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Research Article

An Intelligent Route Planning Approach Using Modified Particle Swarm Optimization for Robot Assisted Minimally Invasive Surgery

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Abstract: Minimally invasive surgery offers several advantages, including reduced blood loss, smaller incisions, less pain, and a lower risk of complications than open surgery. This approach enhances patient comfort and supports faster recovery. When guided by optimal path planning, surgical robots can accurately navigate the body to remove malignant tumors with high precision. This study proposes a Modified Particle Swarm Optimization (MPSO) algorithm to determine the optimal path for robotic-assisted minimally invasive surgery targeting brain tumors. The algorithm improves upon standard PSO by modifying the velocity update equation and incorporating an adaptive inertia weight, enhancing convergence speed, global search ability, and solution accuracy. Experimental results show that the proposed MPSO achieves a maximum fitness value of 19.10 in a sparse obstacle environment, outperforming standard PSO and IPSO in quality and the required number of iterations. The approach effectively balances path efficiency and obstacle avoidance, making it well-suited for complex surgical scenarios. In conclusion, the MPSO-based method provides a reliable and precise solution for robotic surgical navigation, improving outcomes and safety in minimally invasive procedures.

Keywords: Intelligent Surgical Navigation; Modified Particle Swarm Optimization; Optimal Route; Particle Swarm Optimization; Robot Assisted Invasive Surgery.

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1. Introduction

Cancer treatment poses significant challenges due to the aggressive and unpredictable spread of malignant cells. A critical factor in improving therapeutic outcomes lies in understanding how these cells migrate and in accurately localizing tumor regions. Advances in medical imaging, particularly brain MRI segmentation, have enabled the precise identification of malignant tissues. However, removing these cells through minimally invasive procedures remains complex, especially when performed within anatomically dense and sensitive regions such as the brain. Robot-Assisted Invasive Surgery (RAIS)[1] has emerged as a promising solution for enhancing surgical precision and patient recovery. By minimizing incision size, blood loss, and collateral tissue damage, RAIS allows for safer and more efficient tumor resection. A key requirement in RAIS is optimal path planning, which enables robotic instruments to reach the target tumor site with minimal disruption to surrounding structures. This involves determining the shortest and safest route while avoiding obstacles like blood vessels and nerve tissues.

To address this problem, we propose a novel approach using the Modified Particle Swarm Optimization (MPSO) algorithm. MPSO extends the standard PSO by introducing dynamic inertia weight and refined velocity update equations, allowing particles (candidate paths) to better explore and exploit the search space. These enhancements improve convergence speed and prevent stagnation in local optima [2], [3].

Compared to conventional algorithms such as A*, which may falter in dynamic or high-dimensional surgical environments, and Genetic Algorithms (GA), which often require laborious parameter tuning, MPSO offers a more adaptive and computationally efficient framework. Its ability to navigate complex neural structures makes it highly suitable for surgical path optimization in RAIS. Moreover, learning-based optimization strategies similar to MPSO have demonstrated efficacy in autonomous navigation tasks [4]. Further supporting its relevance for robotic surgery. This study presents an intelligent route planning framework based on MPSO for application in RAIS targeting brain tumors. The proposed system is evaluated using segmented MRI images under varying obstacle densities, demonstrating its effectiveness in guiding robotic tools with improved accuracy, safety, and operational efficiency.

2. Literature Review

Tan et al. [5] present an innovative path-planning approach for surgical needles, utilizing adaptive intelligent PSO with force and motion analysis of a bevel-tip flexible needle. The approach addresses challenges in percutaneous puncture therapy by navigating complex obstacles, achieving a path planning error under 1mm and improving accuracy tenfold compared to current methods. Zhang et al. [6] explore preoperative planning for a multi-arm surgical robot, combining PSO with Gaussian Process (GP) techniques to optimize performance metrics like the Global Isotropy Index (GII), Cooperation Capability Index (CCI), and Manipulability Dexterity Index (MDI). The strategy improves surgical robot performance by optimizing port positions and arm placements, with future work planned to test the method on a four-arm system. Ramezanlou et al. [7] introduce a hybrid algorithm combining optimal control and PSO for robot path planning, addressing the weaknesses of individual methods. Applied to a four Degrees of Freedom (DOF) surgical robot system, the algorithm improves cost function independence and reduces reliance on initial guesses, making it more effective than traditional methods. Supakar et al. [8] propose a Modified PSO(MPSO) for robot navigation in unknown environments, improving path planning efficiency and convergence compared to standard PSO. The MPSO algorithm combines global and local search strategies to navigate obstacles and optimize paths in dynamic settings. Baek et al. [9] present a collision avoidance method for resection automation using PRM and RL, tested on the APOLLON laparoscopic robot system. Integrating Q-learning allows the system to adapt and optimize its path planning for tasks like resection and cholecystectomy. Bhattacharya et al. [10] focus on optimizing reader placement in RFID networks within a store using PSO, reducing deployment costs while maintaining read accuracy. The PSO-based algorithm adjusts particle velocity and position to find optimal placements, effectively minimizing costs. Malik and Kim [11] use PSO for optimal travel route recommendations, considering factors like user preferences and road conditions to enhance tourism experiences. The study uses data from Jeju Island to evaluate the method's effectiveness, comparing it to non-optimized techniques and genetic algorithms. Li et al. [12] introduce an Improved PSO (IPSO) algorithm for mobile robot path planning, addressing PSO's slow convergence. IPSO outperforms existing algorithms by combining cubic spline interpolation, exponential attenuation inertia weight, and enhanced control learning factors, reducing path length and processing time. Previous studies on PSO modifications highlight the need for IPSO's improvements in global path planning. Prabu et al. [13] apply PSO to optimize power consumption in Wireless Sensor Networks (WSN), focusing on residual energy to select the optimal controller node. The study emphasizes the importance of fitness functions in WSN optimization. Jakubcova et al. [14] compare 27 modifications of the original PSO algorithm, finding that a version with adaptive inertia weight and SCE PSO distribution strategy achieves the best optimization results for most functions. The study's shuffling mechanism prevents premature convergence. Jain et al. [15] call for continued research on PSO to address challenges like local optima and premature convergence, proposing further exploration in applications and hybridization. "OkayPlan" introduced by [16] is a global path-planning algorithm designed for dynamic environments. By formulating the path planning problem as an Obstacle Kinematics Augmented Optimization Problem (OKAOP), the authors employ a PSO-based optimizer to achieve real-time performance, demonstrating enhanced path safety, optimality, and computational efficiency in dynamic scenarios. Mishra et al. [17] proposed a hybrid path-planning algorithm that combines PSO with Artificial Potential Fields (APF). The integration aims to overcome the individual limitations of each method, resulting in superior path planning performance. The algorithm's efficacy is demonstrated through various 2D experimental scenarios. Xin et al. [18] introduce a Self-Evolving PSO (SEPSO) algorithm tailored for dynamic path planning. The algorithm achieves superior real-time performance and avoids premature convergence by converting particle-wise manipulations to tensor operations and implementing a Hierarchical Self-Evolving Framework (HSEF). Meanwhile, coordination strategies in multi-robot environments using smooth parametric trajectories such as NURBs have also been investigated [19]. Q. Yuan [20] proposes an improved PSO algorithm incorporating differential evolution for mobile robot path planning. The algorithm enhances convergence speed and search precision, effectively optimizing path length and safety in various simulation tests.

3. Proposed Method

This study proposes an intelligent route planning approach using the MPSO algorithm to determine the optimal surgical path for RAIS. The method builds upon the standard PSO framework [21], where a swarm of particles—each representing a potential path—searches the solution space by iteratively updating positions based on personal and global best experiences[22], [23]. In this context, the surgical environment is derived from segmented MRI images, where anatomical obstacles such as blood vessels and nerves are treated as high-cost or impassable regions. The proposed system evaluates three scenarios with increasing obstacle density: sparse, dense, and highly dense, simulating varying levels of anatomical complexity.

The algorithm defines four strategic starting points around the tumor to initiate the process. For each particle (representing the robotic arm and surgical tool path), MPSO dynamically adjusts positions and velocities based on a fitness function that considers five factors: the Euclidean distance to the tumor, proximity to obstacles, energy efficiency, inertia weight, and a number of encountered obstacles[2], [3].

The update mechanism effectively balances exploration and exploitation [24], [25]. Paths that avoid collisions and minimize travel distance receive higher fitness values, while infeasible routes are penalized. Through iterative refinement, the algorithm converges toward an efficient, safe, and feasible path for real-time robotic execution during RAIS. By integrating multiple starting points, the method increases robustness and avoids convergence to suboptimal paths. This design supports practical deployment in neurosurgical procedures, where flexibility and accuracy are critical.

3.1. Implementation Considerations

Several enhancements are introduced in the proposed MPSO framework to improve search efficiency and robustness in surgical path planning. These include:

- Dynamic inertia weight adjustment, which governs the trade-off between global exploration and local exploitation during each iteration;
- Velocity update formulation that incorporates both cognitive and social learning components;
- The fitness function design, tailored for medical imaging contexts, evaluates path feasibility based on anatomical constraints extracted from MRI segmentation.

Each scenario, i.e., sparse, dense, and highly dense, is modeled with 5, 10, and 15 obstacles, respectively. The algorithm iterates over these environments, adapting particle trajectories to avoid high-risk areas and identify the optimal route to the tumor site. The next sections detail the specific learning parameters, fitness function formulation, and algorithmic steps used in this implementation.

3.2. Improved Learning Factor for the Proposed Model

To support effective path planning in RAIS, several learning factors are introduced in the MPSO model to refine the behavior of each particle (i.e., candidate surgical path):

- Distance between a starting point and malignant tumor cell: Initializes the coordinate of a starting point (the insertion points of the robotic arm) and brain tumor cell from a segmented MRI image. In this case, the distance is observed by applying the Euclidean distance formula. It should have the lowest possible value.

- Distance between current operating point and nearby obstacles: Initializes the positions of nearby obstacles randomly. We must choose a maximum distance from obstacles to the current operating point to avoid any possible obstacles.
- The particle's energy (Surgical Instrument): In this paper, the particle's energy initializes to 0.5, which will change subsequently through iterations.
- The number of obstacles: Inside the brain, blood vessels, nerves, etc., are considered obstacles. A minimum number of obstacles along the path results in an efficient route.
- Inertia weight is one important parameter that balances the algorithm's local and global search capacity.

These factors directly influence the particle's movement and contribute to the overall fitness evaluation discussed below.

3.3. Description of the Fitness Function

The fitness function is a crucial component of the PSO algorithm. It converts the particle values into real numbers, indicating how well a given particle solves the optimization problem. The function is designed to evaluate and "reward" particles that are closest to the ideal solution, guiding the search toward the optimal path. The fitness function's formulation depends on the optimisation problem's specific nature. In the context of this work, the maximum fitness value is considered, which should be as close as possible to the optimal solution. This ensures that the particles with the best performance are selected, leading the algorithm to the most efficient and feasible path for the robotic arm to reach the malignant tumor. The fitness function plays a key role in the overall success of PSO, balancing the search for an optimal solution with the need for safe and efficient navigation in a complex environment. The function (f) is formulated as Equation (1).

$$f = \left(\frac{1}{d_1}\right) + d_2 + w\left(\frac{e_p}{n}\right) \tag{1}$$

Where d_1 is the distance between the starting point and the malignant tumor cell; d_2 is the sum of the distance between the current operating point and nearby obstacles; w is inertia weight; e_p is the particle's energy; n is the number of nearby obstacles. Maximum fitness value helps the particle to determine the best neighbouring node along the path to the tumor cell in the segmented MRI image.

3.4. Proposed Route Planning Approach

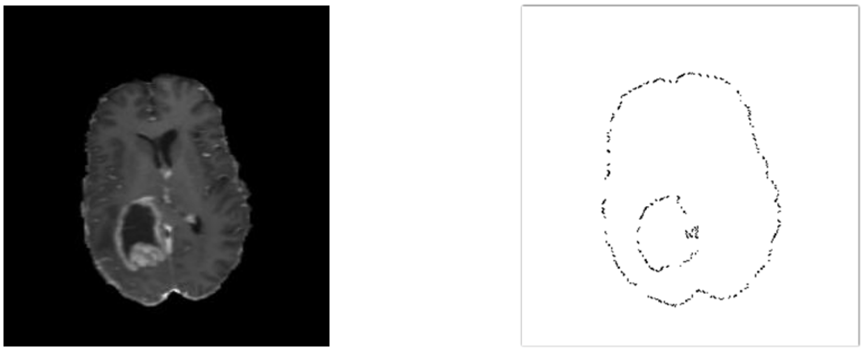
Optimal route planning, especially for navigating to a malignant brain tumor region while avoiding obstacles, involves a sophisticated blend of various parameters and scenarios. A pivotal component of this approach is the MPSO algorithm [24], which regulates its parameters such as inertia weight (w), cognitive parameter (c_1) and social parameter (c_2) to navigate effectively through different environments. The MPSO algorithm is designed to operate in three distinct environments characterized by different obstacle densities:

1. Sparse Environment: Contains 5 obstacles, offering fewer navigational challenges.
2. Dense Environment: Includes 10 obstacles, increasing complexity.
3. Highly Dense Environment: Features 15 obstacles, presenting the highest level of difficulty for pathfinding.

As obstacles increase in a highly dense environment, the fitness function's sensitivity to obstacle contiguity must be heightened. The planning algorithm iteratively adjusts the particles' paths, continuously improving until the optimal path with maximum fitness value is found. Throughout this process, obstacle avoidance mechanisms such as potential fields or additional repulsion terms in the fitness function are critical. These mechanisms dynamically alter paths to circumvent obstacles efficiently. Therefore, the combined effect of finely tuned PSO parameters, an adaptive fitness function and robust obstacle avoidance strategies ensures the identification of an optimal and safe path to the malignant tumor in various environmental complexities. The environmental description and the execution of the proposed approaches are defined below.

Step 1: Create a Simplified Environment from MRI images

Apply a Deep Learning technique to segment brain images[26], identifying and extracting coordinates for the entire image and the tumor region. Next, transform the segmented images into a simplified representation, clearly highlighting the tumor's location within the MRI image. Figure 1. represents both original and segmented MRI images for Brain Tumor.



(a) (b)

Figure 1. MRI image of the brain along with tumor cells. (**a**) Before segmentation; (**b**) After segmentation.

Step 2: Initialize Point

Select multiple random points (up to four) within the segmented image and near the detected tumor region to serve as starting points. Any point within the segmented tumor region will be considered the destination point. Randomly assign additional points between the starting and destination points as obstacles, representing areas such as blood vessels or nerves, based on the segmentation results. These obstacles indicate regions to avoid during further analysis or planning.

Step 3: Apply MPSO Algorithm

Apply the MPSO algorithm as stated in section 5 in three different environments – sparse (number of obstacles is set as 5), dense (number of obstacles is set as 10) and highly dense (number of obstacles is set as 15). In Figure 2, the path originating from the starting point at coordinates (66, 125) has been traced and observed. The path highlights the connection from the selected starting point to the designated destination, navigating around obstacles identified in the segmented image.

(a) (b)

Figure 2. Route generated: (**a**) In a sparse environment; (**b**) In dense environments.

Step 4: Identification of Optimal Route

Once the algorithm converges, the optimal path for the surgical tool to reach the malignant tumor is determined by analyzing the final position of the particle within the solution space. This path ensures minimal interference with obstacles, such as blood vessels or nerves, while providing an efficient and precise approach to the tumor.

Step 5: Execution in Robotic Surgery

The suggested ideal route can be implemented by the Robotic Surgical System during minimally invasive treatment, allowing for precise navigation to the tumor site. This approach minimizes damage to the surrounding healthy tissues, enhancing the accuracy and safety of the procedure. Figure 3 describes the optimal route planning using the MPSO algorithm.

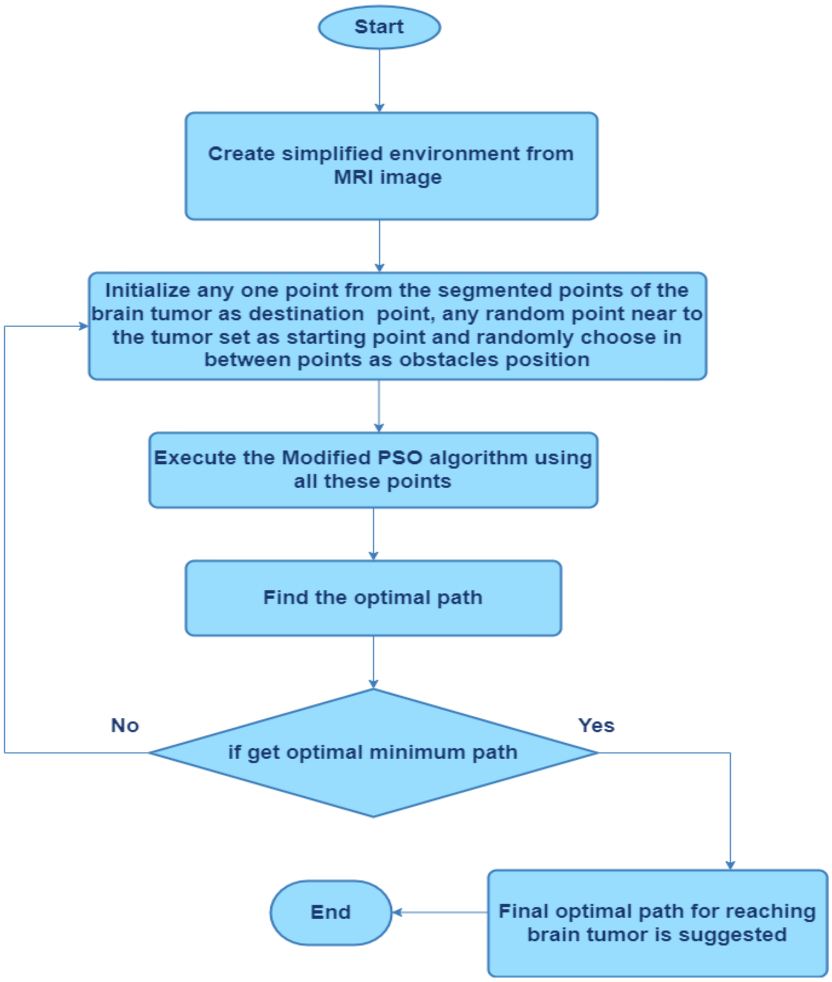


Figure 3. Flowchart of optimal route planning using MPSO.

The step-by-step computational implementation of this proposed approach is outlined in Algorithm 1.

Algorithm 1. Optimal route planning using MPSO

INPUT: Segmented MRI image of brain

OUTPUT: An optimal route to reach the malignant brain tumor region

// Initializes starting point (x_i, y_i), destination point (x_f, y_f), obstacle positions (x_{oi}, y_{oi}) where the range will be starting point to destination point, velocity as [0,0], the energy of the particle as 0.5, max_iteration as 100

Loop:

For i in range (1, $max\_iteration$) do

$dis_{po} = \sum_{oi=1}^{n} \sqrt{(x_i - x_{oi})^2 + \left(y_i - y_{oi}\right)^2}$ //distance between the current point and nearby obstacles.

$dis_{pf} = \sqrt{\left(x_i - x_f\right)^2 + \left(y_i - y_f\right)^2}$ //distance between current point and destination point.

$f = \left({}^{1}/_{dis_{pf}}\right) + dis_{po} + w\left({}^{e}/_{no.of\ obstacles}\right)$ //fitness function used in PSO

end for

//Select maximum fitness value and update p_{best} and g_{best} value according to f value

$x_i = \frac{\left((m \times obstacles[max_{fit}][0]) + (n \times pasticle[0])\right)}{m \times n}$

Algorithm 1. Optimal route planning using MPSO (Cont…)

8: $y_i = \frac{\left((m \times obstacles[max_{fit}][1]) + (n \times pasticle[1])\right)}{m \times n}$
where distance between current point and nearby obstacles divided in $m{:}\,n$ ratio
9: Set (x_i, y_i) as p_{best} and g_{best}
//Update velocity of particle
10: $v_i(t+1) = w \times v_i(t) + c_1 \times r_1 \times \left(p_{best} - x_i(t)\right) + c_2 \times r_2 \times g_{best} - x_i\,(t))$
where w, c_1, r_1, c_2, r_2 constant values, $p_{best} = g_{best}$, $v_i(t)$ initial velocity and $x_i(t)$ is current position of the particle
//Update position of particle
11: new_position = current_position $+ v_i(t+1)$
12: **end loop**
13: **if** $dis_{pf} \neq 0$ then
14: **goto loop**
15: **end if**
16: Output Solution and Return

4. Experiential Results and Analysis

4.1. Experimental Setup

The simulation for optimal path selection in robot-assisted surgery is implemented in Python, using segmented MRI images as the foundation for constructing the surgical environment. These images are preprocessed using libraries such as OpenCV and NumPy to extract anatomical regions of interest, specifically, the tumor (target area) and critical structures like blood vessels and nerve cells, which act as obstacles. The 2D environment is created by mapping the segmented MRI slices into a coordinate grid, where each pixel corresponds to a physical location in the anatomy. Obstacles are introduced by generating binary masks from the segmented images and translating these into an occupancy grid or cost matrix, where obstacle regions are assigned high traversal costs or marked as impassable. The MPSO algorithm searches for the optimal path from a defined surgical entry point to the tumor, with each particle representing a candidate trajectory. The fitness function evaluates each path based on its length, safety (distance from obstacles), and smoothness, applying penalties for intersecting or approaching sensitive structures. Visualization is performed using matplotlib, allowing the dynamic plotting of the surgical field, obstacle regions, tumor location, and particle trajectories. This visual feedback not only aids in interpreting the algorithm's behavior but also helps validate the safety and efficiency of the generated paths. The simulation provides a realistic, flexible environment for testing and refining path-planning algorithms in robot-assisted surgical procedures.

4.2. Empirical Analysis

We have performed experiments to find out the optimal value of inertia weight (w), cognitive parameter (c_1) and social parameter (c_2) considering four starting points (the insertion points of the robotic arm) and the targeted tumor cell. From empirical analysis it can be observed that for four different starting points, it generates different optimal values for w, c_1 and c_2 respectively, as presented in Table. 1.

Table 1. Four starting points and the corresponding optimal values of w, c_1 and c_2.

Starting Points	Inertia Weight (w)	Cognitive Parameter(c_1)	Social Parameter(c_2)
61,155	0.5	0.8	0.8
66,125	0.5	0.6	3.5
70,191	0.6	0.4	2.5
76,68	0.5	0.6	2.5

Figure 4. describes the comparison among all the values of inertia weight (w), cognitive parameter (c_1) and social parameter (c_2) for four different starting points.

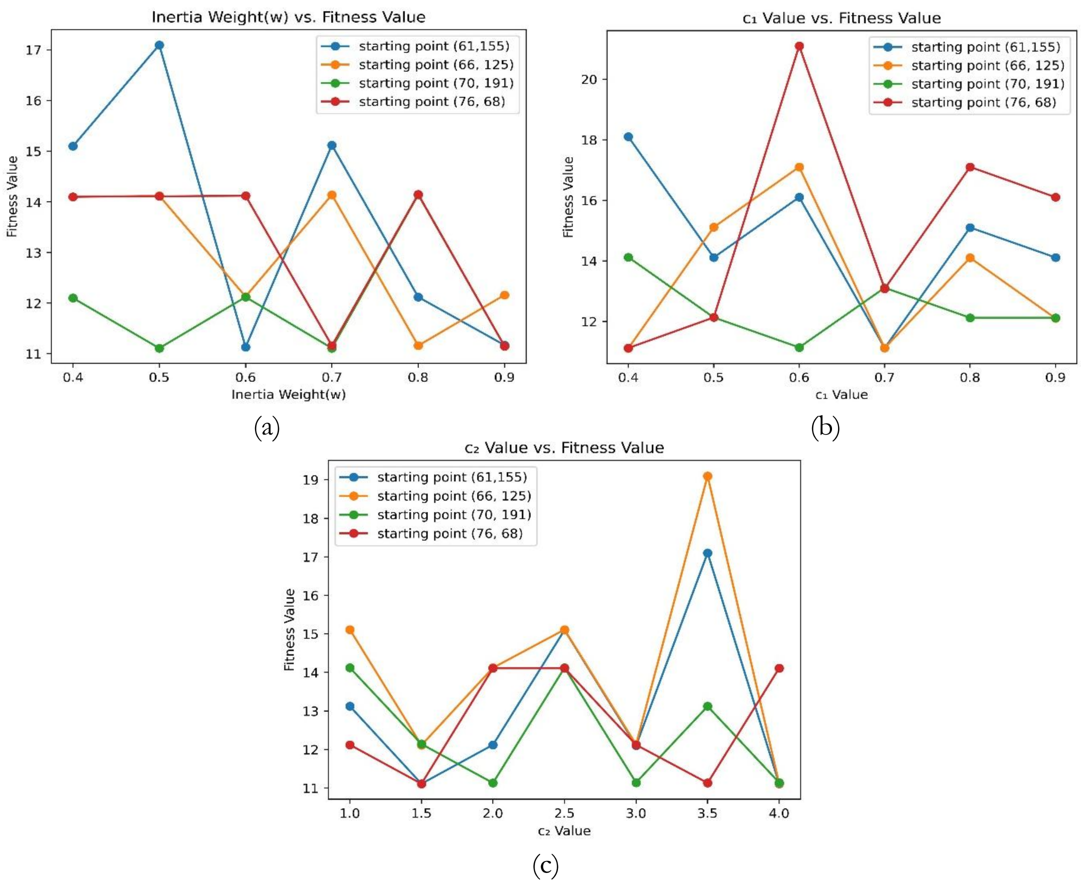


Figure 4. Finding optimal value of (**a**) Inertia weight (w); (**b**) Cognitive parameter (c_1); (**c**) Social parameter (c_2).

4.3. Results analysis

The MPSO algorithm is used for path planning from four distinct starting points toward a targeted tumor cell in a simulated environment. Each starting point represents a potential insertion point for the robotic arm, and the tumor site serves as the destination. The simulated environment contains various obstacles, such as blood vessels and nerves, which must be avoided to ensure safe navigation. The MPSO algorithm initializes particles near each starting point, evaluating their fitness based on path length and obstacle avoidance. The optimal values for inertia weight (w), cognitive parameter (c_1), and social parameter (c_2) are computed for each starting point to balance exploration and exploitation in the search for the optimal path. The particles iteratively update their positions, converging on the ideal route that minimizes the path length while avoiding obstacles. The paths generated by MPSO are distinct for each starting point, adapting to different obstacle configurations and demonstrating efficient and safe navigation. The results show that MPSO provides a reliable and adaptable solution for robotic path planning in minimally invasive surgeries, ensuring precise navigation to the tumor while minimizing damage to surrounding tissues. We have considered three distinct environments, as described below.

4.3.1. Sparse Environment

In a sparse environment where the number of obstacles is set to 5. It can be observed from Fig. 5 that the paths originating from points (66, 125) and (76, 68) achieved the best results, successfully avoiding all obstacles (such as blood vessels, nerves, etc.) along the solution path. However, the paths from the other two starting points failed to produce feasible results. Further analysis revealed that the starting point (66, 125) yielded the best fitness value of 19.10 among the two feasible solutions, making it the recommended optimal solution for this particular problem instance.

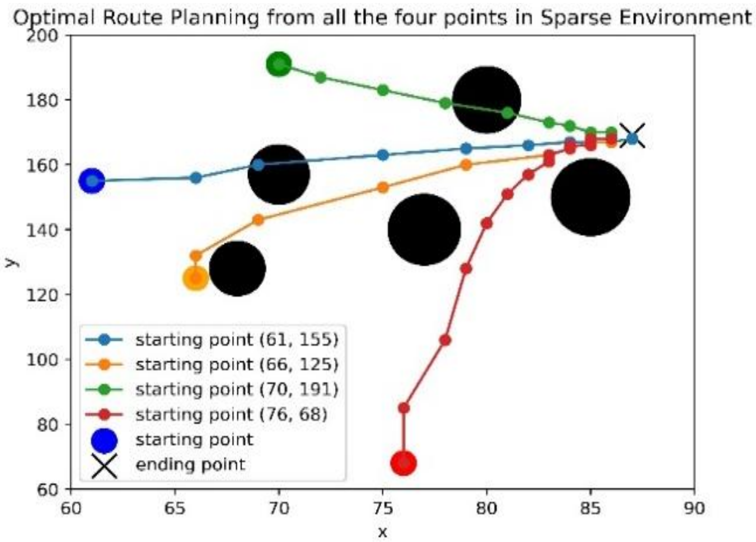


Figure 5. Experimental comparison of the four starting points in a sparse environment

4.3.2. Dense Environment

In a dense environment, where the number of obstacles is set to 10, it can be observed from Fig. 6 that the paths emerging from the points (66, 125) and (76, 68) achieved the best results, as both paths successfully avoided obstacles. However, the other two starting points failed to generate any feasible results. Between the two feasible solutions, the starting point (76, 68) produced the best fitness value of 22.07 and the best solution for the problem instance.

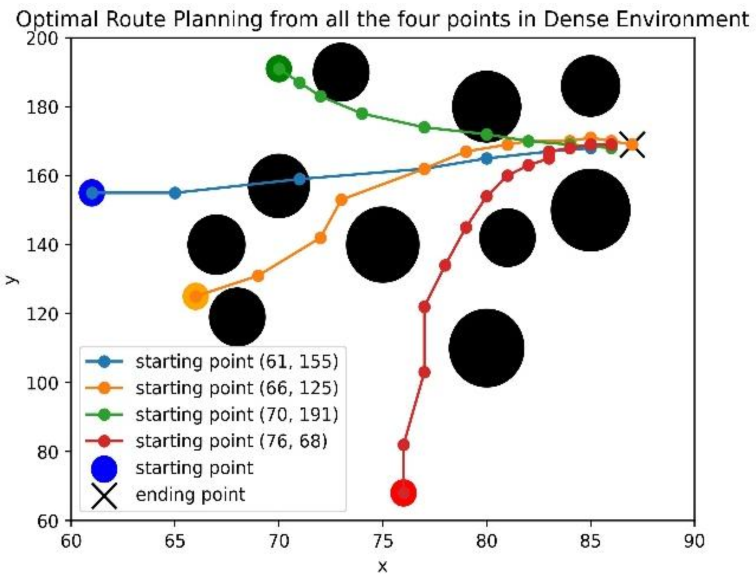


Figure 6. Experimental comparison of the four starting points in a dense environment

4.3.3. Highly Dense Environment

In this complex environment, where the number of obstacles is set to 15, it can be observed from Fig. 7 that the path originating from the point (66, 125) achieved the best result, successfully avoiding all obstacles. The other three starting points failed to generate any feasible results. This experiment also revealed that the starting point (66, 125) provided the best fitness value of 14.08, making it the recommended optimal solution for this particular problem.

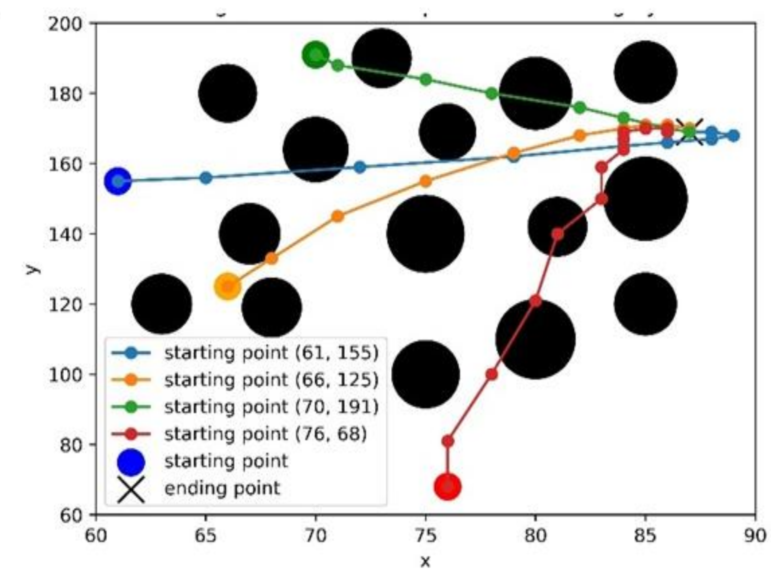


Figure 7. Experimental comparison in a highly dense environment

Another experiment was conducted to determine the best fitness values for sparse, dense, and highly dense environments, considering four different starting points: (61, 155), (66, 125), (70, 191), and (76, 68). As observed in Fig. 8, the starting point (66, 125) yielded the maximum fitness value of 19.10 in the sparse environment. In the dense environment, the starting point (76, 68) produced the most promising solution, with a fitness value of 22.07. In contrast, in the highly dense environment, points (61, 155) and (66, 125) achieved the highest fitness value of 14.08, making them the most promising solutions. The path derived from the point (66, 125) demonstrated the best fitness value at inertia weight (w) = 0.5, cognitive parameter (c1) = 0.6, and social parameter (c2) = 3.5 across all experiments. This path also successfully avoided all obstacles, including blood vessels, nerves, and other objects, even in an extremely dense environment with 15 obstacles.

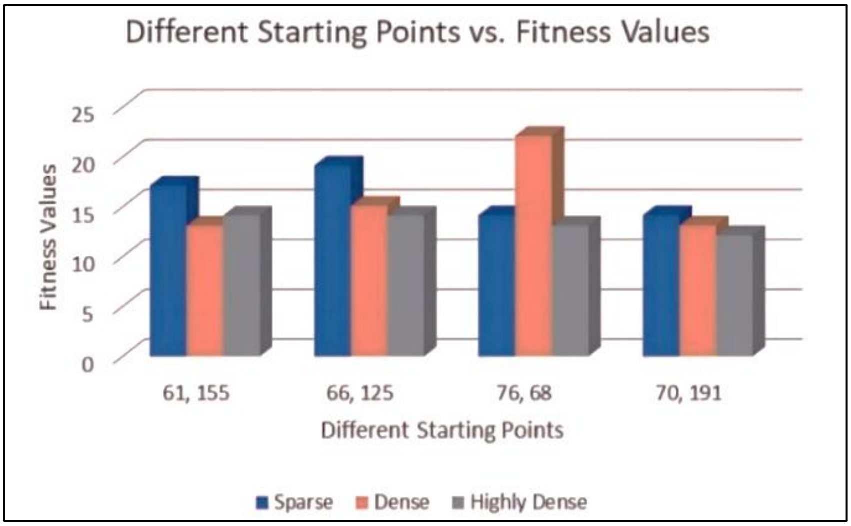
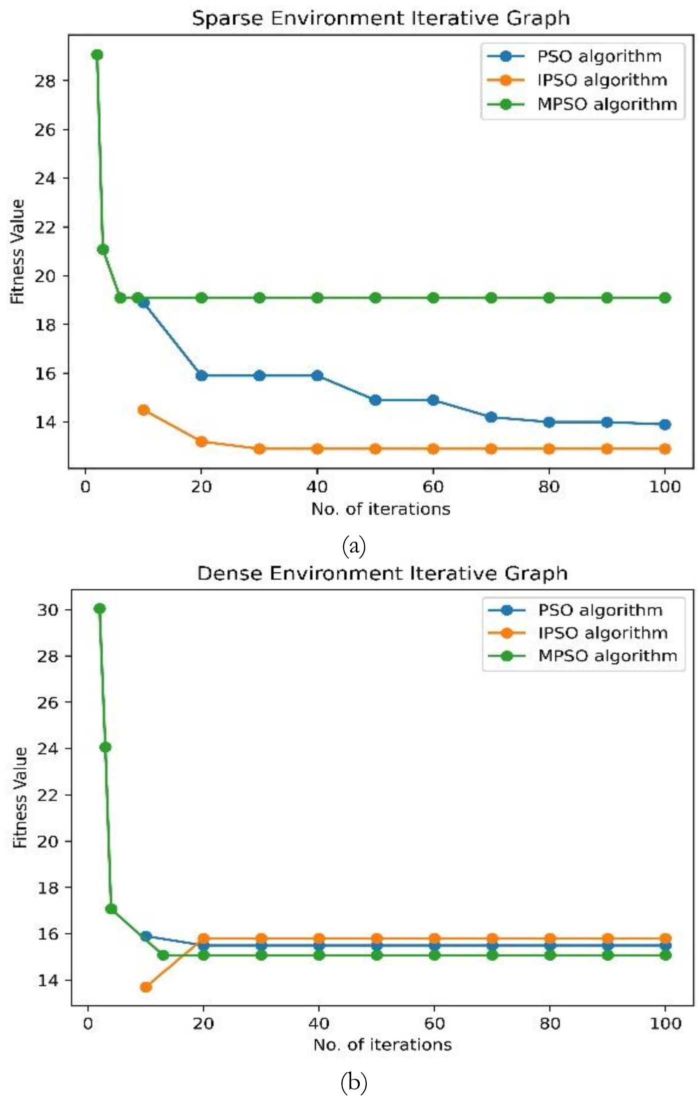


Figure 8. Comparisons of different fitness values

Finally proposed MPSO algorithm was evaluated in both sparse and dense environments, with its performance compared against the standard PSO and Improved PSO (IPSO) algorithms [12]. In the sparse environment Fig. 9. (a), MPSO demonstrated superior performance, achieving a maximum fitness value of 19.10 and converging within approximately 10 iterations. In contrast, PSO and IPSO achieved lower maximum fitness values of 14.00 and 12.90, requiring 80 and 30 iterations, respectively, to reach the target. This indicates that MPSO not only produced better quality solutions but also did so more efficiently in terms of the number of iterations required. In the dense environment Fig. 9. (b), although the maximum fitness value obtained by MPSO was recorded as slightly lower than 15.08, it still showcased faster convergence by reaching this value in about 13 iterations.

On the other hand, PSO and IPSO produced slightly higher fitness values of 15.50 and 15.80, but both required 20 iterations to achieve these results. Despite the marginally lower fitness value in the dense environment, the quicker convergence of MPSO indicates its efficiency and potential for better performance, particularly in sparse environments. These results highlight the MPSO algorithm's capability to produce high-quality solutions more rapidly than the standard PSO and IPSO algorithms, underscoring its effectiveness in varying environmental conditions. Initially, the fitness value was found to be larger compared to successive iterations. This phenomenon can be attributed to the initial condition where the distance between the insertion point of the robotic arm (the starting point) and the targeted malignant cell in the segmented MRI image was at its maximum. As the program progresses and iterates, the algorithm works towards minimizing this distance, gradually decreasing the fitness value. The fitness value reflects how close the robotic arm is to achieving its goal of accurately targeting the malignant cell. The large initial distance initially results in a higher fitness value, indicating a suboptimal state. Each iteration reduces the distance as the algorithm converges towards an optimal solution, lowering the fitness value. This iterative process of minimizing the distance highlights the algorithm's efficacy in improving the precision of the robotic arm's movements, ultimately leading to the accurate targeting of the malignant cell in the MRI image.



(b)

Figure 9. Comparison of Iterative Convergence among PSO algorithm, IPSO algorithm and MPSO algorithm in (**a**) Sparse environment; (**b**) Dense environment.

5. Conclusions

This paper describes the MPSO algorithm to analyse complex patterns in medical images accurately, and the result is an intelligent optimal path planning approach for Robotic Assisted Invasive Surgery. Using an efficient search space exploration approach, this strategy seeks to find optimal solutions that minimise path length, avoid obstacles and maximise tumour region convergence while reducing recovery time and pain for patients undergoing cancer treatment. The MPSO algorithm reduces the risk of damaging healthy tissues, speeds up computation times, allows for real-time decision-making during surgery, shortens operation times and improves accuracy by specifying values for the inertia weight (w), cognitive parameter (c_1) and social parameters (c_2). The suggested ideal path might need to be dynamically adjusted during surgery to account for variations in the tumour's size, shape, or location. Future research should concentrate on strong safety precautions and fail-safe mechanisms to shield patients from unintentional injury. With potential applications extending beyond brain tumour surgery to various cancerous tumour surgeries, the MPSO algorithm significantly improves surgical outcomes by providing a dependable and optimised path that combines safety and precision, crucial components in contemporary medical procedures.

While the MPSO approach demonstrates promising results in surgical path planning, several limitations exist. First, the performance of MPSO is highly dependent on parameter tunings, such as inertia weight and acceleration coefficients—which may require empirical adjustment for different surgical scenarios. Additionally, although MPSO excels in continuous spaces, it may struggle with fine-grained obstacle boundaries, especially in cases where anatomical structures are densely packed or poorly segmented. The method also assumes static obstacles and does not account for tissue deformation or real-time changes during surgery, which limits its applicability in dynamic, real-world environments. Furthermore, MPSO can be computationally expensive for high-resolution MRI-based maps, especially when the search space is large or requires high-precision avoidance. Lastly, validation is currently limited to simulated environments, and the method has not yet been tested on actual surgical robots or in clinical settings, which may introduce unforeseen practical challenges.

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