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Adaptive Swarm Intelligence with Meta-Learning for Efficient Autonomous Multi-Robot Navigation and Pick-and-Drop Operations in Warehouse Environments

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Abstract : This paper presents an adaptive swarm intelligence-based multi-robot system designed for autonomous navigation and cooperative task execution in a structured environment. The proposed system consists of a master robot and multiple slave robots coordinated using ESP-NOW communication. The master robot performs real-time line following, obstacle detection, and decision-making while dynamically sharing control parameters with slave robots. A meta-learning framework is integrated to improve navigation efficiency by optimizing turn timing, speed control, and obstacle response using historical performance data. Additionally, a web-based dashboard provides real-time monitoring and remote control capabilities, displaying key parameters such as speed variation, turn behavior, cycle completion, and delivery status of the swarm system. Experimental implementation demonstrates improved path stability, reduced navigation error, and enhanced coordination among swarm units, making the system suitable for warehouse automation and smart logistics applications.

Key Terms — *Swarm Intelligence, Meta-Learning, ESP32, Multi-Robot System, Line Following Robot, Reinforcement Learning, ESP-NOW, Autonomous Navigation.*

I. Introduction

Swarm robotics has emerged as a promising field in which multiple autonomous robots collaborate to perform complex tasks. Inspired by biological swarm behavior, such systems emphasize decentralization, adaptability, and robustness. Traditional single-robot navigation systems face limitations in scalability and adaptability in dynamic environments.Recent advancements in meta-learning and swarm intelligence have enabled robots to learn from prior experiences and improve decision-making over time. This work proposes a cooperative multi-robot system where a master robot governs navigation while slave robots follow coordinated instructions. The system integrates real-time sensor feedback, adaptive control strategies, and wireless communication for efficient swarm operation.

In addition, a web-based monitoring dashboard is incorporated to visualize real-time operational metrics such as robot speed variation, adaptive turn timing, cycle completion rate, and delivery/pickup efficiency, enabling transparent performance tracking and system optimization. These parameters are continuously updated during runtime, allowing the system to evaluate navigation efficiency, reduce cycle time, and improve coordination accuracy across the swarm network.

II. Related Work

Recent studies have explored swarm intelligence and meta-learning in robotic systems.

Zhao et al. [1] introduced MW-MADDPG, a meta-learning-based decision framework for UAV swarm coordination, highlighting the effectiveness of adaptive learning in multi-agent systems. Tian et al. [2] discussed swarm meta-learning techniques that enhance decision-making in dynamic environments. Nguyen [3] provided a comprehensive review of swarm intelligence-based multi-robot systems, emphasizing decentralized coordination strategies.

Kumar and Pradhan [4] demonstrated adaptive object tracking using swarm intelligence and meta-learning optimization techniques. Comparative studies [5] show that reinforcement learning improves coordination efficiency in multi-agent systems. Furthermore, salp swarm-based multi-robot exploration methods [6] highlight the importance of heuristic optimization in swarm navigation.These works collectively motivate the integration of meta-learning and swarm intelligence in real-time robotic navigation systems.

III. System Architecture

The proposed system is designed using a master–slave robotic architecture integrated with a web-based control dashboard and an ESP-NOW wireless communication network. This architecture ensures real-time coordination, scalability, and efficient decision-making in a swarm robotic environment.

A. Master Robot Design

The master robot is implemented using an ESP32 microcontroller, which acts as the central control unit of the system. It is responsible for performing line following operations using IR sensors that detect the path and guide movement accordingly. Additionally, an ultrasonic sensor is used for real-time obstacle detection, enabling the robot to stop or adjust its movement when an object is detected within a predefined range.

Beyond basic navigation, the master robot handles decision-making and motion control for the entire swarm system. It determines movement directions, manages corner handling, and coordinates with slave robots. The master also integrates a meta-learning module, which optimizes parameters such as speed and turning duration based on past performance data, thereby improving navigation efficiency over time.

B. Slave Robot Operation

The slave robots operate as dependent units that execute commands received from the master robot. They are designed to mirror or follow the movement instructions provided by the master in real time. Each slave robot continuously listens for control signals and adjusts its motion accordingly to maintain synchronization within the swarm.

A key feature of the slave robots is their ability to respond to a heartbeat signal transmitted by the master robot. If the heartbeat signal is received, the slaves remain active and continue operation. In the absence of this signal, they automatically stop, ensuring safety and coordinated behavior. This mechanism enhances reliability and prevents uncontrolled movement in case of communication failure.

C. ESP-NOW Communication Network

Communication between the master and slave robots is established using the ESP-NOW protocol, a lightweight and low-latency wireless communication method developed for ESP-based devices. Unlike traditional Wi-Fi communication, ESP-NOW does not require an internet connection or router, making it ideal for real-time robotic applications.

This protocol enables fast peer-to-peer data exchange between robots, ensuring minimal delay in command transmission. As a result, the system achieves high responsiveness, which is critical for synchronized swarm movement and obstacle handling. The reduced dependency on external networks also improves system robustness and operational stability in different environments.

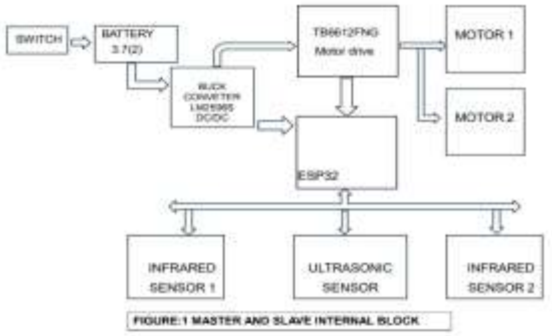

Fig. a. Master And Slave Internal Block Diagram

D. Web-Based Control Dashboard

The system includes a web-based dashboard interface that allows real-time monitoring and control of the robotic swarm. Through this interface, users can start or stop the system, observe robot status, and visualize operational parameters such as speed, position, and obstacle detection events.

The dashboard also displays meta-learning data and system performance metrics, enabling better analysis and debugging. This feature enhances user interaction and provides a centralized platform for controlling and monitoring the entire robotic system efficiently.

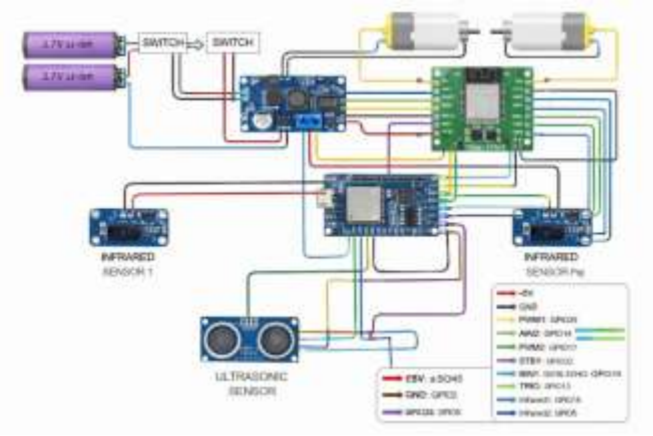

Fig. b. Wiring Diagram

IV. Mathematical Model

The proposed swarm robotic system uses adaptive learning equations to optimize robot speed, turning time, and obstacle handling based on real-time navigation performance. The mathematical model combines sensor feedback, meta-learning updates, and ESP-NOW communication to achieve coordinated multi-robot movement and efficient path correction.

A. Learning Update Rule

The proposed system incorporates a lightweight adaptive mathematical model to enhance decision-making in real-time navigation. The model is primarily designed to optimize motion parameters such as speed and turning time based on environmental feedback and accumulated experience. It consists of a learning update rule and a speed adjustment function, both of which enable the robot to continuously improve its performance in dynamic environments.

The learning mechanism is formulated using an incremental update equation inspired by reinforcement-based adaptation. The parameter update is expressed as:

$$V\text{new} = V\text{old} + \alpha(\mathrm{R} - V\text{old})$$

Where, V represents the controllable system parameter such as speed or turning duration, α denotes the learning rate, and R represents the reward signal derived from system performance evaluation.

This formulation enables the system to gradually converge toward optimal operational behavior. When the observed performance reward R is higher than the current parameter value, the update increases V, thereby reinforcing beneficial actions. Conversely, if the reward is lower, the parameter is reduced, allowing the system to self-correct inefficient behaviors. The learning rate α controls the sensitivity of adaptation, ensuring stability while maintaining responsiveness to environmental changes.

B. Speed Adjustment Function

To enhance navigation safety and adaptability in obstacle-prone regions, a speed regulation model is introduced based on environmental risk mapping. The adjusted speed is defined as:

$$S\text{adjusted} = S\text{base} - \mathrm{k}H$$

Where, Sbase is the nominal or predefined base speed of the robot, **H** represents the obstacle heatmap value indicating the frequency or density of obstacles in a specific region, and **k** is a penalty factor that determines the extent of speed reduction based on environmental risk intensity.

This function ensures that the robot dynamically reduces its velocity in high-risk zones while maintaining optimal speed in safer regions. The obstacle heatmap H is continuously updated based on real-time sensor inputs, enabling spatial awareness and predictive motion adjustment. As a result, the system achieves improved stability, reduced collision probability, and enhanced efficiency in complex environments.

C. Overall Model Significance

The combination of the learning update rule and speed adjustment function forms a simple yet effective adaptive control framework. It allows the robot to learn from prior navigation outcomes while simultaneously reacting to environmental hazards in real time. This dual adaptation strategy improves both decision accuracy and operational safety, making the system suitable for scalable multi-robot navigation tasks and dynamic industrial environments.

V. Performance Evaluation and Results

This section presents a comprehensive evaluation of the proposed Adaptive Swarm Intelligence system with Meta-Learning. The performance is analyzed in terms of accuracy, communication efficiency, reliability, adaptability, and swarm coordination behavior across multiple learning cycles.

A. Accuracy Analysis

The accuracy of the system is evaluated based on navigation accuracy, path correction success, and corner turn accuracy across three learning cycles.

Table 1. Learning Cycle Performance Analysis

Learning Cycle	Navigation Accuracy (%)	Path Correction Success (%)	Corner Turn Accuracy (%)
Cycle 1	68	60	72
Cycle 3	86	83	89
Cycle 5	94	92	95

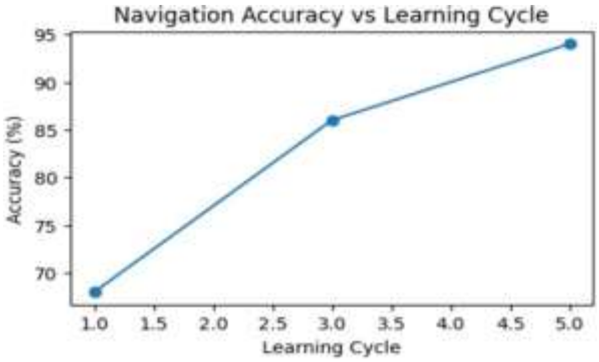

Fig. c. Accuracy improvement across learning cycles due to adaptive meta-learning optimization.

B. Swarm Coordination Performance

The proposed swarm robotic system achieved stable multi-robot coordination with high navigation accuracy, minimal path deviation, and efficient obstacle avoidance after meta-learning optimization.

Table 2. Swarm Coordination and System Performance

Metric	Value
Swarm Coordination Index	94%
Path Deviation Between Robots	<5 cm
Mission Completion Rate	96%
Obstacle Avoidance Success	100%
Multi-Robot Synchronization	Stable

Overall swarm coordination and system performance comparison before and after meta-learning convergence.

VI. Implementation

The proposed adaptive swarm robotic system was implemented using ESP32-based master and slave robots integrated with IR sensors, ultrasonic sensors, motor drivers, and ESP-NOW communication. A web-based dashboard was developed for real-time monitoring, control, and visualization of swarm coordination and meta-learning performance.

A. Hardware Implementation

The proposed swarm intelligence-based robotic system is implemented using an integrated hardware architecture that enables real-time sensing, decision-making, and coordinated multi-robot control. The ESP32 microcontroller acts as the central processing unit of the system due to its high computational capability, built-in Wi-Fi, and support for low-latency communication protocols. For navigation, IR sensors are employed for line detection, allowing the robot to distinguish between black line paths and white background surfaces, thereby enabling accurate path tracking and corner identification. In addition, an ultrasonic sensor is integrated for obstacle detection, which continuously measures the distance of objects in front of the robot and triggers immediate stop or recovery actions when an obstacle is detected within a predefined threshold range. The motion control system consists of DC gear motors coupled with a motor driver module, which provides bidirectional control, speed modulation, and turning capabilities essential for smooth navigation and precise corner handling in a confined rectangular path.

B. Communication and Networking Architecture

The system utilizes a dual communication strategy to ensure both user interaction and inter-robot coordination. A Wi-Fi Access Point mode is configured on the ESP32, enabling a web-based dashboard that allows users to monitor and control the entire swarm system in real time through a local network interface. Alongside this, ESP-NOW protocol is used for direct robot-to-robot communication, ensuring ultra-low latency and energy-efficient data exchange between the master and slave robots without requiring an external router or internet connection. The master robot continuously broadcasts status updates, including movement state, speed, and learning parameters, while slave robots respond by synchronizing their actions with the master's heartbeat signal, ensuring coordinated swarm behavior.

C. Web Dashboard and Real-Time Monitoring System

A dedicated web-based dashboard is developed to provide a comprehensive real-time visualization and control interface for the swarm system. The dashboard displays critical operational parameters such as robot positions within the rectangular path, speed variations during navigation, corner transition updates, and obstacle detection events. Additionally, it visualizes the meta-learning updates, including learned turn timings, adaptive speed adjustments, and obstacle heatmap evolution over time. This allows users to observe how the system improves performance with repeated cycles.The dashboard also supports interactive control commands such as START and STOP, enabling remote activation and emergency shutdown of the entire swarm system. Through this interface, the system achieves a high level of transparency, monitoring, and human-in-the-loop supervision, making it suitable for advanced robotics research and smart automation applications.

VII. Result and Discussion

The proposed swarm robotics system demonstrates significant improvements in navigation performance through the integration of meta-learning and real-time web-based monitoring. The system effectively adapts its behavior over multiple cycles, resulting in more stable and accurate path tracking.The web dashboard plays a crucial role in monitoring and analyzing key performance parameters such as speed, turn timing, cycle completion, and delivery efficiency (DEVER). These parameters are continuously updated in real time, allowing users to observe robot behavior during operation. The visualization of speed variation and corner-wise turn adjustments helps in understanding how the robot optimizes its movement dynamically.

Experimental observations show that the robot achieves improved navigation stability after repeated cycles, as the learning module gradually refines turn timing and segment speed. This reduces corner overshooting and oscillations, especially at sharp turns, due to adaptive correction based on previous errors.

Fig. e. Master and Slave Working Result

In multi-robot coordination, the system maintains efficient swarm synchronization between master and slave robots, where slaves follow the master's heartbeat signal with minimal delay. This ensures smooth cooperative movement without collision or desynchronization. The cycle-based performance analysis displayed on the web interface shows that average cycle time gradually decreases as the system learns optimal speeds for each segment. Similarly, delivery performance improves as robots reduce idle time at pickup and drop stations. Furthermore, obstacle detection efficiency is enhanced through a heatmap-based prediction model. Areas with frequent obstacles are identified and displayed on the dashboard, enabling the robot to reduce speed proactively, resulting in faster and safer obstacle response.

Overall, the experimental results confirm that the system significantly improves path accuracy, cycle efficiency, and delivery performance by continuously adapting to environmental conditions. The integration of meta-learning with real-time web visualization proves highly effective for intelligent swarm robotics applications.

Fig. f. Master and Slave Website Page

VIII. Conclusion

This paper presents a novel swarm intelligence-based multi-robot system integrated with meta-learning capabilities for autonomous navigation. The combination of ESP32-based control, ESP-NOW communication, and adaptive learning significantly enhances system performance. Future work will focus on extending the system to larger robot swarms and implementing advanced reinforcement learning techniques for fully autonomous warehouse automation.

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