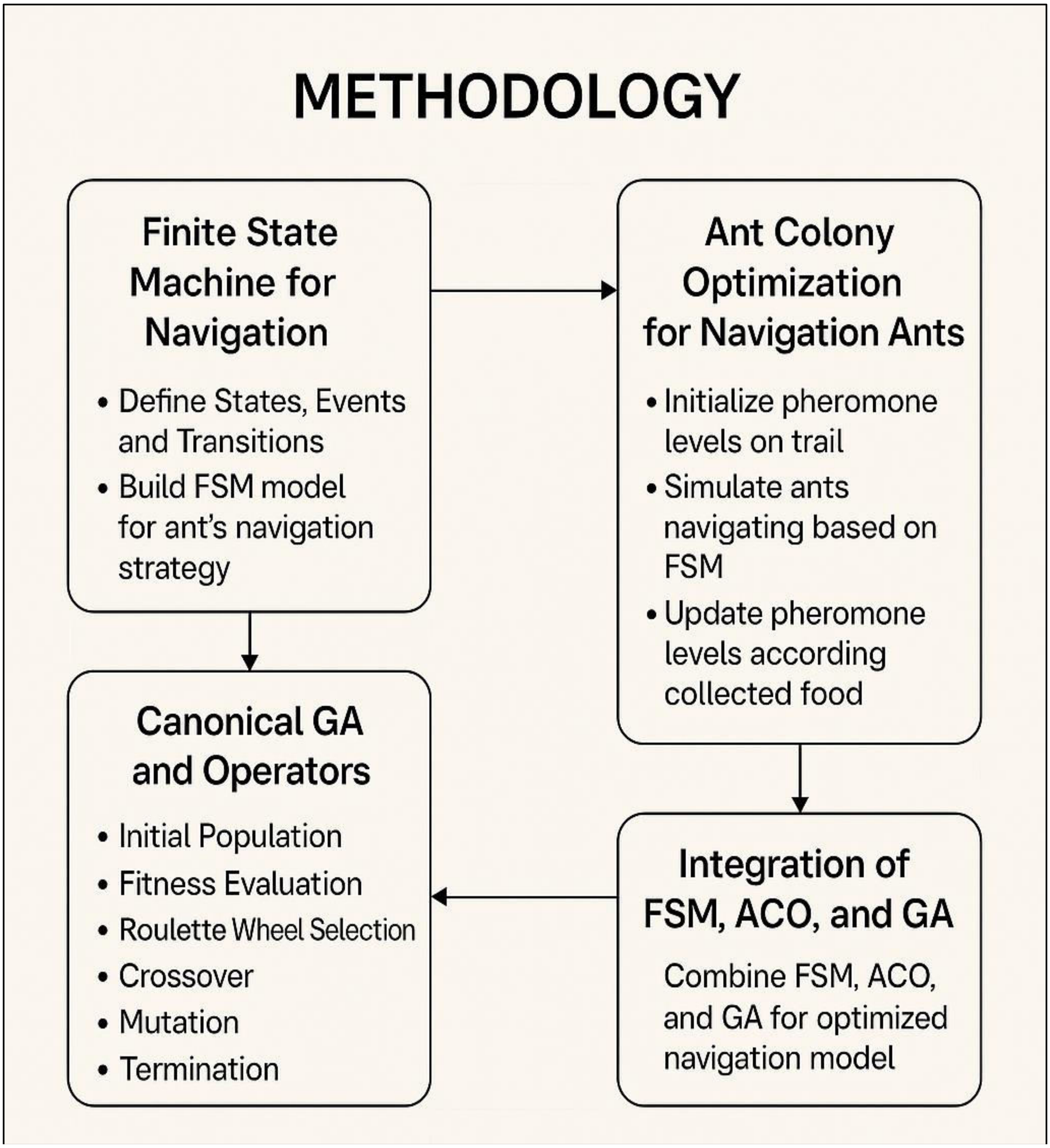

III. SIMULATION AND OUTCOMES

We have implemented method in MATLAB 2024a. Results are as follows: Figure 3 shows ant fitness up to 654 generations. It shows ant movement and total food cells covered by ant. Figure 4 shows that ant remains fit up to 1000 generations and it is able to cover almost all food cells. In both cases we have chose different selection methods using genetic operators.

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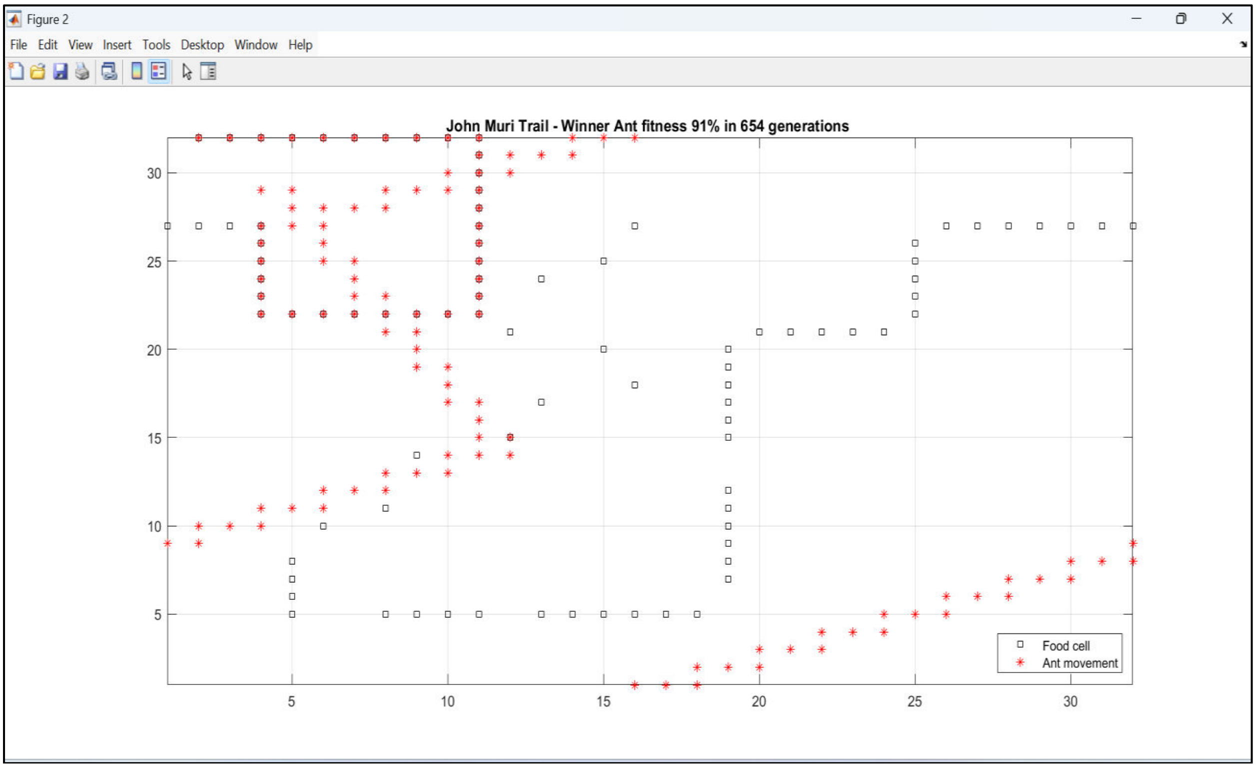

Figure 3: Ant fitness percentage up to 654 generations

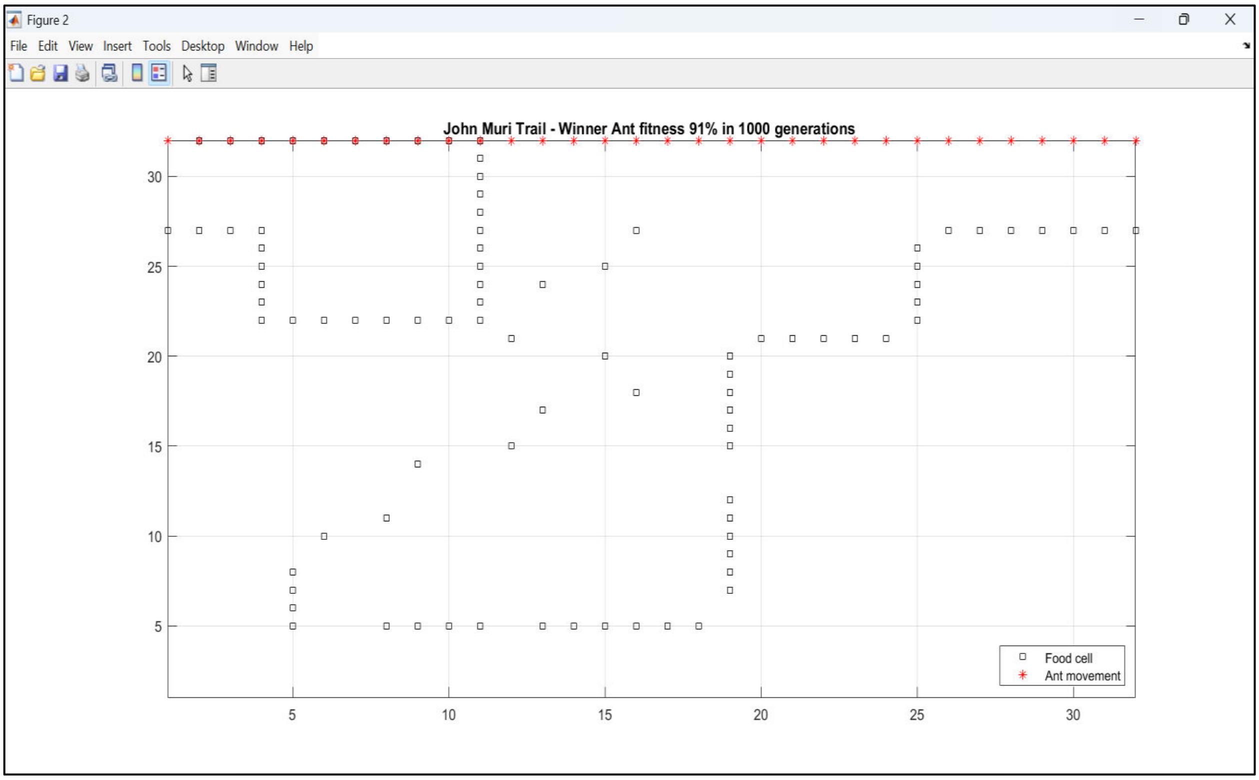

Figure 4: Ant fitness percentage up to 1000 generations

Table1: Comparative study of navigation studies:

Criteria / Method	FSM + ACO + GA (Proposed)	Dijkstra	A*	Reinforcement Learning (RL)	ACO Only	GA Only
Real-time Reactivity	High (via FSM)	None	None	Moderate	None	None
Handles Terrain & Elevation	Yes	No	No	Yes	Partial	Partial
Obstacle Avoidance	Adaptive	Yes	Yes	Yes	Yes	Yes
Food Collection Strategy	Optimized	No	No	Reinforced Reward	Indirect	Indirect
Limited Move Constraint Handling	Yes	No	No	Yes	Partial	Yes
Learning Capability	Hybrid Learning	Static	Static	Learned Policy	Pheromone	Evolution
Global Optimization Ability	Strong (via GA)	Optimal	Optimal	Learned over time	Emergent	Genetic
Convergence Speed	Medium	Fast	Fast	Slow (requires training)	Medium	Medium
Adaptability to Dynamic Environment	High	None	None	High	High	Low
Interpretability of Strategy	FSM-Based Rules	Yes	Yes	Hard to interpret	Limited	Yes
Computational Complexity	High	Low	Low	High	Medium	Medium
Scalability to Large Maps	Yes (with optimization)	Poor	Moderate	Yes	Moderate	Yes

IV. CONCLUSION

The proposed hybrid methodology, combining Finite State Machine (FSM), Ant Colony Optimization (ACO), and Genetic Algorithm (GA), provides a comprehensive and adaptive solution for navigating the John Murli Trail. By leveraging FSM, the artificial ant can react dynamically to real-time environmental stimuli such as obstacles, food sources, elevation changes, and terrain types. ACO enhances this by enabling pheromone-based, swarm-inspired path optimization that improves over time through indirect learning. To further optimize the agent's long-term decision-making, GA is employed to evolve the FSM transition strategies, ensuring global optimization across multiple path planning constraints. This integrated approach not only balances reactive behavior with strategic foresight, but also supports continuous learning and adaptation, even in complex, uncertain, and dynamic environments. Compared to traditional methods like Dijkstra, A*, or standalone ACO/GA techniques, the proposed methodology demonstrates superior performance in handling multi-objective navigation challenges—such as food maximization under move limitations and terrain variability. Ultimately, this method offers a scalable, intelligent, and robust framework for autonomous agent navigation in biologically-inspired scenarios.

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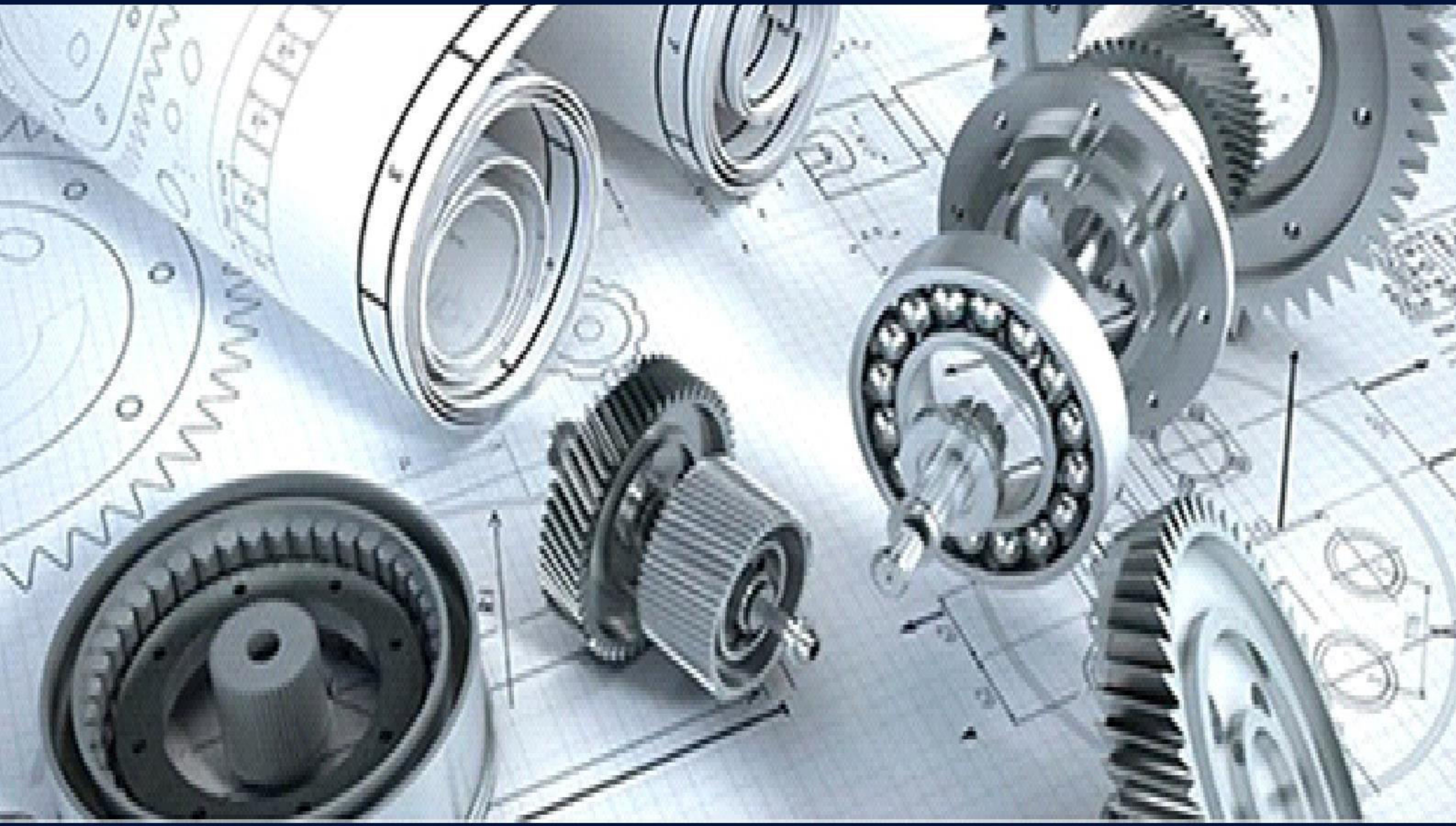

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