Sentry Swarms: An Autonomous Bio-Inspired Approach for Surveillance and Collective Defence

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Abstract—This paper presents Sentry Swarms, a decentralized multi-robot platform designed for pervasive protection and mutual surveillance of secured or sensitive areas. The system employs random patrol methodology with low-cost sensing, modular localization using Wi-Fi RSSI fingerprinting enhanced by machine learning, and an event-triggered alarm aggregation protocol inspired by human squad tactics. This allows local agents to quickly converge on perceived threats. The platform integrates hardware and simulation, establishing localization pipelines, aggregation decision logic, and collision-free motion control. We formalize mathematical models for localization and aggregation, propose algorithms, and outline a statistical analysis approach to assess metrics such as localization accuracy and communication overhead.

Beyond experimental validation, Sentry Swarms show significant potential for practical applications in defence and security contexts, including border surveillance, military reconnaissance, protection of critical infrastructure, and search and rescue missions in unknown or hostile environments. Additionally, this method can be adapted to various robotic systems, such as unmanned ground vehicles (UGVs), unmanned aerial vehicles (UAVs), remotely operated vehicles (ROVs), and humanoid robots, offering a configurable and fault-tolerant solution for practical surveillance and cooperative defence missions.

Index Terms—Swarm Robotics, Surveillance, Aggregation, Lo- cal Positioning, Wi-Fi RSSI Fingerprinting, Machine Learning, Trilateration, Autonomous Patrol

I. INTRODUCTION

Securing restricted perimeters (military compounds, critical infrastructure) requires persistent monitoring with rapid, local response capability. Traditional solutions, such as static cam- eras, centralized controllers, or expensive high-value robotic platforms, are either brittle to single-point failures or expensive to scale. Swarm robotics offers an alternative: large numbers of inexpensive autonomous agents that execute local rules and interactions to deliver scalable, robust surveillance, and collective response.

In this work we propose **Sentry Swarms**: low-cost ground robots (ESP32-based) that patrol assigned sub regions with a random walk. When a robot detects suspicious activity, it localizes itself, broadcasts an authenticated alarm, and nearby agents decide locally whether to aggregate and assist. The algorithm prioritizes (1) limiting communication load through event-triggered messages, (2) collision-safe aggregation, and

(3) modular localization where Wi-Fi RSSI ML fingerprinting is used for rapid prototyping, but swap-in UWB/LoRa/GNSS is supported for higher accuracy, real-life application, or longer ranges. This approach builds on swarm engineering principles (robustness and scalability), consensus and local decision making in networks, and modern ML signal processing for localization.

Zhang and Meng demonstrated a decentralized multi-robot intruder detection system—STAGS—for security defence tasks [1]. Brambilla et al. survey the field of swarm engineering and motivate the design patterns used in our work [2]. Olfati-Saber et al. describe consensus and cooperative multi-agent frameworks that guide our event-triggered coor- dination design [3]. Moreover, Velhal et al. (2022) propose a decentralized, spatiotemporal multi-robot perimeter defence approach that dynamically assigns responsibilities to agents for robust guarding of boundaries [4].

II. RELATED WORK AND MOTIVATION

A. Swarm Robotics and Surveillance

Swarm robotics has been used in exploration, coverage, and surveillance tasks due to decentralization, redundancy, and graceful degradation when units fail [2, 5]. Approaches include random walks with persistence, potential fields, and event-based aggregation strategies. Notable prior work studies multirobot coverage, decentralized search and rescue swarms, and aggregation behaviors for defence and inspection tasks.

B. Localization for Mobile Agents

Accurate positioning underlies coordinated aggregation. Lo- cal positioning methods include: Wi-Fi fingerprinting and trilateration (RSSI/CSI), UWB (ToF/RTT), BLE AoA/AoD, LoRa RSSI fingerprinting, ultrasonic ToF, and magnetic-field fingerprinting. Surveys by Zafari et al. (2019) and Alarifi et al. (2016) summarize tradeoffs among accuracy, cost, and infrastructure [6–8].

Finger printing (ML) approaches using Wi-Fi CSI or RSSI achieve meter-level or sub-meter performance when suffi- ciently sampled and tuned (DeepFi and PhaseFi use CSI features and deep networks) [9, 10]. Trilateration (path-loss model) is simpler but degrades with multipath. UWB provides the best out-of-the-box accuracy (sub-meter to centimeter) but needs dedicated anchors and high cost [7, 11].

C. Event-Triggered Coordination

To reduce communication and energy cost, event-triggered schemes send messages only upon detections or threshold events rather than constant state broadcasts. Event-triggered consensus and local decision rules have been applied to multi-robot systems to preserve bandwidth while guaranteeing performance under assumptions about network connectivity [3].

D. Collision Avoidance for Aggregation

When multiple agents converge during the aggregation phase, collision avoidance must be guaranteed to maintain swarm integrity and ensure successful threat response.

Each robot detects nearby obstacles or peers within a defined sensing radius and dynamically adjusts its motion by reducing speed or altering direction to prevent collisions. This decentralized, sensor-driven approach ensures local safety without the need for global trajectory planning, and scales naturally as the number of agents increases. The simplicity and low cost of ultrasonic sensing make it well-suited for real-time swarm deployment in constrained environments.

III. SYSTEM OVERVIEW

A. Design Goals

The Sentry Swarms design focuses on:

- **Scalability**: System should operate with tens to hundreds of agents (same local rules)
- **Low cost / reproducibility**: ESP32-based robots and commodity sensors
- **Modularity of localization**: Wi-Fi RSSI ML for small testbeds, UWB / LoRa swap-in for field deployments
- **Low communication overhead**: Event-triggered broad- cast and local decision rules
- **Safety**: Collision avoidance

B. Hardware Platform

Each agent comprises:

- **Controller**: ESP32-WROOM-32U module with external antenna
- **Mobility**: 2× N20 DC geared motors with L9110S Dual DC Stepper Motor Driver
- **Sensing:** 3× HC-SR04 ultrasonic (front/left/right) for mid-range obstacle detection, 3× infrared reflectance sensors for border detection, 3-axis magnetometer for bot heading determination
- **Radio anchors (testbed):** 4 ESP32 anchor nodes at known coordinates acting as Wi-Fi beacons for RSSI measurement
- **Power:** LiPo battery and voltage regulation; battery monitor with low-voltage return logic
- The prototype design used for this experiment is shown in Fig 1.

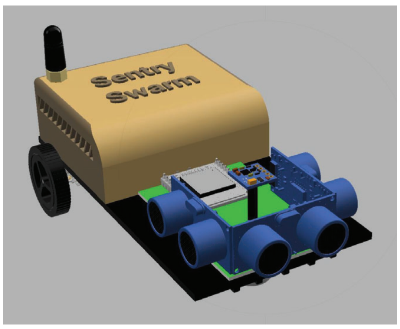


Fig. 1: Prototype agent used in experiment.

C. Software Stack

- **Perception layer**: Sensor fusion of ultrasonic and IR for border/target detection
- **Localization layer**: Wi-Fi fingerprinting ML module (kNN/RF/Regression)
- **Decision layer**: Detection → localize → broadcast alarm
- → local aggregation decision rule
- **Motion layer**: Path fixing + avoidance of obstacles

IV. LOCAL POSITIONING TECHNIQUES

This section summarizes common local positioning approaches and practical tradeoffs for Sentry Swarms.

A. Localization Technologies

- **UWB (Ultra-Wideband)** provides the best "out-of-the- box" ranging accuracy (decimeter to centimeter level) using Time-of-Flight (ToF) or Round-Trip Time (RTT) measurements [7, 11]. Its wide bandwidth signals enable precise distance measurements and good multipath resolution, making it ideal for high-accuracy indoor positioning applications despite requiring dedicated anchor infrastructure.
- **LoRaWAN** enables long-range, low-power localizationsuit- able for coverage in large areas. While offering lower accuracy (typically meter-level) compared to UWB, LoRa's exceptional range (kilometers in open areas) and power efficiency make it suitable for outdoor applications or large facilities. Local- ization can be achieved through RSSI fingerprinting or Time Difference of Arrival (TDoA) techniques [13].
- **Wi-Fi** localization leverages existing infrastructure, making it highly convenient and cost-effective. Performance varies significantly based on whether RSSI (Received Signal Strength Indicator) or CSI (Channel State Information) is used. RSSI-based methods (trilateration or fingerprinting) typically achieve meter-level accuracy, while CSI-based approaches (like DeepFi and PhaseFi) can reach sub-meter accuracy by exploiting detailed channel characteristics [6, 8, 9].

B. Alternative Localization Approaches

Visual Localization techniques, including visual odometry (using camera/optical flow) and marker-based systems, offer high accuracy and rich environmental information. Vision- based methods can achieve centimeter-level precision but are computationally intensive, sensitive to lighting conditions, and raise privacy concerns in surveillance applications [14].

Acoustic Localization utilizes sound waves for position estimation, where agents can follow sound sources through direction finding or time-difference-of-arrival techniques. Acoustic methods work well in environments where RF-based systems face challenges, though they are susceptible to ambient noise and require line-of-sight for optimal performance [15].

GNSS (Global Navigation Satellite Systems) including GPS provide reliable outdoor positioning with meter-level accuracy. While unsuitable for indoor applications due to signal attenuation, GNSS serves as a valuable complement for outdoor segments of hybrid indoor-outdoor surveillance systems [16].

C. Choice for Prototype

For rapid prototyping and reproducibility, we selected Wi-Fi anchors + RSSI (ESP32) for two complementary localization paths:

1.Triangulation / trilateration using a path-loss model and least squares

2.Fingerprinting (ML) using recorded RSSI/CSI fingerprints and regression/classification models (kNN, RF, MLP, Regression)

V. WI-FI Trilateration

We model RSSI using the log-distance path loss model [17]:

$$P_r(d) = P_r(d_0) - 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \quad (1)$$

Where $P_r(d)$ is received power (dBm) at distance d, $P_r(d_0)$ a reference power at d_0, n the path loss exponent, and X_σ zero-mean Gaussian shadowing. Solving for distance estimate:

$$\hat{d}_i = d_0 \times 10^{\frac{\left(P_r(d_o) - P_{r,i}\right)}{10n}} \quad (2)$$

Given $N \geq 3$ anchors with coordinates $p_i = (x_i, y_i)$ and distance estimates d̂$_i$, the object's position $p = (x, y)$ satisfies:

$$(x - x_i)^2 + (y - y_i)^2 = \hat{d}_i^2, \quad i = 1, \ldots, N \quad (3)$$

Linearize by subtracting the first equation from others to obtain a linear system Ap = b and solve via least squares:

$$\hat{p} = \left(A^T A\right)^{-1} A^T b \quad (4)$$

In practice we:

- Calibrate $P_r(d_0)$ and n per anchor via on-site measurements
- Apply median filtering to multiple RSSI samples to reduce burst noise
- Use robust loss (Huber) or RANSAC when multipath yields gross errors

VI. WI-FI FINGERPRINTING (MACHINE LEARNING)

Fingerprinting casts localization as supervised learning. We collect a fingerprint database:

$$D = \left\{\left(r^{(i)}, p^{(i)}\right)\right\}_{i=1}^{M}, \quad r^{(i)} = \left[RSSI_1, RSSI_1, \ldots, RSSI_N\right]$$

Offline: collect RSSI (or CSI features if accessible) at known grid locations, optionally augment with rotations and small translations for robustness [18].

Online: given current RSSI vector r, predict $\hat{p} = f_\theta(r)$. Typical models:

- **kNN:** Return weighted average of k nearest fingerprints (simple, interpretable)
- **Random Forest / Gradient Boosting:** Handles nonlinearities and missing features
- **Neural Networks/RNN:** For CSI multi-antenna and sub-carrier data; DeepFi/ PhaseFi show large improvements by using CSI amplitude/phase features [9, 10]

  Training loss (regression):

$$L(\theta) = \frac{1}{M}\sum_{i=1}^{M}\left\| f_\theta\left(r^{(i)}\right) - p^{(i)}\right\|_2^2 + \lambda R(\theta) \quad (5)$$

Where R is a regularizer. Performance evaluation uses RMSE and P50/ P90 percentiles.

A. *Practical Considerations*

- Spatial cross-validation: Split training/testing by spatial blocks (to avoid over-optimistic interpolation)
- Model update: Periodic re-fingerprinting may be needed in dynamic environments
- CSI vs RSSI: CSI (per-subcarrier amplitude/phase) gives richer features (used by DeepFi / PhaseFi) but typically requires driver access; RSSI is universally available [19]

VII. AGGREGATION AND EVENT-TRIGGERED COORDINATION

A. *Alarm Message Format*

When agent i detects an event, it forms an authenticated alarm packet:

$$m = \left(id_i, t, \hat{p}_i, severity, nonce, sig\right)$$

Where sig is a lightweight MAC (HMAC) using a shared group key to prevent spoofing/replay. Nonce prevents duplicates.

B. *Local Aggregation Decision Rule*

Each receiving agent j computes:

$$d_j = \left\|\hat{p}_i - p_j\right\|$$

If $d_j \leq R_{resp}$ and current number of aggregating allies < k_{req}, then j switches mode to AGGREGATE, else remains in PATROL.

To balance coverage, we use a soft quota policy: at most k_{max} agents are allowed to aggregate; preference given by proximity, residual battery, and urgency (severity).

The aggregation protocol mimics military squad tactics where sentries maintain sector coverage while providing mutual support. When a sentry detects a threat, it immediately signals nearby units while maintaining observation. Adjacent agents closest to the threat location respond first, creating an immediate containment perimeter, while more distant units provide secondary support or maintain their surveillance positions to prevent exploitation of uncovered areas. This approach mirrors infantry tactics where the closest fire team engages while supporting elements provide covering fire and flank security [20].

C. *Motion Control*

Aggregation behavior employs a multi-layer control architecture combining heading control and reactive obstacle avoidance.

Heading control utilizes the HMC5883L magnetometer for robust orientation estimation. The desired heading angle α_j is computed as:

$$\alpha_j = a\tan 2\left(y_{goal} - y_j, x_{goal} - x_j\right)$$

Collision avoidance uses ultrasonic sensors to detect obstacles within a predefined safety threshold d_{safe}. When an obstacle is detected at distance $d_i < d_{safe}$, the robot executes the following procedure:

1) Immediately stops forward motion and assesses the current position
2) Checks if the robot has reached the threat alarm position within tolerance ϵ:

$$\left\|\hat{p}_i - p_j\right\| \leq \varepsilon$$

3) If at target position, maintains position and switches, then stop and declare as aggregate
4) If not at target, calculates an avoidance angle $\theta_{avoid} = \pm 45^o$ (direction chosen based on obstacle distribution)
5) Executes a rotational maneuver by θ_{avoid} while maintaining safe distance from obstacles
6) Resumes forward motion toward the aggregation point after clearing the obstacle
7) Repeats the process until the target position is reached or obstacle clearance is confirmed

   The ultrasonic sensors provide real-time distance measurements to nearby obstacles, enabling reactive navigation in cluttered environments. The avoidance strategy implements a simple yet effective "stop-rotate-proceed" protocol that ensures collision-free movement while maintaining progress toward the aggregation point. This approach minimizes computational complexity while providing reliable obstacle avoidance capabilities suitable for resource-constrained embedded systems. Alternatively, we can use a camera or lidar sensors for obstacle avoidance, these sensors provide better perception of obstacles rather than just distance measurement.

Algorithm 1 Sentry Swarm Main Loop (per agent)

```
Initialize sensors, localization model (WIFI/ Radio/ UWB/
Acoustic)
mode = PATROL
while powered do
  sense environment
  if detection_triggered() then
    p̂ ← localize()
    broadcast(ALARM(p̂))
    mode ← ASSESS
  end if
  if received(ALARM) then
    extract p̂_alarm
    mode = ASSESS
  end if
  if mode == ASSESS then
    p ← localize() {each bot finds its own position}
    broadcast(POSITION(p))
    receive positions of neighbors P_others
    compute d ← ‖p̂_alarm − p‖
    determine nearest bots based on d
    mark_eligible(bot_id, p)
    mode ← AGGREGATE
    goal = p̂_alarm
  end if
  if mode == AGGREGATE then
    if eligible then
      compute_heading_change()
      send_wheel_command()
      move_towards_aggregation()
    end if
  else if mode == PATROL then
    random_walk_step()
  end ife
end while
```

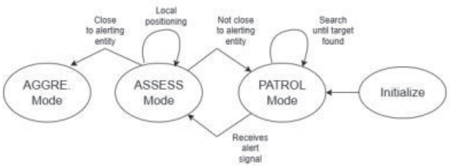


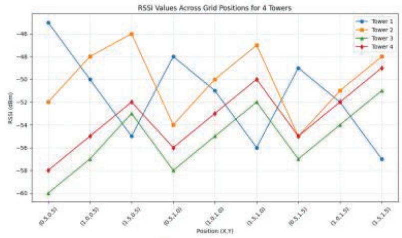
Fig. 2: State transition diagram

VIII. EXPERIMENTAL SETUP

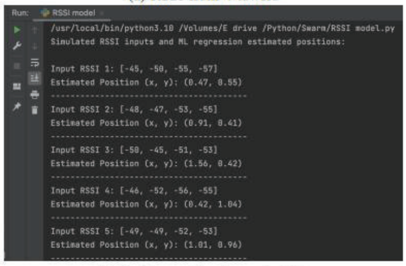
- Area: 2 × 2 m indoor testbed with 4 anchors at corners
- Agents: 5 robots (prototype) in Experiment
- Anchors: ESP32 beacons transmitting scheduled packets at 10 Hz Intruder scenarios: Single intruder walking across the boundary

IX. RESULTS

A. RSSI Measurement Data and Machine Learning Fingerprint



(a) RSSI from 4 towers



(b) Position estimation using ML

Fig. 3: (a) Mean of 50 records from each position. (b) ML model trained for accurate localization.

C. Localization Performance

TABLE I: Localization performance of different methods

Method	RMSE (m)	P50 (m)	P90 (m)
Wi-Fi Trilateration	0.84	0.64	1.56
Wi-Fi Fingerprinting (kNN)	0.42	0.28	0.70
Wi-Fi Fingerprinting (MLP)	0.95	0.70	1.80
UWB (reference [21])	0.06	0.04	0.10

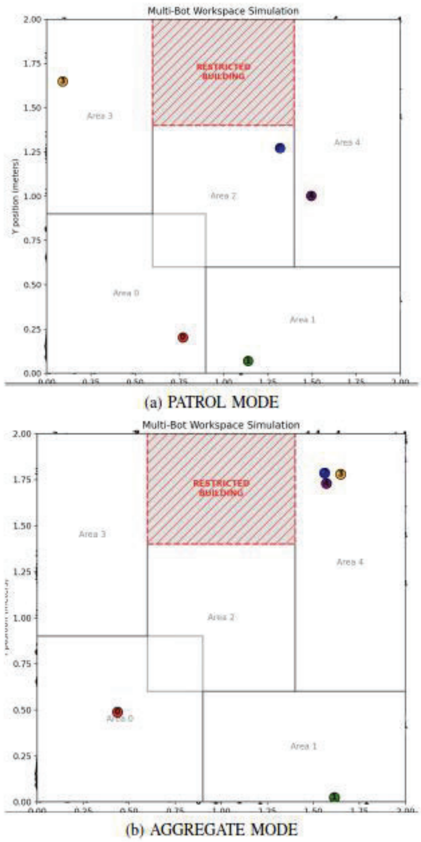


Fig. 4: Illustration of Sentry Swarm behavior: (a) robots patrolling during surveillance and (b) robots aggregating near detected intrusion

X. DISCUSSION

- The trilateration of Wi-Fi with fingerprinting (kNN/MLP/ regression) substantially improves accuracy given an adequate fingerprint database [6, 9].
- Event-triggering significantly reduces communication traffic compared to continuous state broadcasts; quantify via packets/sec metric in experiments.
- For mission-critical deployments, fuse UWB/LoRaWAN for localization and Wi-Fi for known environment surveillance.

XI. CONCLUSIONS AND FUTURE WORK

We presented Sentry Swarms, a modular, low-cost multirobot framework for surveillance and collective defence. The system features rapid response using event-triggered alarms with local decision rules. The localization system supports both Wi-Fi trilateration with machine learning fingerprinting, providing scalable adaptability. The framework can be effective for decentralized monitoring and defensive tasks.

Future Work:

- Conducting large-scale field trials with heterogeneous UGV/UAV swarms
- Enhancing adversarial resilience, including detection of jamming, spoofing, and developing consensus-based defence strategies

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