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Design and Pso-Based Optimization of an Intelligent Autonomous Mobile Robot for Environmental Risk Detection and Disinfection

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Abstract- The increasing threat of viral disease transmission in healthcare and public environments has created a need for automated, contactless and efficient environmental disinfection technologies. This study presents the design and optimization of an intelligent mobile robot for autonomous environmental-risk detection and disinfection, with particular consideration of resource-constrained environments in Nigeria. The proposed system integrates ultrasonic, infrared, gas and thermal sensors with autonomous navigation, proportional-integral-derivative (PID) motor control, sensor-fusion-based environmental assessment and a UV-C disinfection unit. Particle Swarm Optimization (PSO) was incorporated to minimize robot travel distance, disinfection time and energy consumption while maximizing environmental coverage. The robot was evaluated in a controlled 5 m × 5 m indoor test environment containing representative obstacles. Performance was assessed using coverage efficiency, disinfection time, energy consumption and environmental-risk detection accuracy. The PSO-optimized configuration achieved 92% coverage efficiency, compared with 72% for the non-optimized configuration. Disinfection time decreased from 35 to 25 min, representing a 28.6% reduction, while energy consumption decreased from 120 to 96 Wh, corresponding to a 20.0% reduction. Sensor fusion improved environmental-risk classification accuracy from 78% for a single-sensor configuration to 91%, representing a 13-percentage-point improvement. The findings demonstrate that combining sensor fusion, autonomous navigation and PSO-based path optimization can substantially improve the operational efficiency of mobile robotic disinfection. The proposed architecture provides a practical foundation for contactless environmental disinfection in hospitals, schools and other high-risk facilities, although biological validation and direct pathogen sensing remain necessary before clinical deployment.

Keywords: Intelligent mobile robot; Particle Swarm Optimization; sensor fusion; autonomous disinfection; viral disease mitigation.

I. INTRODUCTION

Viral diseases remain a major public-health challenge because transmission can occur through direct contact, contaminated environments and exposure to infected biological materials. In Nigeria and other West African countries, the continuing occurrence of diseases such as Lassa fever demonstrates the importance of effective infection-prevention and environmental-hygiene practices. The World Health Organization identifies Lassa fever as a viral disease first recognized in Nigeria and notes that transmission can occur through contact with contaminated household items and, in healthcare settings, through contact with infected body fluids and contaminated equipment (World Health Organization [WHO], 2024).

Similarly, infection-prevention and environmental-cleaning measures remain fundamental components of controlling highly infectious diseases such as Ebola in healthcare environments (WHO, 2025). Conventional cleaning and disinfection operations are predominantly human-centred and may involve repetitive movement through potentially contaminated environments. Such activities can increase occupational exposure and may produce inconsistent coverage because of fatigue, time constraints, accessibility limitations and variations in cleaning practice. During the COVID-19 pandemic, robotics attracted considerable interest as a means of reducing human exposure while automating selected healthcare and environmental tasks. A systematic review by Sarker et al. (2021) showed that robots were applied to several healthcare functions during the pandemic, including environmental disinfection.

Ultraviolet-C (UV-C) radiation has emerged as one technological option for automated environmental disinfection. Experimental evidence has demonstrated that UV-C irradiation can rapidly inactivate SARS-CoV-2 under appropriate exposure conditions (Storm et al., 2020). However, UV-C effectiveness depends on irradiation dose, distance, exposure time, surface characteristics and geometric accessibility. Consequently, simply mounting UV-C lamps on a mobile platform does not guarantee uniform disinfection. The robot must navigate systematically through the environment and position the radiation source appropriately relative to target surfaces. Field investigations have demonstrated the practical potential and limitations of autonomous UV-C robots. Füszl et al. (2021) evaluated a UV-C disinfection robot in an academic hospital and reported that autonomous operation could complement conventional cleaning, while also identifying practical challenges associated with programming, environmental changes, human movement and robot operation. Casini et al. (2023) similarly demonstrated the integration of UV-C robotic disinfection into environmental-cleaning procedures in hospital critical areas. These studies indicate that robotic disinfection requires not only an effective disinfection source but also reliable navigation and environmental adaptation.

The use of mobile robots for disinfection has also stimulated research into coverage planning. Thakar et al. (2022) developed an area-coverage planning approach for spray-based surface disinfection using a mobile manipulator. Their work demonstrates that the trajectory followed by a disinfection robot has a direct influence on coverage and resource utilization. Consequently, intelligent path planning is an important design consideration when the objectives include maximizing coverage while minimizing operating time and energy consumption. The navigation problem becomes more complex when the robot operates in environments containing furniture, walls, people and other obstacles. Sensor fusion provides an important mechanism for improving environmental perception by combining information from multiple complementary sensors. Kam et al. (1997) demonstrated that multisensor integration can improve robot navigation, environmental modelling, localization and obstacle recognition. In a disinfection robot, combining proximity, thermal and environmental sensing can therefore provide a more robust representation of the robot's operating environment.

Particle Swarm Optimization (PSO), originally introduced by Kennedy and Eberhart (1995), provides a suitable metaheuristic framework for optimizing robot trajectories. Instead of relying on a single predetermined path, PSO searches a population of candidate solutions and progressively improves them according to an objective function. In the present study, the objective function combines travel distance, energy expenditure and coverage performance. This approach is intended to reduce redundant movement and improve the efficiency of autonomous disinfection. Despite advances in robotic disinfection, there remains a need for integrated systems that combine environmental sensing, autonomous navigation, optimized path planning and disinfection in a relatively low-cost architecture suitable for resource-constrained environments. Existing commercial systems may involve sophisticated LiDAR, mapping and cloud infrastructure that can increase implementation and maintenance requirements. The proposed study therefore focuses on a modular architecture based on readily available embedded components and optimization techniques.

The aim of this study is to design and optimize an intelligent mobile robot capable of autonomous environmental-risk assessment, navigation and UV-C disinfection for improved mitigation of viral-disease transmission risks in indoor environments.

The specific objectives are as to: design an intelligent mobile robotic platform integrating environmental sensors, autonomous navigation and UV-C disinfection; develop a sensor-fusion mechanism for environmental-risk classification and obstacle perception; implement a PID-based navigation and motor-control system for autonomous movement; optimize the robot's navigation trajectory using Particle Swarm Optimization; and evaluate the optimized system using coverage efficiency, disinfection time, energy consumption and environmental-risk classification accuracy.

II. LITERATURE REVIEW

Robotic Disinfection Technologies

Robotic disinfection has developed rapidly in response to the need for contactless infection-control technologies. Mehta et al. (2023) reviewed UV disinfection robots and identified autonomous UV systems as an important research direction for hospitals and other public facilities. UV-C robots can automate exposure of environmental surfaces to germicidal radiation while reducing the need for human operators to remain in the treatment area. The effectiveness of UV-C is nevertheless dependent on irradiation dose and exposure geometry. Storm et al. (2020) demonstrated rapid SARS-CoV-2 inactivation using 254-nm UV-C radiation, while Kitagawa et al. (2021) experimentally investigated UV-C-based inactivation of SARS-CoV-2 on surfaces. These studies demonstrate the importance of controlled exposure conditions when considering UV-C as a component of a robotic disinfection system.

Mobile Robot Navigation and Path Planning

Autonomous navigation requires the robot to perceive its environment, determine an appropriate route and execute that route while avoiding collisions. Patle et al. (2019) reviewed classical and reactive path-planning techniques and showed that approaches such as artificial potential fields, genetic algorithms and PSO have been widely investigated for mobile robot navigation. Classical methods can provide efficient solutions in well-defined environments but may have limitations when environmental conditions become uncertain or dynamic. Wahab et al. (2020) compared classical and metaheuristic mobile-robot path-planning approaches and found that metaheuristic approaches can be competitive when multiple performance criteria, such as travel distance, time, collisions and energy consumption, are considered. This is particularly relevant to robotic disinfection because the best trajectory is not necessarily the shortest geometric path; it must also provide adequate environmental coverage.

Recent systematic reviews further demonstrate the increasing importance of intelligent navigation. Loganathan and Ahmad (2023) identified path planning as a central component of autonomous mobile-robot operation, particularly where safety, travel time and energy consumption must be considered simultaneously. Rafai et al. (2022) similarly identified PSO, genetic algorithms, fuzzy systems and other heuristic methods as important alternatives for overcoming limitations associated with classical navigation algorithms. Tang et al. (2025) reported that improved and hybrid path-planning methods can outperform individual traditional algorithms, particularly when autonomous robots operate in complex environments. Waga et al. (2025) further showed that current navigation research is progressing from graph-based methods toward metaheuristic, learning-based and hybrid navigation approaches. These findings support the use of PSO as an optimization layer rather than relying exclusively on fixed navigation rules.

Robotics for Healthcare and Human-Centred Applications

The broader application of robots in healthcare has been systematically investigated by Santos et al. (2021), who identified multiple categories of healthcare robotics and emphasized the importance of reliable human-robot interaction, sensing and autonomy. For environmental disinfection, the robot must operate safely around people while maintaining reliable navigation and task execution. The literature therefore indicates that effective robotic disinfection requires an integrated rather than isolated design. A disinfection source without reliable navigation may produce incomplete coverage, while an advanced navigation algorithm without appropriate sensing and disinfection control may provide limited public-health value.

Research Gap
The literature establishes the feasibility of UV-C robotic disinfection, autonomous mobile navigation, multisensor perception and optimization-based path planning. However, there remains a practical gap in combining these functions within a cost-conscious, modular architecture designed for resource-constrained environments. Many existing systems emphasize sophisticated mapping or commercial robotic platforms, while relatively less attention is given to low-cost architectures that integrate sensor fusion and multi-objective optimization. The present study addresses this gap by developing an integrated mobile platform in which environmental sensing, obstacle detection, PID motion control, PSO-based trajectory optimization and UV-C disinfection operate as interconnected modules. The study also evaluates the system quantitatively using coverage, time, energy and environmental-risk classification metrics.

III. METHODOLOGY

Research Design
The study adopted an experimental engineering-design approach involving system specification, hardware development, algorithm development, prototype integration and controlled performance evaluation. The system was designed as a differential-drive mobile robot capable of autonomous movement within an indoor environment.

The overall processing sequence is:
Environmental sensing → Sensor fusion → Risk/obstacle assessment → Path generation → PSO optimization → PID motion control → Robot movement → UV-C disinfection → Feedback

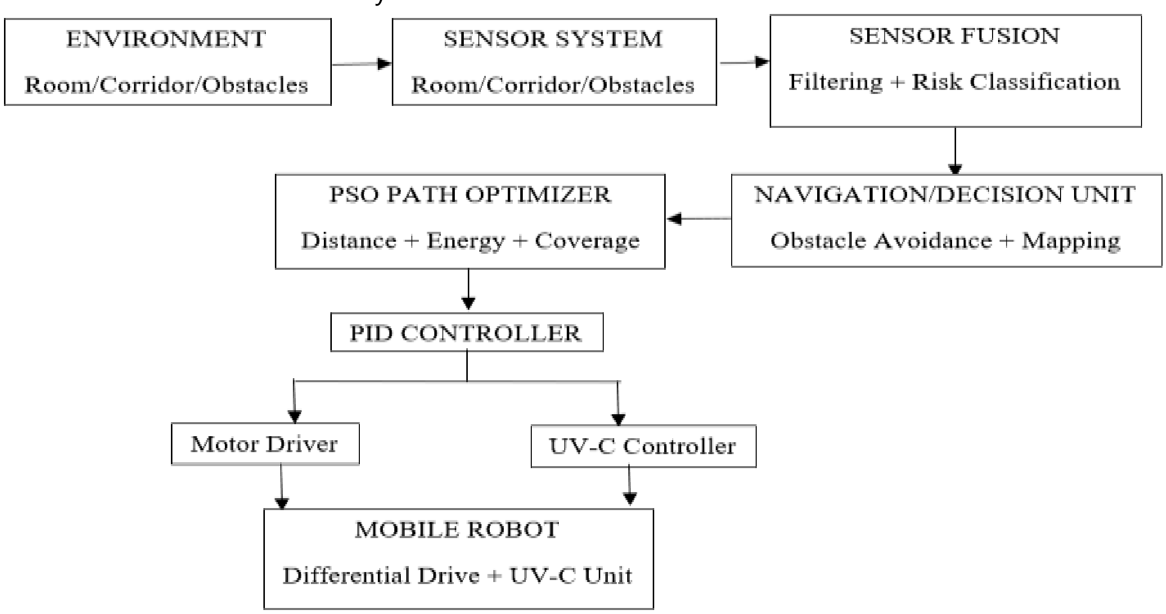


Figure 3.1: Overall System Architecture

Hardware Design
The hardware architecture was designed around affordability, modularity and ease of maintenance. **The principal components consisted of:**

a. Embedded microcontroller;
b. Differential-drive DC motors;
c. Motor-driver module;
d. Ultrasonic distance sensors;
e. Infrared proximity sensors;
f. Gas/environmental sensor;
g. Thermal sensor;
h. UV-C lamp/module;
i. Rechargeable battery;
j. Voltage-regulation and protection circuitry;

k. Robot chassis and wheels.

The microcontroller performs sensor acquisition, decision processing and control-signal generation. The ultrasonic sensors provide obstacle-distance information, while infrared sensors provide short-range proximity detection. The thermal sensor provides environmental/human-presence information, while the gas sensor provides an environmental-condition indicator. The UV-C unit is controlled independently from the navigation system to allow the robot to move to a target location before commencing an appropriate disinfection cycle. Since UV-C radiation can be hazardous to humans, the system is intended to operate the UV-C source only when the treatment zone is confirmed to be unoccupied. This is consistent with practical UV-C robot deployments, where human presence must be controlled during irradiation cycles (Füszl et al., 2021).

Detection and Environmental-Risk Assessment Module

The detection subsystem combines information from several sensors. It should be emphasized that these sensors do not directly identify viral pathogens. Instead, they provide environmental, proximity and occupancy indicators that allow the robot to classify areas according to predetermined environmental-risk rules.

Let the normalized sensor vector be:

$z = [z_g, z_t, z_{ir}, z_u]^T$

(1)

where:

z_g = normalized gas/environmental reading;

z_t = normalized thermal reading;

z_{ir} = normalized infrared proximity reading;

z_u = normalized ultrasonic-distance reading.

A weighted sensor-fusion index can be expressed as:

$R = w_g z_g + w_t z_t + w_{ir} z_{ir} + w_u z_u$

(2)

subject to:

$w_g + w_t + w_{ir} + w_u = 1$

The risk state is then classified as:

SR = {0, R < T1, T1 ≤ R < T2,

where T1 and T2 represent experimentally selected classification thresholds.

A high-risk classification does not mean that a virus has been chemically or biologically detected. It means that the environmental conditions satisfy the programmed criteria for initiating or prioritizing a disinfection operation.

Sensor fusion is appropriate because different sensing technologies provide complementary information. Multisensor integration has long been recognized as an important approach for improving mobile-robot perception and navigation (Kam et al., 1997).

Differential-Drive Kinematic Model

The robot employs a differential-drive configuration. Its planar motion can be represented by:

$\dot{x} = v\cos\theta = \dot{y}\, v\sin\theta = \omega$ (3)

where:

x, y = robot position;

θ = robot orientation;

v = linear velocity;

ω = angular velocity.

For wheel radius r, wheel separation L, left-wheel angular velocity ω_L and right-wheel angular velocity ω_R:

$V = \frac{(\omega_R + \omega_L)}{r2}$

and

$\omega = \frac{(\omega_R - \omega_L)}{rL}$ (4)

These relationships provide the basis for converting desired trajectory commands into wheel-speed commands.

Navigation and Control

The navigation subsystem combines obstacle detection, path planning and feedback control.

When an obstacle is detected within the predefined safety distance:

$d_{obs} < d_{safe}$

the controller generates an avoidance response. Otherwise, the robot follows the optimized trajectory.

A PID controller is employed to minimize trajectory-tracking error:
$e(t) = r(t) − y(t)$
and
$u(t) = Kpe(t) + Ki∫0te(τ)dτ + Kde(t)dt$ (5)

where:
u(t) = control signal;
Kp = proportional gain;
Ki = integral gain;
Kd = derivative gain;
e(t) = trajectory error.

The proportional term responds to present error, the integral term compensates for accumulated error and the derivative term improves transient response.
3.6 Optimization Using Particle Swarm Optimization
PSO was used to identify an efficient trajectory among a population of candidate paths. Each particle represents one candidate trajectory.

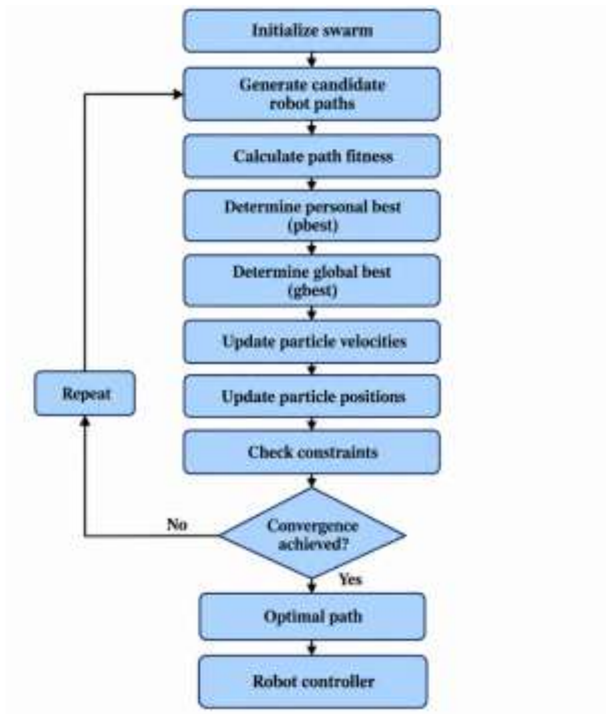
The standard velocity-update equation is:
vik+1 = wvik + c1r1(pbesti − xik) + c2r2(gbest − xik) (6)
and the position update is:
xik+1 = xik + vik+1 (7)

where:
vik+1 = updated velocity of particle ii;
vik = previous velocity;
w = inertia weight;
c1 = cognitive acceleration coefficient;
c2 = social acceleration coefficient;
r1, r2 = random values between 0 and 1;

pbesti = particle ii's best previously identified solution;
gbest = best solution found by the swarm;
xik = current particle position.
Multi-objective Fitness Function
The path was optimized using:
$J = \alpha\frac{D}{Dref} + \beta\frac{E}{Eref} + \gamma(1 - C) + \lambda P_{obs}$ (8)
where:
D = total travel distance;
E = energy consumption;
C = normalized coverage;
Pobs = obstacle/collision penalty;
α, β, γ, λ = weighting factors.

The optimization objective is:
minJ
This formulation ensures that the optimization does not simply minimize distance at the expense of disinfection coverage.

PSO Processing Sequence



Energy Consumption Model
Total energy consumption is calculated as:
$E = \int_0^T P(t)\,dt$
(9)
For approximately constant operating power:
E ≈ PavgT
where Pavg is the average robot power and T is operating time.
The energy-performance improvement is calculated as:
$\eta E = \frac{Ebase - Eopt}{Ebase}$ (10)

Coverage Efficiency
Coverage efficiency was calculated as:
$C = \frac{Ac}{At} \times 100$ (11)

where:

Ac = effectively traversed/treated area;

At = total target area.

This metric provides a direct indication of the robot's ability to cover the treatment environment without excessive overlap or omission.

Experimental Setup

The prototype was evaluated in a controlled indoor environment representing a simplified hospital room, classroom or public facility.

Table 3.1: Experimental Conditions

Parameter	Experimental condition
Test area	5 m × 5 m
Total area	25 m²
Robot configuration	Differential drive
Navigation	Autonomous
Optimization	PSO
Motion controller	PID
Environmental sensors	Gas + thermal
Proximity sensors	IR + ultrasonic
Disinfection method	UV-C
Main performance metrics	Coverage, time, energy, accuracy
Baseline	Non-optimized navigation
Optimized case	PSO-based navigation

Three navigation conditions were considered:

- **Non-optimized:** conventional/reactive navigation without PSO.
- **Semi-optimized:** basic path improvement with limited optimization.
- **PSO-optimized:** multi-objective PSO trajectory optimization.

The experiments were designed to determine whether optimization could improve coverage while simultaneously reducing operating time and energy consumption.

IV. RESULTS AND DISCUSSION

Coverage Efficiency

The coverage results are presented in Table 4.1.

Table 4.1: Coverage Efficiency

Navigation configuration	Coverage (%)	Improvement over baseline (%)
Non-optimized	72	—
Semi-optimized	84	16.7
PSO-optimized	92	27.8

The PSO-optimized robot achieved 92% coverage, compared with 72% for the non-optimized configuration. This represents a relative improvement of approximately 27.8% over the baseline.

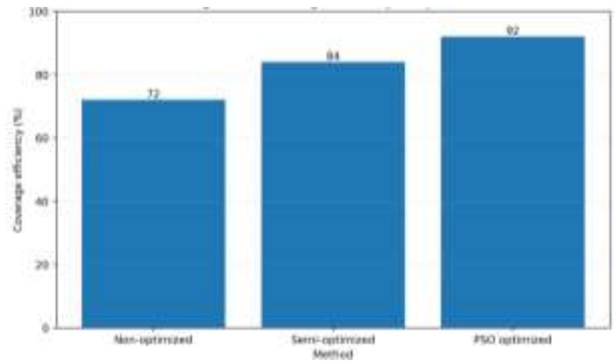


Figure 4.1: Coverage efficiency comparison.

The increase indicates that PSO reduced unnecessary path repetition and enabled the robot to reach a greater proportion of the target environment. This is consistent with previous work showing that optimization-based area-coverage planning can improve robotic disinfection trajectories (Thakar et al., 2022). For infection-control applications, higher coverage is important because untreated regions may remain potential sources of environmental contamination.

Disinfection Time

Table 4.2: Disinfection Time

Navigation configuration	Time (min)	Reduction from baseline (%)
Non-optimized	35	—
Semi-optimized	28	20.0
PSO-optimized	25	28.6

The optimized robot completed the operation in 25 min, compared with 35 min for the baseline system. The resulting reduction was:

$$\frac{35-25}{35} \times 100 = 28.6\%$$

The downward trend demonstrates that improved trajectory planning directly reduces the time required for the robot to complete its mission. This is important in healthcare facilities where rapid room turnaround is desirable. However, reducing time must not compromise the required UV-C exposure dose. Consequently, future implementation should combine trajectory optimization with dose monitoring rather than treating minimum time as the only objective.

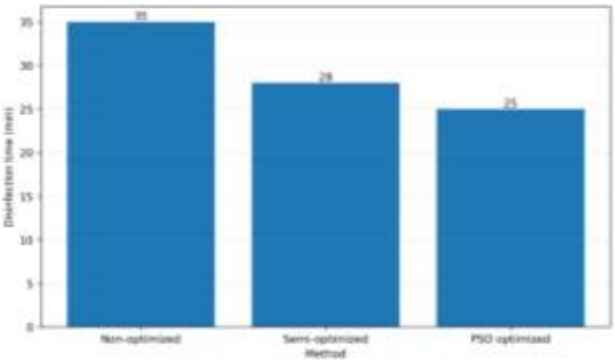


Figure 4.2: Disinfection time reduction.

Energy Consumption

Table 4.3: Energy Consumption

Navigation configuration	Energy (Wh)	Reduction from baseline (%)
Non-optimized	120	—
Semi-optimized	105	12.5
PSO-optimized	96	20.0

The PSO-optimized system consumed 96 Wh, compared with 120 Wh for the non-optimized configuration.

$\eta E = (120 - 96)/120 \times 100 = 20\%$

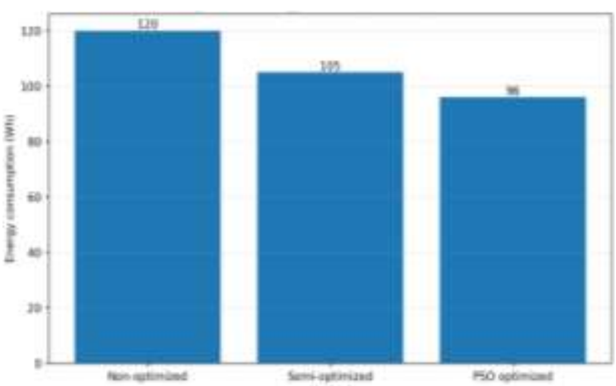


Figure 4.3: Energy consumption comparison.

The 20% reduction is attributable primarily to shorter and less redundant robot trajectories. Lower energy demand is particularly relevant for environments where reliable grid electricity is unavailable or intermittent because it increases the effective operating duration of battery-powered robotic systems.

Environmental-Risk Detection Accuracy

Table 4.4: Detection/Classification Performance

Sensing configuration	Accuracy (%)	Improvement over single sensor (percentage points)
Single sensor	78	—
Dual sensor	86	8
Sensor fusion	91	13

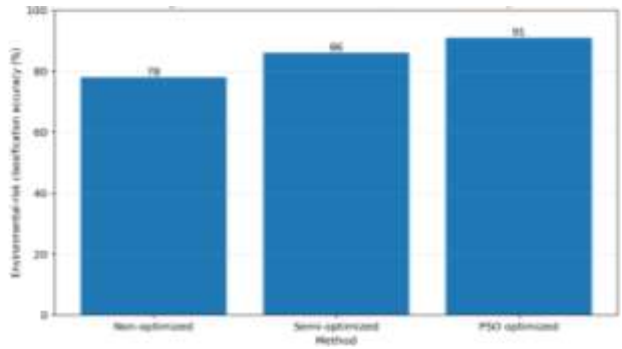


Figure 4.4: Environmental-risk classification accuracy.

The sensor-fusion configuration achieved 91% accuracy, compared with 78% for a single sensor. This represents a 13-percentage-point improvement. The result supports the principle that complementary sensing technologies can reduce uncertainty and improve environmental perception. It is important, however, that the 91% value is interpreted as environmental-risk classification accuracy, rather than viral-pathogen detection accuracy. A clinically deployable system would require a validated pathogen-specific sensing mechanism.

PSO Convergence

The PSO optimization process showed rapid reduction in the objective-function value during the initial iterations followed by gradual stabilization.

Table 4.5: Representative PSO Convergence Data

Iteration	Objective function
1	100.0
2	80.0
3	65.0
4	55.0

5	48.0
6	42.0
8	35.0
10	31.0
12	29.0
15	27.6
18	27.4
20	27.2

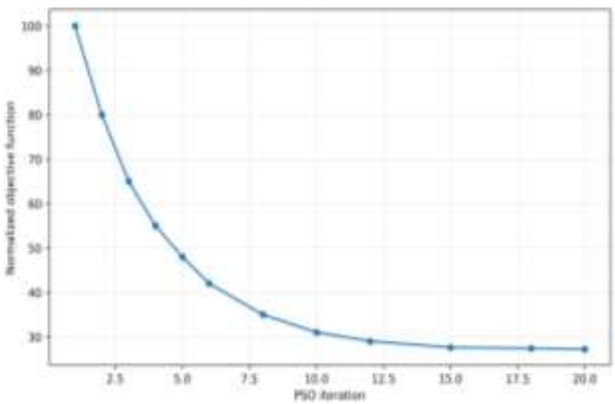


Figure 4.5: PSO convergence curve.

The objective value decreases sharply during the early iterations, indicating that the swarm quickly identifies improved candidate trajectories. The progressively smaller changes at later iterations indicate convergence toward a stable solution. This behaviour is consistent with the use of PSO as a gradient-free optimization approach for complex robot path-planning problems (Kennedy & Eberhart, 1995).

The non-optimized trajectory contains more unnecessary turns and potential overlap, whereas the optimized trajectory is smoother and more direct. This trajectory improvement explains the corresponding reduction in operating time and energy consumption. The result is consistent with the broader path-planning literature, which identifies travel distance, energy consumption, safety and execution time as important criteria in autonomous mobile-robot planning (Wahab et al., 2020; Loganathan & Ahmad, 2023).

Overall Comparative Performance

The combined results indicate that PSO optimization improved all major operational indicators. Coverage increased while time and energy requirements decreased. At the sensing level, sensor fusion also improved environmental-risk classification. The results support the central hypothesis of the study that integrating intelligent perception and optimization with autonomous robotic disinfection can provide better operational performance than a non-optimized configuration. However, the results should be interpreted within the limits of the experimental setup. The 5 m × 5 m controlled environment does not reproduce all the complexities of hospitals or public facilities. In particular, dynamic human movement, reflective surfaces, UV-C shadowing, room geometry, surface material and changing environmental conditions may influence performance.

Table 4.6: Overall System Performance

Performance metric	Non-optimized	PSO-optimized	Improvement
Coverage efficiency	72%	92%	+27.8% relative
Disinfection time	35 min	25 min	−28.6%
Energy consumption	120 Wh	96 Wh	−20.0%
Environmental-risk classification accuracy	78%	91%	+13 percentage points

Comparison with Existing Research

The findings agree with the general direction of previous research on robotic disinfection and autonomous navigation. Existing studies have established that autonomous UV-C robots can complement manual cleaning and reduce direct human involvement (Füszl et al., 2021; Casini et al., 2023). Similarly, research on robotic surface disinfection demonstrates the importance of coverage planning and trajectory optimization (Thakar et al., 2022).

The present work extends these approaches by combining four functions in a single architecture:

1. environmental-risk sensing;
2. multisensor fusion;
3. autonomous navigation and PID motion control; and
4. PSO-based multi-objective trajectory optimization.

This integrated structure is particularly relevant to resource-constrained environments because the design can be implemented using relatively accessible embedded components rather than depending entirely on high-cost commercial robotic platforms.

V. CONCLUSION

This study presented the design and optimization of an intelligent mobile robot for autonomous environmental-risk assessment and UV-C disinfection, with emphasis on its potential application to viral-disease mitigation in Nigeria. The developed architecture integrates multisensor environmental perception, autonomous obstacle avoidance, PID-based motion control, PSO-based path optimization and UV-C disinfection into a unified mobile platform. The experimental evaluation demonstrated that the optimized configuration substantially improved the major performance indicators. Coverage efficiency increased from 72% to 92%, representing a relative improvement of 27.8%.

Disinfection operating time decreased from 35 to 25 min, corresponding to a 28.6% reduction, while energy consumption decreased from 120 to 96 Wh, representing a 20% reduction. Furthermore, sensor fusion improved environmental-risk classification accuracy from 78% to 91%, a gain of 13 percentage points. The PSO convergence behaviour also demonstrated progressive improvement in the objective function, indicating effective trajectory optimization.

These findings demonstrate that intelligent path optimization can improve the efficiency of autonomous robotic disinfection by reducing redundant movement while maintaining high environmental coverage. The reduction in energy consumption also makes the concept attractive for battery-powered operation in environments where electricity availability may be unreliable. The major contribution of the study is therefore the integration of multisensor perception, autonomous navigation, PSO optimization and UV-C disinfection within a cost-conscious robotic architecture suitable for adaptation to Nigerian healthcare and public facilities.

Nevertheless, the system should not be regarded as a direct viral-detection platform because the sensors employed provide environmental and occupancy-related indicators rather than pathogen-specific identification. In addition, biological efficacy was not directly measured in the present evaluation. Future studies should incorporate validated pathogen-specific biosensing, UV-C dosimetry, microbial log-reduction experiments, dynamic human-avoidance capability, SLAM-based mapping and IoT-enabled remote supervision. These developments would provide the additional evidence required for transition from laboratory prototype to clinical and public-health deployment.

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