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A New Hybrid Water Cycle Algorithm for Path Planning with Obstacle Avoidance for Indoor Assistant Autonomous UAV Navigation

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Abstract

Assisting elderly individuals in indoor environments is crucial, as they often encounter mobility and safety challenges. Autonomous Unmanned Aerial Vehicles (UAVs) navigation offers a transformative solution, significantly enhancing safety, efficiency, and quality of life. These UAVs can perform tasks such as monitoring, delivering essential items, and responding to emergencies, providing invaluable support and promoting greater independence for elderly individuals. To achieve effective assistance, autonomous UAV navigation relies on robust path planning with obstacle avoidance to ensure optimal performance. A newly developed path planning, based on a new hybrid Water Cycle Algorithm (WCA), stands out by addressing the challenge of avoiding obstacles while adhering to non-holonomic constraints and conserving energy in complex, cluttered indoor environments. In Population-Based Algorithms (PBAs), the initial population plays a crucial role, as it greatly impacts the algorithm's efficiency in exploring the search space and its rate of convergence. The new developed hybrid algorithm, called WCA-HS, is based on using the Harmony Search (HS) algorithm to identify the optimal initial population for the WCA. The results indicate that the hybrid WCA-HS outperforms classical WCA and other metaheuristic algorithms, such as HS, Firefly Algorithm (FA), Cuckoo Search (CS), Genetic Algorithm (GA), Differential Evolution (DE), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC), over 20 independent runs, highlighting the effectiveness of the population initialization technique. Additionally, the developed indoor path planning system was evaluated in highly cluttered and low-light environments, showcasing its robustness and real-world applicability, making it highly effective for assisting elderly individuals in complex indoor environments.

Keywords

Indoor Assistant Autonomous UAV Navigation, Water Cycle Algorithm, path planning, obstacle avoidance, optimization

1 Introduction

New trends and technologies are enhancing the quality and flexibility of assistant systems for the elderly, offering enhanced protection and promoting their independence [1]. With the aging global population, the need for innovative solutions to support elderly individuals in preserving their independence has significantly increased. Unmanned Aerial Vehicles (UAVs) present a promising assistant system for various tasks, not only in outdoor environments but also indoors, including monitoring [2], delivering essential items [3], object detection [4], and responding to emergencies [5]. These applications are driven by UAVs' autonomous navigation capabilities, allowing them to navigate complex environments independently [6]. Path planning is essential for UAVs, as it significantly influences both delivery time and energy [7]. Navigating cluttered indoor spaces under varying lighting conditions requires precise obstacle avoidance for a safe trajectory. Advanced navigation algorithms enable UAVs to identify safe and efficient routes, avoid obstacles, and dynamically adapt to environmental changes. These capabilities make autonomous UAVs navigation an invaluable addition to modern assistive technologies, offering elderly individuals greater independence and security. Path planning for UAVs typically involves sampling-based, graph-based, and gradient-based approaches. Among the sampling-based techniques, Rapidly-exploring Random Tree (RRT), its variant RRT*, and the Probabilistic Roadmap (PRM) are commonly used. In Belaid et al. [8], a new variant of RRT*, called Narrow

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Passage RRT*, was developed for quadrotor path planning, demonstrating an improved ability to navigate through narrow and complex spaces. The PRM approach was further applied in Dias et al. [9] to create two real-time 3D path planning algorithms for UAVs: Grid Path Planning Roadmap (GPRM) and Particle PRM, called PPRM, which demonstrated practical applications in search and rescue missions. Graph-based methods, such as Dijkstra's algorithm, have also been utilized for UAV path planning, as seen in Xushi [10] for delivery services. Gradient-based methods, such as the Artificial Potential Field (APF) and A-star (A*) methods, have been proposed for path planning and obstacle avoidance. A variant of the APF, introduced in Selvam et al. [11], shows superior performance compared to the classical APF. Combining traditional approaches has further improved path planning efficiency. For example, Chen et al. [12] integrates the Particle Filter (PF) method into PRM, resulting in greater efficiency than the standard PRM. Similarly, Zhou and Liu [13] combines A* with RRT* to provide both optimal and adaptable paths, enhancing the adaptability of UAVs in dynamic urban air mobility environments. In Dirik and Kocamaz [14], a hybrid RRT-Dijkstra algorithm was introduced, improving RRT efficiency by minimizing path length, reducing turning points, and decreasing execution time, thus enhancing real time path following performance. Despite these advances, traditional path planning techniques still face limitations, such as high computational complexity, challenges in dynamic environments, difficulties with collision avoidance, and susceptibility to local minima.

Metaheuristic algorithms offer effective solutions to overcome the limitations of traditional path planning methods and serve as versatile problem-solving tools that can adapt to various driving scenarios [15]. An Enhanced Gravitational Search Algorithm (EGSA) is applied in Jiao et al. [16] to optimize UAV path length by utilizing optimal memory and chaotic Lévy flight, outperforming seven other algorithms in diverse environments. In Han et al. [17], an advanced ABC algorithm is introduced for path planning, combining swarm intelligence with human cognitive mechanisms, leading to improved fuel efficiency and safer trajectories compared to other algorithms. The Improved Bat Algorithm (IBA), introduced in Zhou et al. [18], incorporates a Lévy-based flight strategy and dynamic speed adjustments, enhancing both global and local optimization for more efficient path planning in complex environments. It demonstrates faster convergence and better performance compared to other algorithms. An improved Harris Hawk Optimization (HHO) algorithm is developed in Huang and Liu [19] for UAV path planning in dynamic environments, incorporating enhanced search strategies and path smoothing techniques, leading to superior path efficiency and smoothness. The Bat-Pigeon Algorithm (BPA), presented in Lei et al. [20], enables adjustable speed navigation and effective obstacle avoidance. Additionally, hybrid metaheuristic approaches improve optimization by merging the strengths of different algorithms, leading to better performance and adaptability in complex environments, thereby enhancing path planning strategies. In Gupta and Verma [21], a novel hybrid optimizer combining Particle Swarm Optimization (PSO) with the Coyote Optimization Algorithm (COA) improves trajectory planning for aerial robots in complex environments, showing superior performance compared to other metaheuristics. A new hybrid algorithm which merges the Golden Eagle Optimizer (GEA) and Grey Wolf Optimizer (GWO) using an adaptive strategy, is introduced in Lv et al. [22], offering superior performance and stability in path. In He et al. [23], a hybrid Chaotic Aquila Optimizer (CAO) combined with Simulated Annealing (SA) is proposed for an UAV path planning, outperforming nine leading algorithms in terms of fitness, cost, and execution. A hybrid GWO and DE algorithm, presented in Yu et al. [24], enhances exploitation with a GWO position update and a rank-based mutation strategy in DE algorithm, achieving superior performance and generating smoother, shorter paths compared to GWO and its variants.

This work aims to address the mobility and safety challenges faced by elderly individuals in indoor environments by proposing autonomous UAV navigation as a crucial robotic solution. In cluttered indoor environments, path planning presents a significant challenge, as it must address on obstacle avoidance, incorporate non-holonomic constraints, and optimize energy efficiency. A new hybrid metaheuristic algorithm, called Water Cycle Algorithm-Harmony Search (WCA-HS), is introduced for global optimization problem, and applied in this study to develop a new path planning system. The results reveal that the proposed WCA-HS is highly competitive, with the population initialization technique significantly enhancing performance compared to the standard WCA, which lacks optimized population initialization, as well as other metaheuristics such as HS, Firefly Algorithm (FA), Cuckoo Search (CS), Genetic Algorithm (GA), Differential Evolution (DE), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC). This improvement is particularly beneficial for global optimization problems, especially in autonomous UAV navigation during assisting elderly individuals, where effective path planning is crucial. The enhanced path planning was tested in highly cluttered, low-light environments, demonstrating its robustness and practical usability, making it highly effective for supporting elderly individuals in complex indoor settings.

The main contributions of this paper are summarized below:

- New hybrid metaheuristic algorithm named WCA-HS is introduced for global optimization problems.
- The latter is applied to develop an advanced path planning system for autonomous UAVs navigation during assisting elderly individuals, addressing the challenges of navigation in indoor environments by efficiently avoiding obstacles and optimizing performance.
- The results show that the new hybrid WCA-HS significantly outperforms the standard WCA, and other metaheuristics such as HS, FA, CS, GA, DE, ACO, and ABC. The newly developed path planning system ensures safe, efficient, and sustainable navigation through complex indoor environments, proving highly effective in assisting elderly individuals with mobility and safety challenges.

The remainder of this paper is organized as follows: Section 2 presents the UAV's mathematical model, while Section 3 introduces the proposed hybrid algorithm. Section 4 explores the path planning system, followed by the presentation and analysis of results in Section 5. Finally, Section 6 provides the conclusion.

2 Quadrotor dynamics and modelling

The UAV used to assist elderly individuals is a quadrotor, equipped with four rotors that provide six Degrees of Freedom (DOF) [25, 26]. Fig. 1, sourced from [5], illustrates a quadrotor employed in emergency response efforts within cluttered indoor environments.

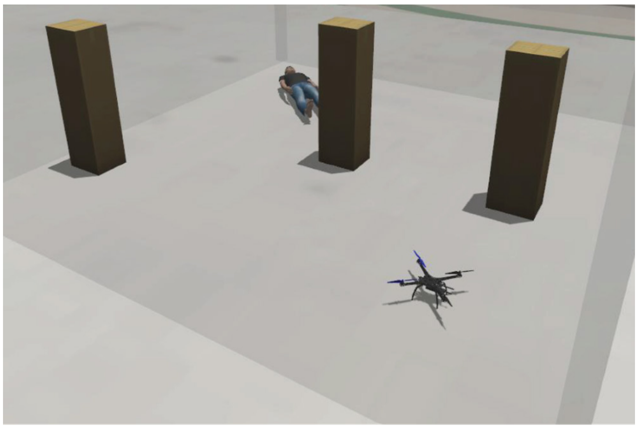

Fig. 1 Quadrotor used for emergency response efforts within cluttered indoor environments [5]

The motion equations for the quadrotor, derived through the Newton-Euler formalism, are as follows [27].

2.1 Rotation dynamics

The rotation dynamics of the quadrotor are expressed as follows:

$$\begin{cases} \dot{p} = \frac{1}{I_x}\left[\left(I_y - I_z\right)qr - K_{fax}p^2 - J_r\bar{\Omega}q + U_\phi\right] \\ \dot{q} = \frac{1}{I_y}\left[\left(I_z - I_x\right)pr - K_{fay}q^2 + J_r\bar{\Omega}p + U_\theta\right]. \\ \dot{r} = \frac{1}{I_z}\left[\left(I_x - I_y\right)pq - K_{faz}r^2 + U_\psi\right] \end{cases} \tag{1}$$

2.2 Translation dynamics

The translation dynamics of the quadrotor are expressed as follows:

$$\begin{cases} \ddot{x} = \frac{1}{m}\left[\left(\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi\right)U_z - K_{ftx}\dot{x}\right] \\ \ddot{y} = \frac{1}{m}\left[\left(\cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi\right)U_z - K_{fty}\dot{y}\right]. \\ \ddot{z} = \frac{1}{m}\left[\left(\cos\phi\cos\theta\right)U_z - K_{ftz}\dot{z}\right] - g \end{cases} \tag{2}$$

2.3 Rotor's dynamics

The dynamics of the UAV's rotors are as follows [27]:

$$\dot{\omega}_i = bv_i + \beta_0 + \beta_1\omega_i + \beta_2\omega_i^2, \tag{3}$$

with:

$$\beta_0 = \frac{-C_s}{J_r},\ \beta_1 = \frac{-K_e K_m}{RJ_r},\ \beta_2 = \frac{-K_r}{J_r},\ b = \frac{K_m}{RJ_r}.$$

The UAV parameters are described in Table 1.

3 The proposed hybrid WCA-HS

3.1 Classical WCA

The WCA, inspired by the natural water cycle, was proposed in Eskandar et al. [28] for solving constrained optimization problems. In this nature-based metaheuristic, raindrops represents the population: those reaching the ocean correspond to global optima, while those flowing toward rivers are local optima, and those in streams are less optimal. Key stages of the WCA are summarized below, with algorithm parameters provided in Table 2.

The raindrop is represented as a $\mathbf{1} \times \boldsymbol{N}$ matrix:

$$\boldsymbol{X} = \left[\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \ldots, \boldsymbol{x}_N\right]. \tag{4}$$

Table 1 UAV parameters [27]

Parameter	Description	Value
ϕ, θ, ψ	Roll, pitch, and yaw angles, respectively	–
x, y, z	Longitudinal, lateral, and vertical motions, respectively	–
p, q, r	Roll, pitch, and yaw rates, respectively	–
$U_z, U_\phi, U_\theta, U_\psi$	Altitude, roll, pitch, and yaw commands, respectively	–
m (kg)	Quadrotor's mass	0.486
d (m)	UAV's mass center to propeller axis distance	0.25
g (N/m/s)	Gravity acceleration	9.81
I_x, I_y (N m/rad/s^2)	Roll and pitch inertia moments, respectively	3.8278×10^{-3}
I_z (N m/rad/s^2)	Yaw inertia moment	7.6566×10^{-3}
$K_{ftx}, K_{fty}, K_{ftz}$ (N/m/s)	Positive drag coefficients	5.5670×10^{-4}
K_{fax}, K_{fay} (N/rad/s)	Aerodynamic friction coefficients	6.3540×10^{-4}
K_{faz} (N/rad/s), b	Aerodynamic friction and lift force coefficients, respectively	2.9842×10^{-5}
C_D	Drag coefficient force	3.2320×10^{-7}
J_r (N m/rad/s)	Rotor inertia	2.8385×10^{-5}
C_s	Solid friction	538.26×10^{-5}
K_r	Load constant torque	0.0346×10^{-5}
R (Ω)	Motor internal resistance	0.4
K_m	Mechanical torque	318.12×10^{-5}
K_e	Electrical torque constant	0.0216

Table 2 WCA's parameters

Parameter	Description
N_{pop}	Population size
N	Number of design variables
N_{sr}	Top individuals
N_{Sn}	Number of streams that flow into a specific river or sea
N_r	Number of rivers
C	Constant that ranges from 1 to 2
t	Index of iteration
$d_{\max}$	Variable that controls exploration range near the sea
LB	Minimum limit of the optimization problem
UB	Maximum limit of the optimization problem

The initial population of raindrops is given by:

$$pop = \begin{bmatrix} x_1^1 & x_2^1 & x_3^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & x_3^2 & \cdots & x_N^2 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ x_1^{N_{pop}} & x_2^{N_{pop}} & x_3^{N_{pop}} & \cdots & x_N^{N_{pop}} \end{bmatrix}. \quad (5)$$

Each raindrop is evaluated as follows:

$$C_i = Cost_i = f\left(x_1^i, x_2^i, \ldots, x_N^i\right), \quad (6)$$

with:

$$i = 1, 2, 3, \ldots, N_{pop}.$$

After generating N_{pop} raindrops, the top N_{sr} form the sea and rivers, the rest flow into streams or the sea:

$$N_{sr} = N_r + 1, \quad (7)$$

$$N_{stream} = N_{pop} - N_{sr}. \quad (8)$$

Precipitation allocation based on flow intensity:

$$NS_n = round\left\{\left|\frac{C_n}{\sum_{i=1}^{N_{sr}} C_i}\right| \times N_{stream}\right\}, \quad (9)$$

with:

$$n = 1, 2, \ldots, N_{sr}.$$

Streams flow into rivers before reaching the sea, sometimes flow directly. The position update formulas are Eqs. (10) to (12):

$$\boldsymbol{x}_{stream}^{i+1}(t+1) = \boldsymbol{x}_{stream}^{i}(t) + rand \times C \times \left(\boldsymbol{x}_{sea}(t) - \boldsymbol{x}_{stream}^{i}(t)\right), \tag{10}$$

with:

$$i = 1,2,3,\ldots,N_{stream},$$

$$\boldsymbol{x}_{stream}^{i+1}(t+1) = \boldsymbol{x}_{stream}^{i}(t) + rand \times C \times \left(\boldsymbol{x}_{river}^{i}(t) - \boldsymbol{x}_{stream}^{i}(t)\right), \tag{11}$$

with:

$$i = 1,2,3,\ldots,N_{stream},$$

$$\boldsymbol{x}_{river}^{i+1}(t+1) = \boldsymbol{x}_{river}^{i}(t) + rand \times C \times \left(\boldsymbol{x}_{sea}(t) - \boldsymbol{x}_{river}^{i}(t)\right), \tag{12}$$

with:

$$i = 1,2,3,\ldots,\left(N_{sr} - 1\right).$$

Similar to the water cycle, the algorithm adapts to evaporation conditions as follows:

$$R_j(t) = \begin{cases} 1, & \text{if } x_{sea}(t) - x_{river}^{j}(t) < d_{\max} \text{ or } rand < 0.1 \\ 0, & \text{otherwise} \end{cases}, \tag{13}$$

with:

$$j = 1,2,\ldots,N_{sr} - 1,$$

$$S_j(t) = \begin{cases} 1, & \text{if } x_{sea}(t) - x_{stream}^{j}(t) < d_{\max} \text{ or } rand < 0.1 \\ 0, & \text{otherwise} \end{cases}. \tag{14}$$

The parameter $d_{\max}$ is dynamically reduced every generation's end as:

$$d_{\max}(t) = d_{\max}(t) - \frac{d_{\max}(t)}{t_{\max}}, \tag{15}$$

with:

$$t = 1,2,3,\ldots,t_{\max}.$$

After evaporation, the raining process generates new raindrops at various locations, as follows:

$$\boldsymbol{x}_{stream}^{i}(t+1) = LB + rand \times (UB - LB). \tag{16}$$

Fig. 2 provides a visual representation of the WCA, and its pseudo-code is shown in Algorithm 1.

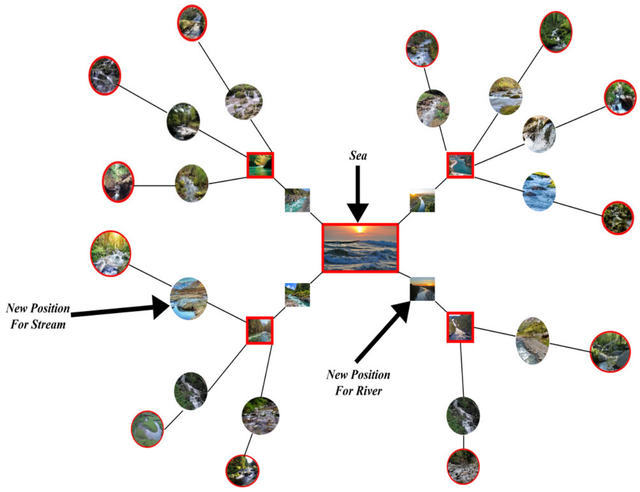

Fig. 2 Visual representation of the WCA

3.2 Hybrid WCA-HS

In our previous research, the WCA was applied for the first time to develop a novel path planning and obstacle avoidance system for a quadrotor [29]. The results demonstrated the effectiveness of the WCA-based planner outperforming other metaheuristic algorithms. This success inspired further optimization of the WCA in the current work. The quality of the initial population in PBAs is crucial, as it significantly impacts the algorithm's convergence speed and solution quality. The main challenges with the initial population in WCA are depicted in Table 3. The HS algorithm [30] is proposed to address these challenges through several key mechanisms, as shown in Table 3. Consequently, this paper introduces a new hybrid metaheuristic algorithm named WCA-HS.

The key strategy of the introduced hybrid WCA-HS is to employ HS algorithm to identify the best initial population for the WCA. Selection of initial population is an important parameter that significantly influences the efficiency with which the algorithm explores search space and convergence properties of the algorithm. Fig. 3 illustrates the simplified flowchart of the proposed hybrid WCA-HS.

4 New indoor path planning system

4.1 Indoor environment modeling

The environmental map used for the autonomous navigation of a quadrotor, aimed at assisting elderly individuals in indoor environments, is a 3D model. This map includes 35 obstacles of varying heights and widths to accurately simulate cluttered indoor real-world conditions. The environmental map is shown in Fig. 4.

Algorithm 1 Pseudocode of the WCA

```
Set initial parameters (N_pop, N_sr, t_max, d_max, C)
Compute stream quantity using Eq. (8).
Create initial population using Eq. (5).
Establish flow intensity according to Eq. (9).
while t ≤ t_max do
    for i=1: N_pop
        Direct Streams to Sea: Apply Eq. (10) to allow streams to flow
        directly to the sea.
        Evaluate Stream performance: Use Eq. (6) to calculate the
        objective function for each stream.
            /* Update sea*/
                if Cost (New_stream) < Cost (Sea)
                    Sea = New Stream
                end if
        Direct Streams to Rivers: Use Eq. (11) to direct streams
        towards their rivers.
        Evaluate Stream performance: Use Eq. (6) to calculate the
        objective function for each stream.
            /* Update river and sea*/
                if Cost (New_stream) < Cost (River)
                    River = New_Stream
                        if Cost (New_Stream)< Cost (Sea)
                            Sea = New_Stream
                        end if
                end if
        Direct Rivers to Sea: Use Eq. (12) for rivers to flow towards
        the sea.
        Evaluate River Performance: Compute the objective function
        for the river using Eq. (6).
            /* Update sea*/
                if Cost (New_River)< Cost (Sea)
                    Sea = New_River
        Check Evaporation Conditions: Assess the evaporation criteria
        using Eq. (13) and Eq. (14).
            if evaporation condition is satisfied
            /* Create new streams*/
                for i=1: (N_sr − 1)
                    if (distance (Sea and River) < d_max or (rand < 0.1)
                        New streams are created using Eq. (16)
                    end if
                end for
                for i = 1: (N_stream)
                    if (distance (Sea and Stream) < d_max or (rand < 0.1)
                        New streams are created using Eq. (16)
                    end if
                end for
            end if
        end for
    Adjust d_max: adjust the value of d_max using Eq. (15)
end while
```

4.2 Path planning strategy

The developed path planning system employs a novel hybrid WCA-HS to optimize quadrotor trajectory planning. The objective is to minimize the total path length while ensuring a collision-free and feasible trajectory under real-world constraints. To achieve this, the system determines optimal coordinates for virtual waypoints between the start and end points. The objective function, described below, is defined as the total path length and serves as the optimization criterion in the proposed algorithm. The WCA-HS iteratively adjusts waypoint positions to minimize this function while satisfying the constraints detailed in Section 4.3.

A key constraint in this optimization is the non-holonomic constraint, which ensures that the UAV follows a physically feasible trajectory. Since the UAV cannot move instantaneously in any direction, its velocity and acceleration must be constrained to match its dynamics. To enforce this, the UAV's velocity components and acceleration are calculated. These values are then used to check if the roll ϕ and pitch θ angles remain within their allowed limits. If these constraints are violated, a penalty is applied, discouraging infeasible trajectories. Additionally, the UAV's velocity is constrained to not exceed a predefined maximum value, ensuring safe and controlled motion. Obstacle avoidance constraints further refine the trajectory by ensuring that the height of any obstacle does not exceed the altitude of the UAV's path. A safety margin, defined as the sum of the UAV's radius and the obstacle's radius, guarantees that the UAV maintains a minimum safe distance from obstacles. The final cost function incorporates these constraints using a penalty factor, increasing the cost for infeasible solutions. This ensures that WCA-HS prioritizes both the shortest path and feasibility, guiding the UAV toward an optimized and constraint-compliant trajectory.

Once the optimal waypoints are determined, a cubic spline method is applied to connect them, ensuring a smooth and continuous trajectory that adheres to the given constraints. The cubic spline interpolation ensures continuity in position, velocity, and acceleration. This enforces kinematic constraints by preventing sudden changes in movement, which could lead to instability or infeasibility in real-world execution. By smoothing the trajectory, the spline method ensures the UAV follows a dynamically feasible path while respecting both motion constraints and obstacle avoidance requirements. The indoor path planning system strategy is described in Fig. 5.

4.3 Optimization problem statement

The constrained global optimization problem aims to determine the optimal waypoints for the quadrotor flight path, from the start point S: (x_S, y_S, z_S) to the goal point G: (x_G, y_G, z_G), minimizing the objective function subject to the given constraints. The problem is formulated as:

$$\min J(x, y, z), \tag{17}$$

$$\text{subject to: } g_i(x, y, z) \le 0, \ i = 1, 2, \ldots, m,$$

$$x \in [x_{\min}, x_{\max}], \ y \in [y_{\min}, y_{\max}], \ z \in [z_{\min}, z_{\max}],$$

Table 3 Challenges in WCA and corresponding proposed solutions

Challenge	Cause	HS solution
Poor distribution and limited exploration	WCA's random initialization causes uneven solution spread, limiting search space exploration.	HS combines random and high-quality solutions using memory, ensuring better distribution and broader exploration.
Lack of diversity and premature convergence	Random initialization can cause solutions to lack diversity, leading to early convergence to local optima.	HS uses pitch adjustment and memory-based initialization to maintain diversity and prevent premature convergence.
Suboptimal solutions	WCA doesn't adapt the initial population to problem constraints, resulting in poor starting solutions.	HS adapts the initial population based on problem characteristics, using harmony memory.

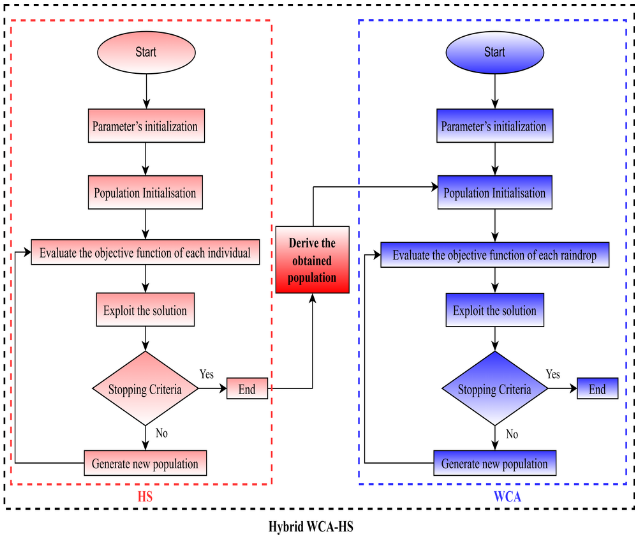

Fig. 3 Simplified flowchart of the proposed hybrid WCA-HS

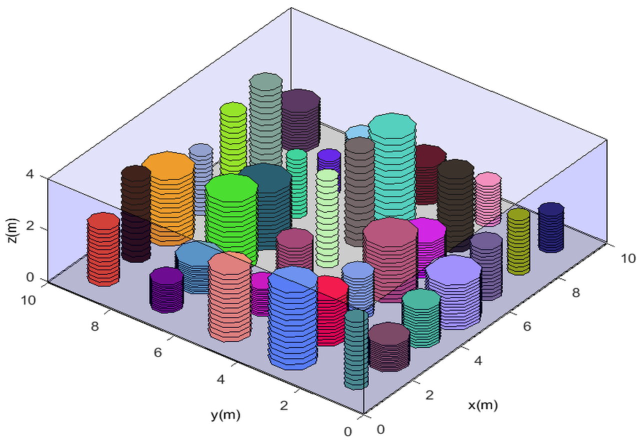

Fig. 4 Environmental map

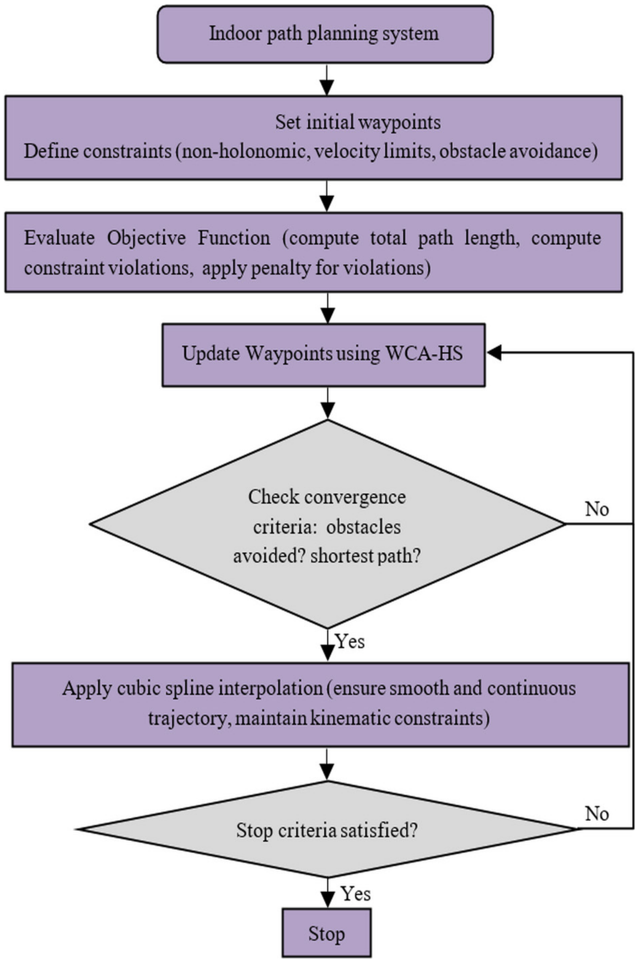

Fig. 5 Indoor path planning system strategy

where $J(x, y, z)$ is the objective function to be minimized, $g_i(x, y, z) \leq 0$ represents the inequality constraints that must be satisfied. The variables $x \in [x_{\min}, x_{\max}]$, $y \in [y_{\min}, y_{\max}]$ and $z \in [z_{\min}, z_{\max}]$ specify the allowable ranges for x, y and z, respectively.

4.3.1 Objective function

The objective function for this optimization problem is the path length, which represents the total distance the UAV must travel autonomously from the start point to the goal point while assisting elderly individuals.

The goal of the optimization is to determine an optimal trajectory that minimizes this distance while ensuring feasibility and safety within the indoor environment.

The path length L is mathematically defined as:

$$L = \int \sqrt{\left(\left(\frac{dx}{dt}\right)^2 + \left(\frac{dy}{dt}\right)^2 + \left(\frac{dz}{dt}\right)^2\right)} dt. \tag{18}$$

4.3.2 Constraints

For safe and efficient navigation, the quadrotor's trajectory must satisfy key constraints, including obstacle avoidance, non-holonomic motion, and velocity limits. These constraints, illustrated in Fig. 6, are integrated into the optimization process to ensure a smooth, collision-free, and feasible path.

$$\begin{cases} \tan\theta = \dfrac{\left(\ddot{x} - \dfrac{K_{ftx}}{m}\dot{x}\right)\cos\psi + \left(\ddot{y} - \dfrac{K_{fty}}{m}\dot{y}\right)\sin\psi}{\ddot{z} + g - \dfrac{K_{ftz}}{m}\dot{z}} \\ \sin\phi = \dfrac{-\left(\ddot{x} - \dfrac{K_{ftx}}{m}\dot{x}\right)\sin\psi + \left(\ddot{y} - \dfrac{K_{fty}}{m}\dot{y}\right)\cos\psi}{\sqrt{\left(\ddot{x} - \dfrac{K_{ftx}}{m}\dot{x}\right)^2 + \left(\ddot{y} - \dfrac{K_{fty}}{m}\dot{y}\right)^2 + \left(\ddot{z} + g - \dfrac{K_{ftz}}{m}\dot{z}\right)^2}} \end{cases} \quad (19)$$

5 Simulation results and discussion

Numerical simulations were conducted using MATLAB to evaluate the proposed indoor path planning system based on the new hybrid WCA-HS for autonomous quadrotor navigation. The system is designed to assist elderly individuals in navigating challenging indoor environments. The UAV, with parameters specified in Table 1, begins at the starting point S: (1, 2, 0.6) and aims to reach the goal point G: (8.5, 8.1, 1.1). The quadrotor must navigate through a complex environment containing 35 obstacles and identify five waypoints along its path to successfully achieve this goal.

The hybrid WCA-HS was evaluated with the HS over 100 iterations to find the best initial population, then the WCA over 1000 iterations. The performance of the hybrid WCA-HS was compared with standard WCA, HS, FA, CS, DE, ACO, and ABC algorithms. For all algorithms, a population size of 50 was used, and each was tested over 1000 iterations.

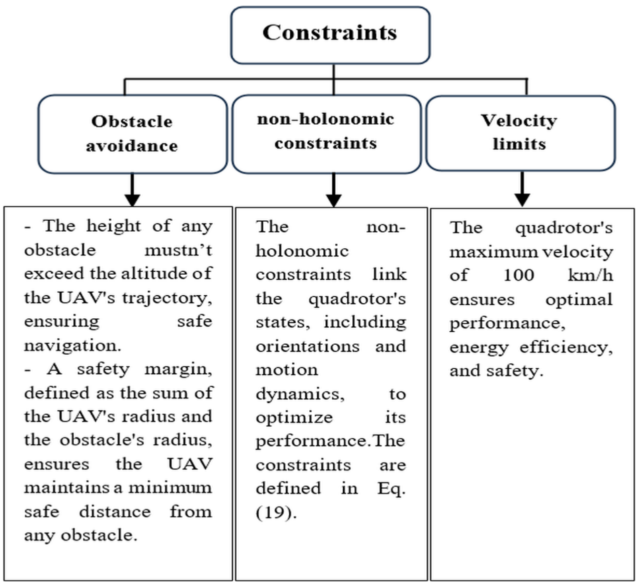

Fig. 6 Constraints for safe navigation

To assess the robustness of the proposed path planning system, evaluations were conducted with 20 independent runs. Table 4 presents the cost function results obtained from obtained from these 20 runs. The results clearly show that the hybrid WCA-HS outperforms both the standard WCA and the other metaheuristic algorithms, as evidenced by the minimum cost function (path length). Notably, the final independent run demonstrated the best results, which will be the basis for further evaluations. Fig. 7 illustrates the objective function of the HS algorithm employed to determine the optimal population for the WCA in the latest independent run. Meanwhile, Fig. 8 shows the evolution of the objective functions, demonstrating the effectiveness of the hybrid WCA-HS. Unlike classical metaheuristics, which converge to the same solution interval, the proposed algorithm finds a better range, escaping local optima and achieving superior results. Table 5 presents the waypoint coordinates corresponding to the optimal path lengths achieved using both the classical WCA and the hybrid WCA-HS.

Figs. 9 and 10 comprehensively illustrate the quadrotor's 3D and 2D path planning visualizations for assisting elderly individuals in a complex indoor environment, utilizing the proposed WCA-HS, respectively. Similarly, Figs. 11 and 12 illustrate the 3D and 2D path planning visualizations in the same environment, employing the classical WCA, respectively.

The 2D visualizations focus on the UAV's navigation in the longitudinal (x) and lateral (y) axes, demonstrating its ability to perform precise collision avoidance maneuvers. Meanwhile, the 3D visualizations emphasize the UAV's altitude along the vertical (z) axis, showcasing its capability to maintain a safe flight path, particularly in scenarios involving assistance for elderly individuals in very cluttered indoor environments.

In such scenarios, where various obstacles present significant challenges, the UAV's ability to seamlessly integrate obstacle avoidance with precise navigation becomes critical. The 3D visualization further highlights the UAV's capability to adapt its flight path dynamically, ensuring it can navigate over obstacles without compromising safety or efficiency. In Fig. 10, it is crucial to note that the 2D path planning visualization may appear to show the quadrotor in contact with obstacles due to the absence of altitude

Table 4 Path length comparison of the algorithms from 20 independent runs

No. runs	WCA-HS	WCA	HS	FA	CS	GA	DE	ACO	ABC
1	10.9608	26.2687	27.5803	29.1001	30.1101	30.1526	33.2675	27.1145	27.3394
2	11.2031	22.7981	23.2318	25.2521	29.1599	25.3636	36.6068	24.0012	23.0045
3	11.5128	29.6480	30.6361	31.4584	30.0555	31.1405	39.0012	30.8845	30.3791
4	10.8990	30.0014	33.8832	30.1220	32.0814	31.0025	30.5540	31.9998	31.1547
5	12.4042	27.5188	32.3675	29.5976	33.1616	33.1965	34.1793	29.8465	32.7744
6	11.1822	22.8191	32.8191	30.1289	30.9874	25.1114	23.4123	23.8203	30.2473
7	13.8192	24.1142	30.0152	26.2821	30.0563	29.0015	28.1336	26.4631	27.7894
8	11.4275	24.1724	27.0003	29.292	31.7896	33.9155	33.1474	25.9132	30.0047
9	10.9431	25.4376	29.1272	27.1458	30.2156	34.0078	36.5204	26.3346	30.1178
10	14.2178	26.5204	28.3092	30.8971	32.2028	34.5589	36.7091	28.0110	30.3775
11	12.3891	27.0437	32.0982	30.2137	31.9870	33.7254	34.3489	29.7204	31.4506
12	11.3471	28.8321	29.6582	30.5729	32.3640	31.4019	33.1063	30.0390	29.7345
13	11.8392	30.7154	33.1908	30.8765	32.0779	32.5096	34.2065	30.2523	31.1357
14	12.4102	28.9923	30.4167	32.1498	31.2042	34.8155	33.9583	29.8660	32.4208
15	11.6935	27.6342	32.1231	29.8259	30.8204	31.6920	34.3787	30.1235	31.7845
16	10.9105	24.7632	29.5719	28.5510	30.4183	31.1404	33.0112	27.3651	29.5280
17	12.0943	28.3246	30.2125	32.0772	30.5892	33.7253	34.1620	29.1589	31.4060
18	11.1589	25.9291	31.3847	29.7645	30.1894	32.0089	33.0652	28.1847	29.9934
19	11.0233	26.1823	30.2710	31.0459	32.5290	31.2208	33.6351	29.5065	30.5722
20	10.7208	28.2687	30.8641	31.7303	29.1908	31.5307	31. 5887	32.0997	30.6421

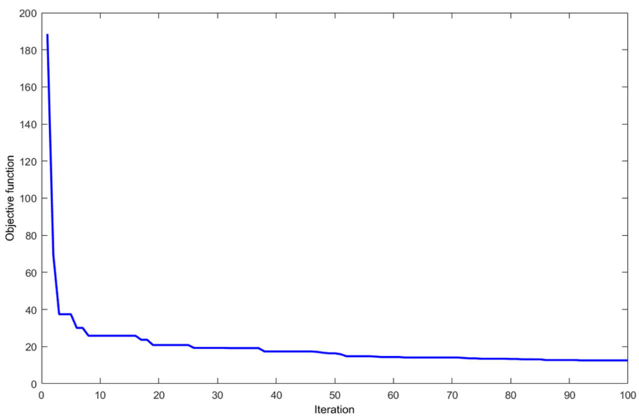

Fig. 7 Evolution of the objective function for the HS algorithm in the proposed hybrid WCA-HS

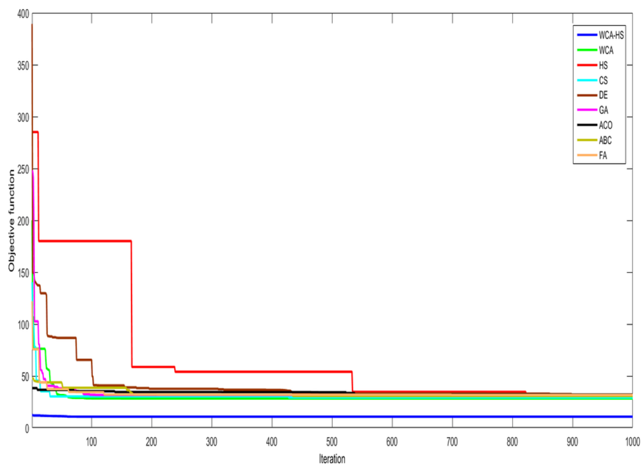

Fig. 8 Comparison of objective function evolution between hybrid WCA-HS and other metaheuristics

(z-axis) information. However, the 3D visualization clearly illustrates that the quadrotor maintains an appropriate altitude, avoiding all obstacles effectively. This capability is vital in assisting elderly individuals, ensuring that the UAV can deliver services or perform tasks without disrupting the environment or posing a risk. Both the classical WCA and the proposed hybrid WCA-HS effectively navigate around obstacles, ensuring safe UAV operation. However, the hybrid WCA-HS outperforms the classical WCA in terms of path optimization. Specifically, the hybrid WCA-HS achieves a reduction in total path length of over 18 m compared to the classical WCA, demonstrating its superior trajectory planning capabilities. This significant improvement is especially advantageous in cluttered indoor environments, where minimizing flight distance is critical for energy efficiency and operational effectiveness.

Fig. 13 illustrates the velocity components (V_x, V_y and V_z) of the quadrotor as determined by the path planning system, utilizing both the standard WCA and hybrid WCA-HS. These components successfully keep velocities within the 100 km/h (27.78 m/s) limit. As shown in

Table 5 Waypoint coordinates, optimal path lengths, and energy consumption

Waypoints	1	2	3	4	5	Path length (m)	Energy consumption (J)
WCA	(4.33, 2.85, 0)	(4.16, 3.85, 0)	(4.94, 3.95, 0)	(5.87, 3.57, 0)	(7.85, 6.31, 0.40)	28.2687	6.9236
WCA-HS	(1.96, 2.73, 1.96)	(2.75, 3.79, 2.75)	(3.59, 4.61, 2.33)	(4.27, 5.27, 2.26)	(5.48, 5.82, 2.22)	10.7208	2.0974

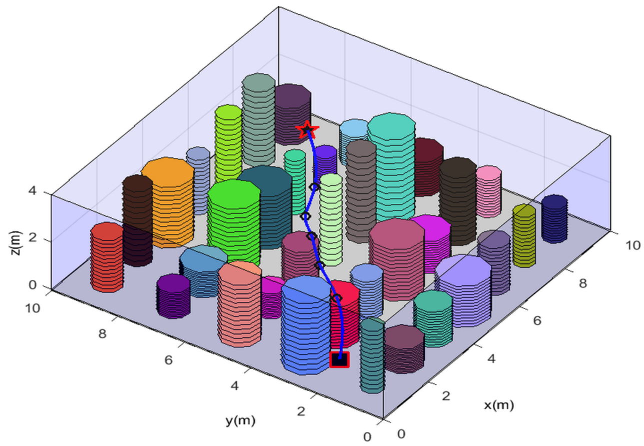

Fig. 9 3D visualization of path planning using the hybrid WCA-HS

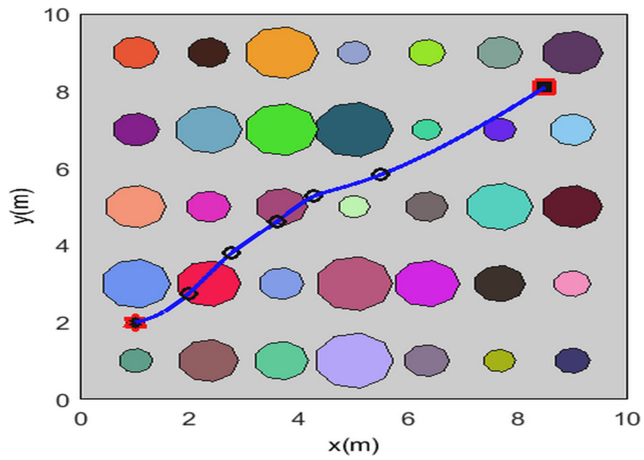

Fig. 10 2D visualization of path planning using the hybrid WCA-HS

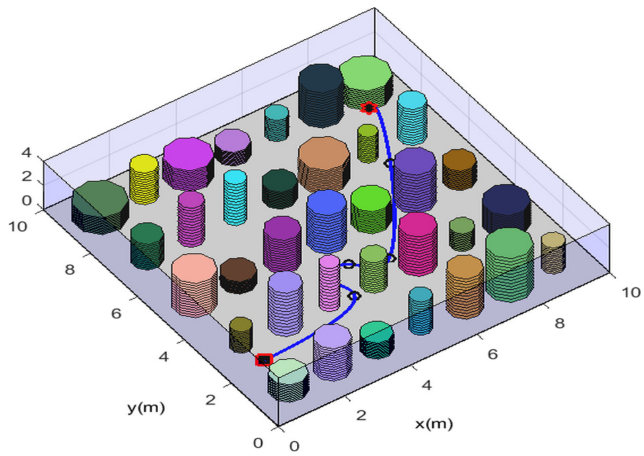

Fig. 11 3D visualization of path planning using the WCA

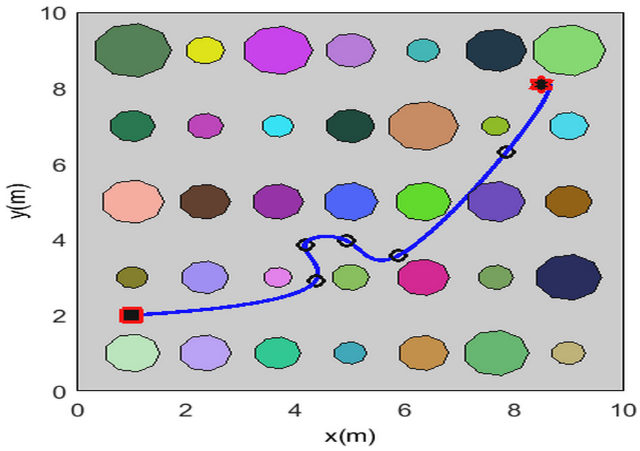

Fig. 12 2D visualization of path planning using the WCA

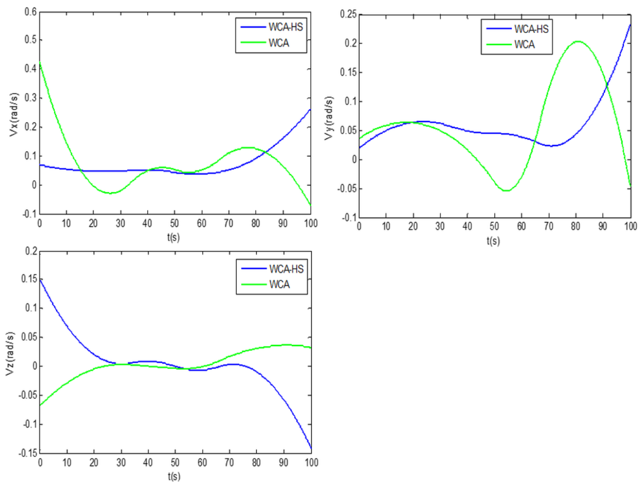

Fig. 13 UAV's velocities

Table 5, the proposed hybrid WCA-HS demonstrates the lowest energy consumption, highlighting its efficiency.

5.1 Evaluating the indoor path planning system in a highly cluttered environment

The proposed path planning system was tested in a highly cluttered indoor environment with 50 obstacles, using the same start and goal positions as previous experiments.

Figs. 14 and 15 illustrate the 3D and 2D trajectories, confirming the system's robustness and efficiency in complex environments. Despite the increased complexity, the UAV successfully avoided all obstacles, maintaining an optimized path length of 10.80 m and energy

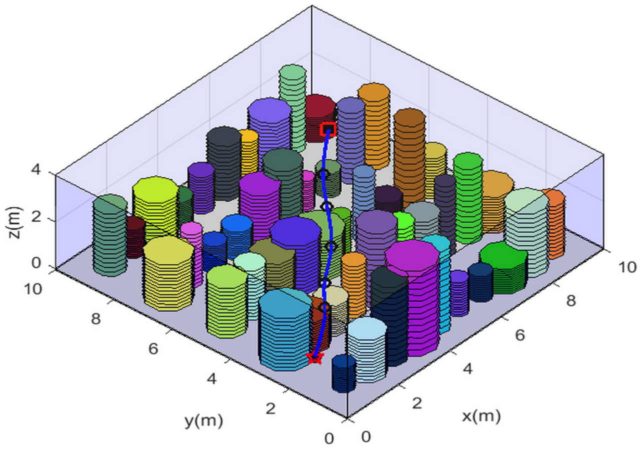

Fig. 14 3D visualization of path planning using the hybrid WCA-HS in a highly cluttered environment

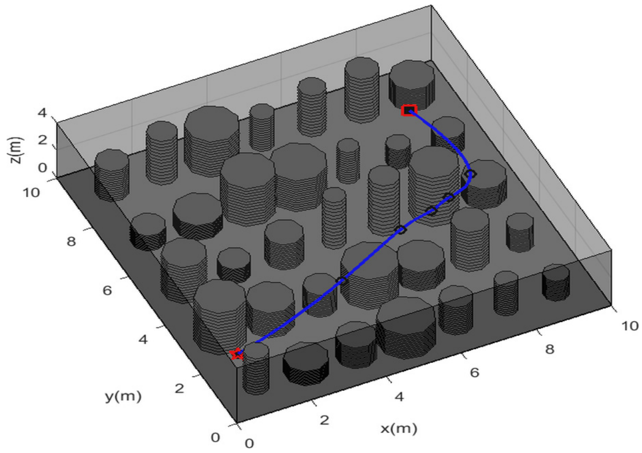

Fig. 16 3D visualization of path planning using the hybrid WCA-HS in low-light condition

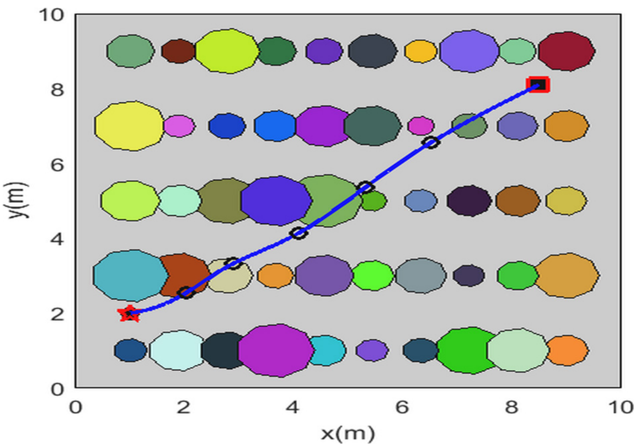

Fig. 15 2D visualization of path planning using the hybrid WCA-HS in a highly cluttered environment

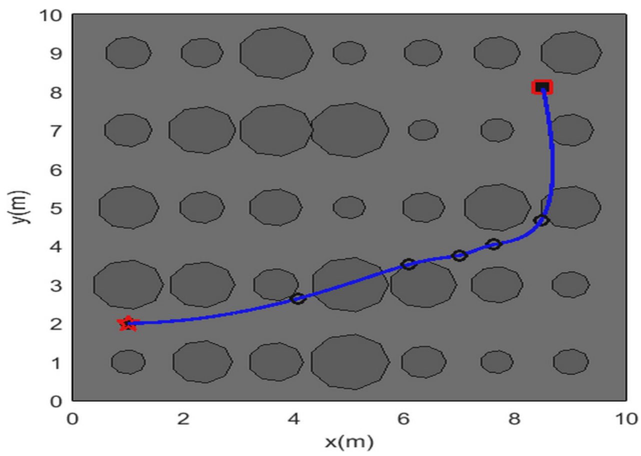

Fig. 17 2D visualization of path planning using the hybrid WCA-HS in low-light conditions

consumption of 2.2115 J, closely matching the results from the previous 35-obstacle test.

5.2 Evaluating the indoor path planning system in low-light conditions

To assess the system's performance under varying lighting conditions, test was conducted in a low-light using the same setup as the previous 35-obstacle experiment.

The results, illustrated in Figs. 16 and 17, confirm the system's robustness and adaptability to challenging indoor conditions. Despite reduced visibility, the UAV successfully navigated the space, avoiding obstacles while maintaining an optimized path length of 11.61 m and energy consumption of 2.5891 J.

5.3 Evaluating the indoor path planning system in a highly cluttered environment under low-light conditions

The system was tested in a highly cluttered indoor environment with 50 obstacles under low-light conditions to assess its robustness. Despite the increased complexity and reduced visibility, the UAV successfully avoided obstacles, achieving an optimized path length of 12.9183 m and energy consumption of 3.0291 J. Figs. 18 and 19 illustrate the 3D and 2D trajectories, confirming the system's adaptability to challenging indoor scenarios.

6 Conclusion

In this study, new hybrid metaheuristic algorithm named WCA-HS has been introduced for global optimization problems. The WCA-HS has been applied to develop an advanced path planning system for autonomous UAVs navigation during assisting elderly individuals, addressing the challenges of navigation in indoor environments by efficiently avoiding obstacles and optimizing performance. This algorithm is utilized to plane a shortest collision free path within an indoor cluttered environment. The results show that the new hybrid WCA-HS significantly outperforms the standard WCA, and other metaheuristics such as HS, FA, CS, GA, DE, ACO, and ABC,

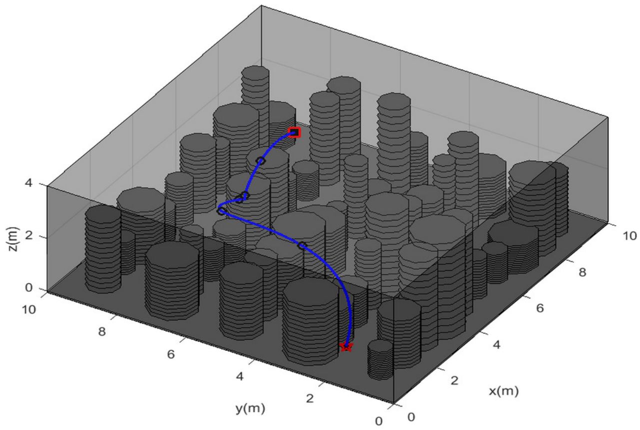

Fig. 18 3D visualization of path planning using the hybrid WCA-HS in a highly cluttered environment under low-light conditions

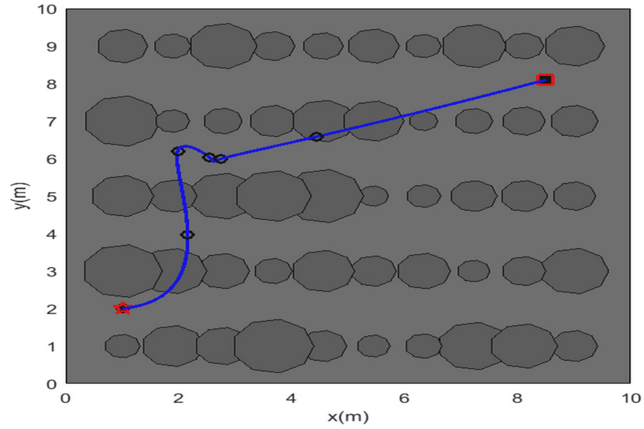

Fig. 19 2D visualization of path planning using the hybrid WCA-HS in a highly cluttered environment under low-light conditions

over 20 independent runs. The indoor path planning system ensures safe and efficient navigation in complex environments. Tested in cluttered, low-light conditions, it demonstrated robustness and real-world applicability, effectively assisting elderly individuals.

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