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# Selecting Dynamic Path Planning Algorithm Based-Upon Ranking Approach for Omni-Wheeled Mobile Robot

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**ABSTRACT**

Four Omni Wheels Mobile Robot (4OWMR) are widely utilized for indoor navigation applications such as autonomous transportation, surveillance, rescue, and search. This paper proposes a ranking approach to select the dynamic path planning algorithm. The selection process involves implementing the four path planning techniques (PRM, RRT, RRT*, Hybrid A*) on three different maps. The Weighted Sum Model (WSM) is then applied to each map to rank these algorithms based on several factors. Finally, the points of each algorithm in the three maps are added up, and the algorithm with the highest score is selected as the dynamic path planning algorithm. The results indicate that the Hybrid A* algorithm surpasses the others, scoring 46 points, which represents a 21.7% increase compared to PRM and RRT, and a 30.4% increase compared to RRT* when using the weighted sum ranking technique. Therefore, it can be selected as the dynamic path planning algorithm.

## 1. Introduction

In contemporary times, the progress of intelligent and adaptable mobile robots has been propelled by modern industry and logistics. The demand for teleoperated or self-governing wheeled mobile robots has been continuously growing to support or take the place of human laborers in diverse work settings as discussed by Li *et al.,* [1]. The utilization of mobile robots is necessary for indoor applications such as offices, warehouses, pharmacies, and various industrial sectors. In hazardous or inaccessible situations, mobile robots can be the ideal option for navigation or assistance tasks as discussed by several authors [2-5].

In recent times, substantial research has been conducted in the field of mobile robots, specifically concentrating on their path planning techniques, design, and control. Omni-directional wheels on mobile robots provide instantaneous omnidirectional motion, including lateral movement, without requiring more area to change direction. As Massoud *et al.,* [6] have demonstrated, this enables these

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robots to move in any direction, irrespective of their orientation, and successfully arrive at their destinations, even in constricted aisles or cramped areas.

Mobile robots' path planning generation and optimization are major research topics. Path planning involves planning a robot's route from an initial location to a final destination within a predetermined area or chamber. Often, the produced path for the robot necessitates additional optimization and improvement, particularly in indoor, complex, and narrow environments as seen in the paper by Zhang *et al.,* [7]. It is imperative that the generated path is safe and efficient, with minimal time, energy consumption, and distance.

As Mohanty *et al.,* [8] have noted, path planning in Mobile Robot (MR) field can be broadly categorized into local path planning and global path planning based on the scale of knowledge related to the surroundings.

The term global path planning pertains to when a robot is cognizant of its surroundings and can reach its intended destination by pursuing a predetermined route. This aspect also classifies global path planning as offline or static path planning, as Liu *et al.,* [9] have explained. In contrast, local path planning pertains to when the robot has limited or no prior knowledge of the surroundings and performs real-time monitoring through its components to respond accordingly. This characteristic also defines local path planning as online or dynamic path planning, as explained by Liu *et al.,* [9].

Local path planning is known for its flexibility, but it has a disadvantage in that the path designed may only be the most optimal option in a local area and not globally guaranteed, or it may not even lead to the target point. On the contrary, global path planning necessitates that a mobile robot possesses an extensive comprehension of the environment by constructing a global map model. Subsequently, a seek and search algorithm is employed to locate the most efficient or relatively efficient path, allowing the robot to safely navigate toward the intended destination in the real environment. Practical path planning methods typically require the integration of systems that merge local path planning, which aims to achieve real-time obstacle avoidance planning, with global path planning, which endeavors to identify the globally optimal route.

Global and local path planning are not fundamentally different from each other. Various techniques utilized in the generation of global path planning can also be enhanced for local path planning purposes, and vice versa. When they work together, a robot can plan its route more efficiently, traveling from the beginning to the end. Global path planning focuses on modeling the environment and evaluating path quality, while local path planning focuses on utilizing various devices for environmental acquisition to detect obstacles and other real-time information.

In recent years, there are several studies about dynamic path planning techniques for a Mobile Robot (MR). A novel mutation operator was proposed for the genetic algorithm (GA) and used in research by Tuncer *et al.,* [10] to solve the path planning difficulty faced by mobile robots in dynamic surroundings. The effectiveness of this approach was demonstrated by applying it in two distinct dynamic environments and contrasting it against prior research that had enhanced GA techniques.

The problem of choosing the best path for an independent mobile robot in situations that are both immobile and continually changing was addressed by Ajeil *et al.,* [11]. The algorithm employs the physical dimensions of the robot and obstructions to establish a moving point in unoccupied areas, closely replicating real-life situations. Three components make up the proposed algorithm. By using a hybridized Particle Swarm Optimization-Modified Frequency Bat (PSO-MFB) technique to reduce the distance, the first module improves the route. The hybrid PSO-MFB Algorithm produces unfeasible spots, which are identified by the second module. Finally, when the robot detects barriers within its sensory range, the Obstacle Detection and Avoidance (ODA) module activates, allowing it to avoid collisions.

Ma *et al.,* [12] introduced a fresh approach to path planning, which incorporated a time-rolling window tactic and the algorithm of Artificial Bee Colony (ABC). To satisfy the real-time demand, local paths were employed within a sequence of rolling windows rather than a universal path. A fitness function that was suitable for the specific environment was devised to evade moving obstructions when using the Artificial Bee Colony algorithm. Wu *et al.,* [13] suggested a method for real-time path planning for a mobile robot that can avoid both fixed and moving obstructions. This intelligent optimization strategy not only creates a better path but also has the advantage of shorter planning times. The suggested algorithm is a fusion of the Artificial Potential Field (APF) and Beetle Antennae Search (BAS) methods, referred to as the BAS-APF technique.

The development of dynamic path planning techniques for mobile robots remains an ongoing research area. So, this paper presents a selection of dynamic path planning algorithms based on the ranking approach which applies to four path planning algorithms. The four techniques for path planning consist of the Probabilistic Roadmaps (PRM), Rapidly exploring Random Tree (RRT), Rapidly exploring Random Tree Star (RRT*), and Hybrid ASTAR (A*) algorithms. The 4OWMR was designed and used in previous studies by Massoud *et al.,* [6,14].

This paper is composed of seven sections. Section 1 of the document includes the introduction and literature review of the subject matter. Section 2 exhibits the mechanical design of the created robot. The forward and inverse kinematics of the robot are elaborated upon in section 3. Section 4 explains the four path planning algorithms. The Weighted Sum Model (WSM) is shown in section 5. Section 6 presents and discusses the experimental results, including the working environment and path planning outcomes. Lastly, section 7 presents the final remarks and potential areas for future research.

## 2. Mechanical Design of 4OWMR

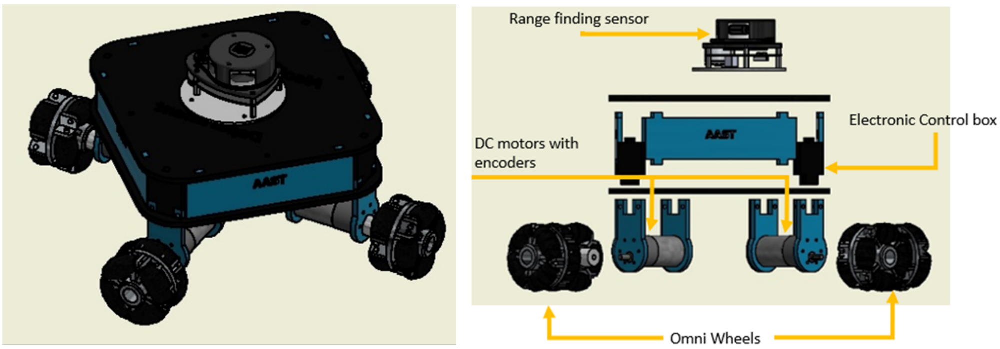
The recently devised robot is known as the 4OWMR, which is an abbreviation for Four Omni Wheeled Mobile Robot. Its primary characteristic is its capacity to move and traverse through constricted areas within indoor settings. The robot's design elements, including the actuators and sensors employed, the wheel arrangement, and the wheel design, are essential for achieving this capability. The mechanical design of the 4OWMR is elaborated further below.

The primary design standards for the 4OWMR usually rely on its intended purposes. In the instance of this robot, it is expected to navigate through indoor and office settings that are constructed with human-scale dimensions, encompassing specific aspects such as furniture, passages, and doorways. To guarantee optimal maneuverability in such environments, the primary dimensions of the robot must not surpass the length and width of the 4OWMR. To keep the robot lightweight and maneuverable, the greatest amount of weight of the base is limited to 3.5 kg, with an additional weight allowance of 2 kg for carrying objects. The height of the robot should not exceed 210 mm, allowing it to move easily beneath and around common furniture pieces such as sofas, tables, and workbenches. The ultimate mechanical design of the 4OWMR is illustrated in Figure 1(a).

The mobile robot is primarily intended for use in human environments, and its key specifications are presented in Table 1 for easy reference. Figure 1(b) displays the exploded design of the robot, showcasing its primary components.

**Table 1**
Overall specifications of the designed 4OWMR

| Four Omni Wheeled Mobile Robot (4OWMR) | |
|---|---|
| Dimensions | (360 x 360 x 210) mm |
| Weight | 3.5 kg |
| Payload | 2 kg |
| Operating time | 30 minutes |




(a) (b)

**Fig. 1.** (a) The completed design of the 4OWMR (b) An exploded perspective of the 4OWMR's design [6]

## 3. Forward and Inverse Kinematics of 4OWMR

The movement attributes of the robot can be computed by examining its kinematics. Each of the wheels has two positional parameters: its position relative to the mobile robot's center and the appropriate orientation angle. Figure 2 displays two views of the frames connected to the robot's center $XY$ and the axis center of an omni-wheel $X'Y'$. $l_{ix}, l_{iy}$ are the XY coordinates of the wheel in reference to the XY frame, and $\theta_i$ is the rotation angle of the wheel's center around the same frame. $\alpha_i$ is the deflection angle of each roller and $\beta_i$ is the angle between lines $OO'$ and $OX$.

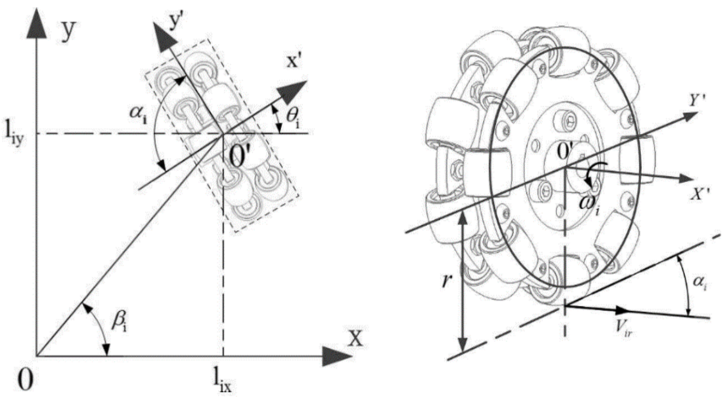



**Fig. 2.** The Omni wheel analysis related to mobile robot center [6]

There are dual velocity vectors: $[\,v_{ix} \quad v_{iy} \quad \omega_i\,]^T$, which represent the Omni-wheels' center speed related to the coordinate XY, and $[\,v'_{ix} \quad v'_{iy} \quad \omega'_i\,]^T$, which represents the Omni-wheels' center speed relative to the coordinate $X'Y'$. The forward and inverse kinematic computations of the 4OWMR are obtained based on the works of Maulana *et al.,* [15] and Ramirez *et al.,* [16] as outlined below.

$$\begin{bmatrix} \boldsymbol{v'}_{ix} \\ \boldsymbol{v'}_{iy} \end{bmatrix} = \boldsymbol{K}_{i1} \begin{bmatrix} \boldsymbol{\omega}_i \\ \boldsymbol{v}_{ir} \end{bmatrix}, \ \boldsymbol{K}_{i1} = \begin{bmatrix} \mathbf{0} & \sin \boldsymbol{\alpha}_i \\ \boldsymbol{r} & \cos \boldsymbol{\alpha}_i \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} \boldsymbol{v}_{ix} \\ \boldsymbol{v}_{iy} \end{bmatrix} = \boldsymbol{K}_{i2} \begin{bmatrix} \boldsymbol{v'}_{ix} \\ \boldsymbol{v'}_{iy} \end{bmatrix} = \boldsymbol{K}_{i2} \boldsymbol{K}_{i1} \begin{bmatrix} \boldsymbol{\omega}_i \\ \boldsymbol{v}_{ir} \end{bmatrix} \tag{2}$$

$$\boldsymbol{K}_{i2} = \begin{bmatrix} \cos \boldsymbol{\theta}_i & -\sin \boldsymbol{\theta}_i \\ \sin \boldsymbol{\theta}_i & \cos \boldsymbol{\theta}_i \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} \boldsymbol{v}_{ix} \\ \boldsymbol{v}_{iy} \end{bmatrix} = \boldsymbol{K}_{i3} \begin{bmatrix} \boldsymbol{v}_x \\ \boldsymbol{v}_y \\ \boldsymbol{\omega} \end{bmatrix}, \boldsymbol{K}_{i3} = \begin{bmatrix} \mathbf{1} & \mathbf{0} & -\boldsymbol{l}_{iy} \\ \mathbf{0} & \mathbf{1} & \boldsymbol{l}_{ix} \end{bmatrix} \tag{4}$$

By utilizing Eq. (3) and Eq. (4), the platform's inverse kinematic equation can be acquired as follows

$$\boldsymbol{K}_{i2} \boldsymbol{K}_{i1} \begin{bmatrix} \boldsymbol{\omega}_i \\ \boldsymbol{v}_{ir} \end{bmatrix} = \boldsymbol{K}_{i3} \begin{bmatrix} \boldsymbol{v}_x \\ \boldsymbol{v}_y \\ \boldsymbol{\omega} \end{bmatrix}, \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4} \tag{5}$$

By assuming that,

$$\boldsymbol{K}_{i2} = [\boldsymbol{K}_{i1}]^{-1} [\boldsymbol{K}_{i2}]^{-1} * \boldsymbol{K}_{i3}, \qquad \boldsymbol{\gamma}_i = \boldsymbol{\theta}_i - \boldsymbol{\alpha}_i, \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4},$$

Subsequently, the Omni-wheel's inverse kinematic equation is deduced as follows

$$\begin{bmatrix} \boldsymbol{\omega}_i \\ \boldsymbol{v}_{ir} \end{bmatrix} = [\boldsymbol{K}_{i1}]^{-1} [\boldsymbol{K}_{i2}]^{-1} \boldsymbol{K}_{i3} \begin{bmatrix} \boldsymbol{v}_x \\ \boldsymbol{v}_y \\ \boldsymbol{\omega} \end{bmatrix} = \boldsymbol{K}_i \begin{bmatrix} \boldsymbol{v}_x \\ \boldsymbol{v}_y \\ \boldsymbol{\omega} \end{bmatrix}$$
(6)

where,

$$\boldsymbol{K}_i = \frac{\mathbf{1}}{-\boldsymbol{r} \, \boldsymbol{sin} \, \boldsymbol{\alpha}_i} \begin{bmatrix} \cos \boldsymbol{\gamma}_i & \sin \boldsymbol{\gamma}_i & \boldsymbol{l}_{ix} \sin \boldsymbol{\gamma}_i - \boldsymbol{l}_{iy} \cos \boldsymbol{\gamma}_i \\ \boldsymbol{r} \cos \boldsymbol{\theta}_i & -\boldsymbol{r} \, \boldsymbol{sin} \, \boldsymbol{\theta}_i & \boldsymbol{l}_{iy} \boldsymbol{r} \cos \boldsymbol{\theta}_i - \boldsymbol{l}_{ix} \boldsymbol{r} \sin \boldsymbol{\theta}_i \end{bmatrix}$$

By assuming that,

$$\mathbf{E} = \begin{bmatrix} \frac{\cos \gamma_1}{\sin \alpha_1} & \frac{\sin \gamma_1}{\sin \alpha_1} & \frac{l_1 \sin(\gamma_1 - \beta_1)}{\sin \alpha_1} \\ \frac{\cos \gamma_2}{\sin \alpha_2} & \frac{\sin \gamma_2}{\sin \alpha_2} & \frac{l_2 \sin(\gamma_2 - \beta_2)}{\sin \alpha_2} \\ \frac{\cos \gamma_3}{\sin \alpha_3} & \frac{\sin \gamma_3}{\sin \alpha_3} & \frac{l_3 \sin(\gamma_3 - \beta_3)}{\sin \alpha_3} \\ \frac{\cos \gamma_4}{\sin \alpha_4} & \frac{\sin \gamma_4}{\sin \alpha_4} & \frac{l_4 \sin(\gamma_4 - \beta_4)}{\sin \alpha_4} \end{bmatrix}$$

Therefore, the revolution rate of each of the Four Omni-wheels can be conveyed as follows

$$\begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \end{bmatrix} = \frac{1}{-r}\mathbf{E}\begin{bmatrix} v_x \\ v_y \\ \omega \end{bmatrix}, v = r\omega \tag{7}$$

A kinematic model is required to control the robot's speed and location. First, the geometric characteristics of the platform are established, as shown in Figure 3. Because the distance between the platform's center and the Omni wheel center is uniform across all four wheels, the measurement of that length is demonstrated solely on one wheel.

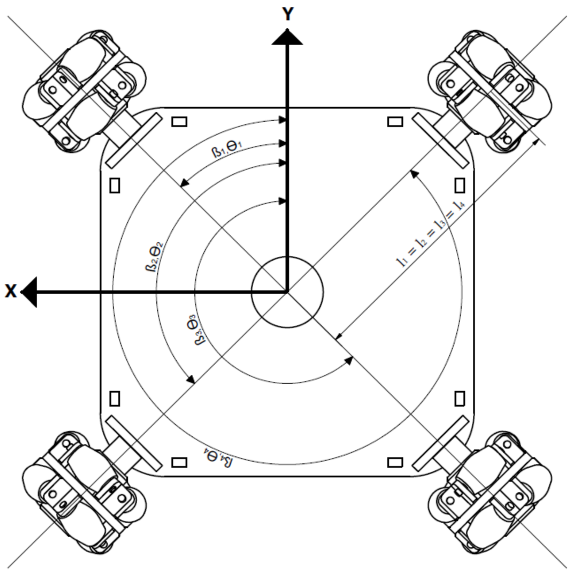



**Fig. 3.** Omni-wheels' geometric values [6]

Table 2 displays the final numerical values for the 4OWMR.

**Table 2**
4OWMR's geometric values [6]

| Parameter | $\beta_1, \theta_1$ | $\beta_2, \theta_2$ | $\beta_3, \theta_3$ | $\beta_4, \theta_4$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ |
|---|---|---|---|---|---|---|---|---|
| Value | $45^\circ$ | $135^\circ$ | $225^\circ$ | $315^\circ$ | $90^\circ$ | $90^\circ$ | $90^\circ$ | $90^\circ$ |

## 4. Path Planning Techniques

The definition of path planning indicates to the procedure of discovering a trajectory within the configuration space that links the initial and desired locations of the robot, as described by Utama *et al.,* [17]. The path generated should adhere to the forward and inverse kinematic restrictions of the 4OWMR. The restrictions mean the minimum change in velocity and position that can be achieved by 4OWMR hardware (Motors and Encoders).

Several algorithms have been chosen to be employed on the 4OWMR. The Hybrid A*, RRT*, RRT, and PRM algorithms are outlined theoretically, implemented practically, and evaluated through experimentation. The next subsections provide conceptual clarifications of the path planning techniques.

### *4.1 Probabilistic Roadmaps Method (PRM) Algorithm*

The PRM algorithm was initially suggested in the early 1990s, as illustrated in Chen *et al.,* [18]. This sampling-based strategy addresses the issue of creating an effective path graph in high-dimensional space. The path graph's connectedness is established by sampling in the configuration space, identifying collisions among the sampling points, and determining whether neighbouring sample points may be linked. The pseudo-code for this process is demonstrated in Table 3.

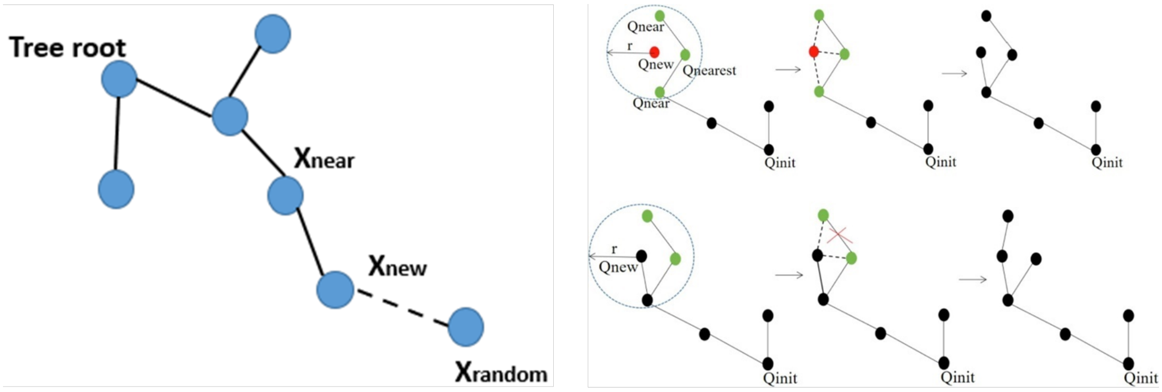
**Table 3**
The pseudo-code for the algorithm of PRM

```
I/P: Number of samples (n), number of nearest
neighbors (k)
O/P: PRM G = (V, E)
initialize E = Ø, V = Ø
while |V| < n do
Repeat
   q ← random sample from C
   until q is collision-free
   V ← V ∪ {q}
end while
for all q ∈ V do
   Nq ← k nearest neighbors of q in V
   for all q' ∈ Nq do
      if path (q', q) ∈ Cfree then E ← E ∪ {(q', q)}
      end if
   end for
end for
```

The algorithm commences with initializing the sets of vertices and edges with a null set. During each iteration, If the total number of vertices is less than the set number of samples, the method chooses a point q at random from the configuration space. It then checks whether $q \in C_{free}$ or not. If $q \in C_{free}$, it is appended to G as a vertex. The subsequent step involves attempting to link q to neighbouring vertices in the graph G. The technique confirms the feasibility of constructing a path from $q$ to $q'$ and adds a new edge to the edges set if successful, as suggested by Karaman *et al.,* [19].

### *4.2 Rapidly Exploring Random Tree (RRT) Algorithm*

The RRT algorithm is a frequently employed technique for solving control problems concerning path planning area. The approach establishes a tree-like structure by random sampling of the configuration space, and the resulting route may be determined, as proposed by Liu *et al.,* [9]. RRT commences with the first set of parameters and grows as a tree from that configuration, using random samples from the resulting search area, as illustrated in Figure 4(a). The RRT approach's pseudo-code can be found in Table 4.




(a) (b)

**Fig. 4.** (a) The fundamental idea behind the RRT algorithm for path planning (b) A diagrammatic representation of the RRT* algorithm [6]

**Table 4**
The pseudo-code for the algorithm of RRT

| | |
|---|---|
| | I/P: $q_I$, nodes (n), step size (α) |
| | O/P: Tree T = (V, E) |
| 1) | initialize E = ∅, V = $\{q_S\}$ |
| 2) | for i = 0: n do |
| 3) | $q_i$ ← random sample from C |
| 4) | $q_{near}$ ← nearest neighbor of $q_i$ in C |
| 5) | $q_{new} \leftarrow q_{near} + \frac{\alpha}{\lvert q_i - q_{near} \rvert}(q_i - q_{near})$ |
| 6) | if $q_{new} \in C_{free}$ |
| 7) | then V ← V ∪{ $q_{new}$}, E ← E ∪ {( $q_{near}$, $q_{new}$)} |
| 8) | end if |
| 9) | end for |

### *4.3 Rapidly exploring Random Tree Star (RRT*) Algorithm*

The RRT* method is an asymptotically optimum solution that improves the process of selecting parent nodes in the original RRT algorithm. It uses a cost function to identify the parent as the node with the lowest cost in the domain's collection of enlarged nodes. As stated by Karaman *et al.,* [19] and Aria *et al.,* [20], it additionally reconnects the nodes on the current tree after each iteration, ensuring computational difficulty and an asymptotically optimum solution. The algorithm's approach is similar to that of RRT up to the point of finding $q_{new}$, with two stages following its discovery as shown in Figure 4(b).

### *4.4 Hybrid A* Algorithm*

One of the most successful strategies for mobile robots or self-driving cars is this Hybrid A* algorithm. It has two parts: the forward search stage and the cost function, which is directed by a function called g(n) that runs from the starting node to the current node (n). Two new functions are included: $h_1(n)$ and $h_2(n)$. The $h_1(n)$ is a heuristic function in the discrete state that utilizes the obstacle map to determine the cost of the distance from the current node to the destination. Another heuristic function, $h_2(n)$, takes into account the mobile robot's kinematics. The kinematics of the robot are used to predict the trajectory, considering the direction, steering angle, and velocity of the mobile robot in the continuous state. The method then selects the best successor in the continuous coordinate system and instructs the mobile robot to follow it. Eq. (8) shows the total objective function of the planner algorithm at each node n. In our scenario, the weight of h2(n) is low due to the 4OWMR being able to move in any direction

$$\boldsymbol{F}(\boldsymbol{n}) = \boldsymbol{g}(\boldsymbol{n}) + \mathrm{h}_1(\boldsymbol{n}) + \mathrm{h}_2(\boldsymbol{n}) \tag{8}$$

The second phase is denoted as the analytical expansion stage, which confirms that the approach attains the destination state's continuous coordinates. Such as standard A* and Hybrid A* can be applied for generating Omni-wheel mobile robot's path planning. More descriptions of A* and Hybrid A* algorithms discussed by Sariff *et al.,* [21] and Petereit *et al.,* [22].

## 5. Weighted Sum Model (WSM) Ranking Approach

The WSM is acknowledged as one of the most well-known and straightforward multi-criteria decision-making approaches among various authors. It assesses several alternatives based on multiple decision criteria as seen by Helff *et al.,* [23] and Miljković *et al.,* [24].

In the weighted sum model (WSM) for ranking many alternatives $(A_1, \ldots, A_m)$ by criteria $(C_1, \ldots, C_n)$ presented in Table 5. In this model, the point at which alternative $A_i, (i = 1, \ldots, m)$ satisfies the condition $C_j, (j = 1, \ldots, n)$ is denoted by $a_{ij}$.

**Table 5**
Ranking matrix

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $\cdots$ | $C_n$ |
|---|---|---|---|---|---|---|---|
| $A_1$ | $a_{11}$ | $a_{12}$ | $a_{13}$ | $a_{14}$ | $a_{15}$ | $\cdots$ | $a_{1n}$ |
| $A_2$ | $a_{21}$ | $a_{22}$ | $a_{23}$ | $a_{24}$ | $a_{25}$ | $\cdots$ | $a_{2n}$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| $A_m$ | $a_{m1}$ | $a_{m2}$ | $a_{m3}$ | $a_{m4}$ | $a_{m5}$ | $\cdots$ | $a_{mn}$ |

The below Eq. (9) describes the calculation of the one alternative. Where $W_j$ is the weight of each criterion.

$$A_i = \sum_{j=1}^{n} W_j * a_{ij} \tag{9}$$

## 6. Result of Experiments

This portion is divided into two parts. The primary section will go over the working environment and its restrictions. The second section will exhibit the results of global and local path planning experiments. All the suggested methods were implemented on a laptop computer with a 2 GB memory GPU, 4 GB RAM, and a 1.7 GHz CPU using MATLAB/SIMULINK.

### *6.1 The Working Environment*

To experimentally evaluate the 4OWMR's navigation, an indoor office area with measurements of 863 cm × 406 cm was selected. The 4OWMR's working area is indicated by the blue rectangle as presented in Figure 5(a). The operational region is partitioned into 10 cm x 10 cm small squares to record the real path. The three maps are composed by adding the barriers and the unknown static obstacles to the working area presented in Figure 5(a). Various static objects are placed in different configurations on this map to evaluate the mobility of the 4OWMR and the efficiency of the utilized path planning techniques. The three maps (Map1, Map2, and Map3) are used for different experiments as shown in Figure 5(b) where the stationary obstructions are indicated in red. The reason for selecting these maps (L-shape, U-shape, and I-shape) is because they have been utilized in previous articles.

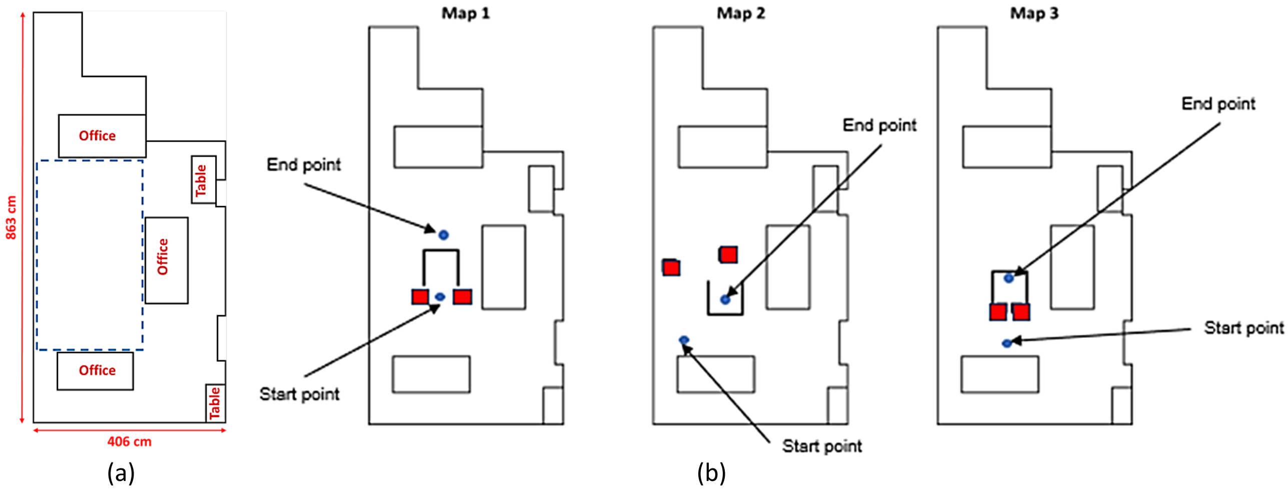



**Fig. 5.** (a) Dimension of experimental map (b) Three maps used in experimental works [6]

### *6.2 Global and Local Path Planning Experiments*

The flowchart of the 4OWMR path planning is explained in the following steps

i. It starts by entering the inflated map (black and white) with knowledge of all obstacles except for unknown obstacles (red obstacles as shown in Figure 5(b)).
ii. Then, the global path planning algorithm is applied.
iii. The LIDAR sensor data is used as feedback to generate the immediate map with the unknown obstacles.
iv. Finally, the local path planning algorithm is applied to generate the updated path.

The example of map 1's experimental work can be found in Figure 6. The blue path is the planned route generated by algorithms, while the red path is the actual path taken by the mobile robot.

The outcomes of global and local path planning approaches (Hybrid A*, PRM, RRT, RRT*) will be demonstrated by utilizing a ranking approach to arrange them. Local path planning pertains to situations where certain map obstacles are unknown before the creation of the intended path. For validating the experiments, the 4OWMR is navigated on three different maps, as shown in Figure 5(b). After applying the WSM ranking approach, it's possible to select the dynamic path planning algorithm based on the approach results.

For each map, the Weighted Sum Model (WSM), a multi-criteria decision-making technique, is employed on the four algorithms. The comparison parameters are the absolute error of the X-direction and Y-direction, travel time, average velocity, and traveled distance. The weighting of five parameters is equal (20%) and the maximum point is four points then decreasing by one in each step. The highest item takes four points, and the lowest item takes one point.

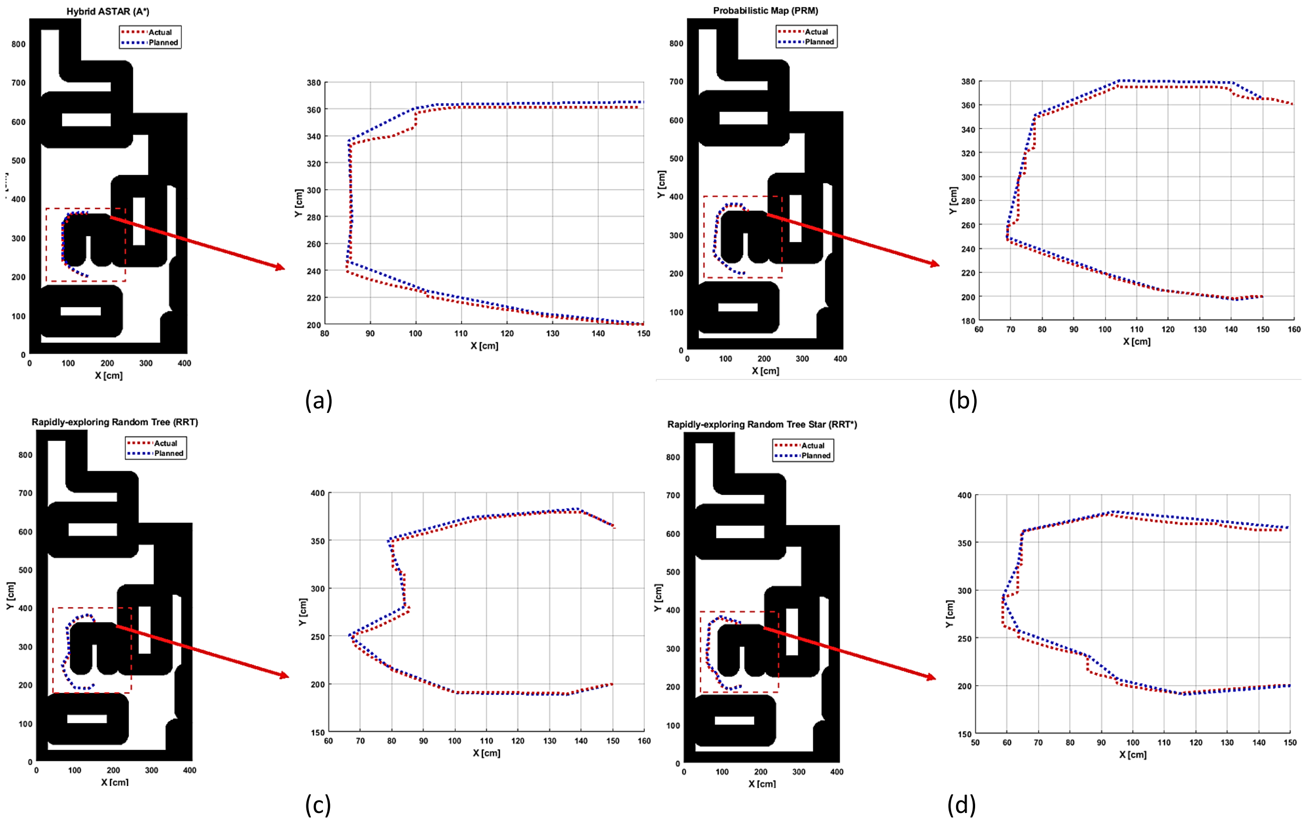



**Fig. 6.** (a) The path planned by using the Hybrid A* (b) The path planned by using the PRM (c) The path planned by using the RRT (d) The path planned by using the RRT*

Figure 7, Figure 8, and Figure 9 present the results of WSM for map 1, map 2, and map 3, respectively.

| Method of path planning | Travelled distance (cm) | Average velocity (m/s) | Travel time (s) | Absolute error x | Absolute error y |
|---|---|---|---|---|---|
| PRM | 1.56E+02 | 0.1028 | 17.5895613 | 1.8 | 1 |
| Hybrid A* | 1.31E+02 | 0.1189 | 13.6218695 | 0.3 | 2.1 |
| RRT | 1.58E+02 | 0.138 | 15.18 | 0.1 | 5 |
| RRT* | 1.37E+02 | 0.1078 | 14.04 | 1.7 | 2.3 |

| | | | | |
|---|---|---|---|---|
| Hybrid A* | RRT | Hybrid A* | RRT | PRM |
| RRT* | Hybrid A* | RRT* | Hybrid A* | Hybrid A* |
| PRM | RRT* | RRT | RRT* | RRT* |
| RRT | PRM | PRM | PRM | RRT |

| Ranking | |
|---|---|
| Hybrid A* | 17 |
| RRT | 12 |
| RRT* | 12 |
| PRM | 9 |

**Fig. 7.** WSM ranking algorithm result (Map 1)

| Method of path planning | Travelled distance (cm) | Average velocity (m/s) | Travel time (s) | Absolute error x | Absolute error y |
|---|---|---|---|---|---|
| PRM | 2.79E+02 | 0.1079 | 26.89 | 0.3 | 0.3 |
| Hybrid A* | 2.47E+02 | 0.1106 | 23.62 | 4.2 | 0.9 |
| RRT | 2.77E+02 | 0.091 | 31.44 | 1.6 | 0.7 |
| RRT* | 2.77E+02 | 0.0877 | 32.31 | 2.1 | 0.4 |

| | | | | |
|---|---|---|---|---|
| Hybrid A* | Hybrid A* | Hybrid A* | PRM | PRM |
| RRT | PRM | PRM | RRT | RRT* |
| RRT* | RRT | RRT | RRT* | RRT |
| PRM | RRT* | RRT* | Hybrid A* | Hybrid A* |

| Ranking | |
|---|---|
| Hybrid A* | 14 |
| RRT | 12 |
| RRT* | 9 |
| PRM | 15 |

**Fig. 8.** WSM ranking algorithm result (Map 2)

| Method of path planning | Travelled distance (cm) | Average velocity (m/s) | Travel time (s) | Absolute error x | Absolute error y |
|---|---|---|---|---|---|
| PRM | 2.94E+02 | 0.1667 | 24.68 | 9.4 | 4.3 |
| Hybrid A* | 2.51E+02 | 0.1321 | 20.44 | 0.8 | 4 |
| RRT | 3.19E+02 | 0.1316 | 25.35 | 0.5 | 2.8 |
| RRT* | 3.21E+02 | 0.1331 | 25.75 | 2.2 | 2.2 |

| | | | | |
|---|---|---|---|---|
| Hybrid A* | PRM | Hybrid A* | RRT | RRT* |
| PRM | RRT* | PRM | Hybrid A* | RRT |
| RRT | Hybrid A* | RRT | RRT* | Hybrid A* |
| RRT* | RRT | RRT* | PRM | PRM |

| Ranking | |
|---|---|
| Hybrid A* | 15 |
| RRT | 12 |
| RRT* | 11 |
| PRM | 12 |

**Fig. 9**. WSM ranking algorithm result (Map 3)

To select one algorithm based on the previous results, the total point of each algorithm will be added. Then, this algorithm can be used in dynamic path planning experiments.

$$Hybrid\ A* = 17\ (Map\ One) + 14\ (Map\ Two) + 15\ (Map\ Three) = 46\ Points$$
$$RRT = 12\ (Map\ One) + 12\ (Map\ Two) + 12\ (Map\ Three) = 36\ Points$$
$$PRM = 9\ (Map\ One) + 15\ (Map\ Two) + 12\ (Map\ Three) = 36\ Points$$
$$RRT* = 12\ (Map\ One) + 9\ (Map\ Two) + 11\ (Map\ Three) = 32\ Points$$

Based on the last result, hybrid A* is selected as a dynamic path planning for future experiments.

## 7. Conclusions and Potential Future Work

This article centers on the choice of dynamic path planning for a mobile robot, and substantial research has been dedicated to this field. The work is presented experimentally to ensure dependable outcomes. The Four Omni Wheeled Mobile Robot (4OWMR) is utilized as the mobile platform, enabling instantaneous rotation and lateral movement, specifically in limited areas.

To initiate the selection procedure, three distinct maps are utilized to implement four path planning techniques (Hybrid A*, RRT*, RRT, and PRM). Then, the Weighted Sum Model (WSM) technique is applied to each map based on the traveled distance, average velocity, travel time, and absolute error in the X-direction, and Y-direction. Hybrid A* outperforms the other algorithms, scoring 46 points, which represents a 21.7% increase compared to PRM and RRT, and a 30.4% increase compared to RRT* when utilizing the weighted sum ranking technique. Therefore, it can be chosen as the dynamic path planning algorithm.

Future work will involve experimental testing on more complicated and intricate maps. Additionally, Future work will investigate the utilization of machine learning techniques to generate smoother pathways, decrease energy usage, and improve convergence precision and accuracy. Multiple hardware changes will be sought to achieve smoother routes, avoid potential discontinuities in path creation, and enhance sampling speeds. For future implementations, quicker programming languages such as Python will be investigated.

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**References**

[1] Li, Shufei, Pai Zheng, Sichao Liu, Zuoxu Wang, Xi Vincent Wang, Lianyu Zheng, and Lihui Wang. "Proactive human–robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives." *Robotics and Computer-Integrated Manufacturing* 81 (2023): 102510. https://doi.org/10.1016/j.rcim.2022.102510

[2] Farooq, Muhammad Umar, Amre Eizad, and Hyun-Ki Bae. "Power solutions for autonomous mobile robots: A survey." *Robotics and Autonomous Systems* 159 (2023): 104285. https://doi.org/10.1016/j.robot.2022.104285

[3] Rubio, Francisco, Francisco Valero, and Carlos Llopis-Albert. "A review of mobile robots: Concepts, methods, theoretical framework, and applications." *International Journal of Advanced Robotic Systems* 16, no. 2 (2019): 1729881419839596. https://doi.org/10.1177/1729881419839596

[4] Zulkefli, M. H., KA Mohd Annuar, S. H. Johari, MR Mohamad Sapiee, and S. Ahmad. "Graphical user interface (GUI) controlled mobile robot." *Journal of Advanced Research in Computing and Applications* 1, no. 1 (2015): 42-49.

[5] Suntharamurthy, R., A. Anuar, and F. Mahamud. "The Design of a Compact and Lightweight Wheelchair for Disabled Children." *Journal of Advanced Research Design* 9 (2015): 26-33.

[6] Massoud, M., A. Abdellatif, and Mostafa RA Atia. "Mechatronic Design and Path planning optimization for an Omni wheeled mobile robot for indoor applications." In *2021 31st International Conference on Computer Theory and Applications (ICCTA)*, pp. 90-98. IEEE, 2021. https://doi.org/10.1109/ICCTA54562.2021.9916626

[7] Zhang, Lin, Yingjie Zhang, and Yangfan Li. "Path planning for indoor mobile robot based on deep learning." *Optik* 219 (2020): 165096. https://doi.org/10.1016/j.ijleo.2020.165096

[8] Mohanty, Prases K., Anand Kumar Singh, Amit Kumar, Manjeet Kumar Mahto, and Shubhasri Kundu. "Path Planning Techniques for Mobile Robots: A Review." In *International Conference on Soft Computing and Pattern Recognition*, pp. 657-667. Cham: Springer International Publishing, 2021. https://doi.org/10.1007/978-3-030-96302-6_62

[9] Liu, Lixing, Xu Wang, Xin Yang, Hongjie Liu, Jianping Li, and Pengfei Wang. "Path planning techniques for mobile robots: Review and prospect." *Expert Systems with Applications* (2023): 120254. https://doi.org/10.1016/j.eswa.2023.120254

[10] Tuncer, Adem, and Mehmet Yildirim. "Dynamic path planning of mobile robots with improved genetic algorithm." *Computers & Electrical Engineering* 38, no. 6 (2012): 1564-1572. https://doi.org/10.1016/j.compeleceng.2012.06.016

[11] Ajeil, Fatin H., Ibraheem Kasim Ibraheem, Mouayad A. Sahib, and Amjad J. Humaidi. "Multi-objective path planning of an autonomous mobile robot using hybrid PSO-MFB optimization algorithm." *Applied Soft Computing* 89 (2020): 106076. https://doi.org/10.1016/j.asoc.2020.106076

[12] Ma, Qianzhi, and Xiujuan Lei. "Dynamic path planning of mobile robots based on ABC algorithm." In *Artificial Intelligence and Computational Intelligence: International Conference, AICI 2010, Sanya, China, October 23-24, 2010, Proceedings, Part II 2*, pp. 267-274. Springer Berlin Heidelberg, 2010. https://doi.org/10.1007/978-3-642-16527-6_34

[13] Wu, Qing, Zeyu Chen, Lei Wang, Hao Lin, Zijing Jiang, Shuai Li, and Dechao Chen. "Real-time dynamic path planning of mobile robots: a novel hybrid heuristic optimization algorithm." *Sensors* 20, no. 1 (2019): 188. https://doi.org/10.3390/s20010188

[14] Massoud, Mostafa Mo, A. Abdellatif, and Mostafa RA Atia. "Different Path Planning Techniques for an Indoor Omni-Wheeled Mobile Robot: Experimental Implementation, Comparison and Optimization." *Applied Sciences* 12, no. 24 (2022): 12951. https://doi.org/10.3390/app122412951

[15] Maulana, Eka, M. Aziz Muslim, and Veri Hendrayawan. "Inverse kinematic implementation of four-wheels mecanum drive mobile robot using stepper motors." In *2015 international seminar on intelligent technology and its applications (ISITIA)*, pp. 51-56. IEEE, 2015. https://doi.org/10.1109/ISITIA.2015.7219952

[16] Ramirez-Serrano, A., R. Kuzyk, and G. Solana. "Elliptical double mecanum wheels for autonomously traversing rough terrains." *IFAC Proceedings Volumes* 43, no. 16 (2010): 7-12. https://doi.org/10.3182/20100906-3-IT-2019.00004

[17] Utama, Khasia Vidra, Rifqi Amalya Fatekha, Senanjung Prayoga, Daniel S. Pamungkas, and Rizky Pratama Hudhajanto. "Positioning and Maneuver of an Omnidirectional Robot Soccer." In *2018 International Conference on Applied Engineering (ICAE)*, pp. 1-5. IEEE, 2018. https://doi.org/10.1109/INCAE.2018.8579148

[18] Chen, Gang, Ning Luo, Dan Liu, Zhihui Zhao, and Changchun Liang. "Path planning for manipulators based on an improved probabilistic roadmap method." *Robotics and Computer-Integrated Manufacturing* 72 (2021): 102196. https://doi.org/10.1016/j.rcim.2021.102196

[19] Karaman, Sertac, and Emilio Frazzoli. "Sampling-based algorithms for optimal motion planning." *The international journal of robotics research* 30, no. 7 (2011): 846-894. https://doi.org/10.1177/0278364911406761

[20] Aria, Muhammad, and Jana Utama. "An Autonomous Parking System using the Hybridization of the Rapidly-Exploring Random Trees Star and Ant Colony System." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 31, no. 1 (2023): 291-297. https://doi.org/10.37934/araset.31.1.291297

[21] Sariff, N., and Norlida Buniyamin. "An overview of autonomous mobile robot path planning algorithms." In *2006 4th student conference on research and development*, pp. 183-188. IEEE, 2006. https://doi.org/10.1109/SCORED.2006.4339335

[22] Petereit, Janko, Thomas Emter, Christian W. Frey, Thomas Kopfstedt, and Andreas Beutel. "Application of hybrid A* to an autonomous mobile robot for path planning in unstructured outdoor environments." In *ROBOTIK 2012; 7th German Conference on Robotics*, pp. 1-6. VDE, 2012.

[23] Helff, Florian, Le Gruenwald, and Laurent d'Orazio. "Weighted Sum Model for Multi-Objective Query Optimization for Mobile-Cloud Database Environments." In *EDBT/ICDT Workshops*. 2016.

[24] Miljković, Boža, Mališa R. Žižović, Aleksandar Petojević, and Nada Damljanović. "New weighted sum model." *Filomat* 31, no. 10 (2017): 2991-2998. https://doi.org/10.2298/FIL1710991M