Autonomous Robot Adopting Multi-Axis Robotic Arm and ACO Algorithm

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Abstract. The autonomous robot being introduced aims to facilitate activities in hospitals, especially in the isolation wards, and bio/chemical laboratories. The text begins with introducing the parallelogram design of the robot, which permits 3 degrees of freedom (DoF), comprising 2 translational axes and 1 rotational axis. Macanum wheels provide high maneuverability and dexterity regarding robot motion, and its dynamic kinematic analysis is encompassed in the passage. Then, the essay specifically explains the methodology for testing the robot's path-planning competence. Adopted by the robot, ant colony optimization (ACO) is a route-planning algorithm that has strong potential. It can deal with convoluted map configurations and has the value of incorporating advanced route planning and mapping technologies including SLAM. The essay then displays and analyzes the results from the test runs by inserting ACO into the route planning of a hospital map. Finally, the essay elicits the challenges and discusses the opportunities that the technologies being applied and how can the entire robot design be elaborated for a higher investigation value.

Keywords: Autonomous robotics, multi-axis robotic arm, ant colony optimization.

1. Introduction

In the past decades, autonomous robots have offered significant convenience and opportunities for human labor. However, most of those are applied in the primary or secondary working sector. They do have the potential to step on a higher stage where they can aid sophisticated or meticulous jobs that humans handle. This paper will introduce an autonomous robot design that requires grasping contaminated waste and hazardous substances such as chemical bottles, and bio-hazardous daily supplies while moving freely and flexibly in indoor environments. Initially, we proposed the combination of a multi-axis mechanical arm and attached with a mobile platform for convenience in doing operations on the platform. However, in the final selection of the robot arm, due to factors such as the small indoor activity space, we decided to forfeit part of the translational moving range and the load that the robot could grasp at once. After such adjustments, the robot is relatively specialized in gripping instead of palletizing. To this end, we went with a small mechanical structure with lowered steering gear strength (high strength steering gear means that the volume will be relatively increased, resulting in reduced flexibility) with a higher dexterity to deal with medicines and small hazardous substances in isolation wards.

According to Farman et al. (2018), different types of joints and links exist in an articulated robot arm [1]. Our robot adopts a multi-axis robotic arm which provides the entire figure 3 degrees of freedom (DoF), with 2 translational axes and 1 rotational axis. It is attached with 4 Macanum wheels (omni-directed) for ensuring agility and manipulability. The robot also studies 2-dimensional maps (in bird’s view) by implementing the meta-heuristic algorithm Ant Colony Optimization. It combines the forecasting information about a promising optimized path with the pertinent and trustworthy information given from the previously obtained trials by the ant groups [2]. This algorithm can deal with convoluted map configurations by dispatching ant testers randomly and incorporating a positive rewarding mechanism to converge the result to the nearest path. ACO was implemented on three different map routes. Except for the first route which failed due to its complexity before adjusting the parameters, the optimal route for the first, second, and third routes all successfully converged with a converging rate of 75%. There are different parameters comprised within the ACO algorithm, including the evaporation rate of the pheromone (positive rewarding), the number of ants, and the
pheromone weight along with others. Therefore, ACO is a powerful algorithm with potential when it comes to reading simulated hospital maps after a comprehensive interpretation of the map. If there are accidents that happen in the isolation wards, sensors adopted on the robot should act correspondingly to avoid collision and prevent derailing from its pre-planned optimal route.

2. Robot design

2.1. Sensors

In terms of sensors on the platform, laser radar, and ultrasonic sensors were selected due to their independency in luminosity. The laser radar, which can perform rotatory motion, sensing the environment in a broad range, has numerous advantages such as higher accuracy and resolution [3]. The ultrasonic sensor acts as a backup sensor when the laser radar encounters a mechanical or technical issue. Note that we reserved a few spare ports for future sensor upgrades (see Figure 1).

![Figure 1. Overview of the robot model in Solidworks, a robotic design application (Photo credit: original).](image)

2.2. Multi-axis robotic arm

The main structure of the robot arm is composed of mechanical claws, two transmission joints, and a rotating base, which makes the robot arm have three angles of freedom. The motion design method of the robot arm is to design its mechanical action scheme according to different motion directions. In addition, the clamp part of the robotic arm is always parallel to the ground during operation (see Figure 2).

![Figure 2. The robot arm of the robot has 3 degrees of freedom (Photo credit: original)](image)
2.2.1. Left side view of the multi-axis robotic arm

The assembly parts of the mechanical arm part controlled by the motor on the left side constitute one complete parallelogram structure, and its fixed point is the intersection point of the parallelogram structure and the triangular structure, which makes the transverse movement have a radian running path, and because one side of the triangular structure of the mechanical claw part is always parallel to the side of the parallel quadrilateral. So, the mechanical claw part of the arm is always parallel to the ground (see Figure 3 and Figure 4).

![Fixed angle](image1)

**Figure 3.** Left side arm body view (Photo credit: original).

The triangular structure (red region) and the parallel structures (bounded by the grey edges) contribute to maintaining robot stability. Since the two opposite edge pairs will always maintain parallel, the holistic configuration (including the end effector) of the robotic arm always remains horizontal to the ground.

![Dynamic simulation](image2)

**Figure 4.** Dynamic simulation of the left part of the arm body (Photo credit: original).

The motor-controlled arm assembly on the right side forms two complete parallelogram structures, and the fixed point of the arm operation becomes the only point in the figure below (see Figure 5). Because of the special position of the fixed point, the robot arm will also have a small deviation in the horizontal direction when it is operated longitudinally (see Figure 6).

![Parallelogram structure](image3)

**Figure 5.** Parallelogram structure ensures a fixed angle, because of the two stable parallelogram structures (Photo credit: original).
2.3. Macanum Wheels

The robot is attached with 4 omni-directed Macanum wheels, each controlled by an individual voltage supply and motor. On each wheel, nine rolls make 45-degree angles with the movement axis. At the same time, there are A-type wheels and B-type wheels that are mirror reflections of each other (in terms of the direction of rolls) and make a combination sequence of ABBA (shown in Figure 7) [4].

Fundamentally, the mechanism of this type of wheel’s ability to move in omni-directions is vector combinations because the velocity vector of the wheel, pointing 45 degrees away from both the x and y movement axis, can be divided into two vectors pointing towards the two axes mentioned due to vector’s property of addition. Since the four wheels are individually controlled, as long as the angular velocities of the four motors that control the four wheels remain constant, the robot could then achieve multi-directional mobility [5].

Through inverse kinematic analysis, the velocity values of the four Macanum wheels can be calculated by the following formula:

\[
\begin{align*}
    v_{w1} &= v_{ty} - v_{tx} + \omega(a + b) \\
    v_{w2} &= v_{ty} + v_{tx} - \omega(a + b) \\
    v_{w3} &= v_{ty} - v_{tx} - \omega(a + b) \\
    v_{w4} &= v_{ty} + v_{tx} + \omega(a + b)
\end{align*}
\]  

(1)
\[ v_{wk} = \text{the Velocity of wheel } #k \]

\[ v_{ty} \text{ and } v_{tx} = \text{The divided velocities of } v_t \text{ in y and x axis respectively of the rigid body (the robot’s plate)} \]

\[ \omega = \text{Angular velocity of the rigid body} \]

\[ a \text{ and } b = \text{the Horizontal and perpendicular distance between the motion center and the wheel center} \]

This formula helps to derive the voltage allocation on each wheel, permitting flexible control on each wheel to achieve omni-directed motion [5].

3. Path planning by applying ant colony optimization algorithm

3.1. Introducing ACO

The algorithm that has been applied to simulate the path planning of our autonomous robot is the Ant Colony Optimization (ACO algorithm). ACO was proposed by Marco Dorigo in the early 1990s, inspired by the foraging behavior of large colonies of ants [6]. According to Ahmed, Zeinab E., et al. [7]: “At the core of this behavior is the indirect communication between the ants with the help of chemical pheromone trails, which enables them to find short paths between their nest and food sources.” It is a robust algorithm that shows great performance in conquering complex optimization problems by its heuristics.

3.2. Theory

The fundamental theory of this algorithm is the positive rewarding mechanism. Essentially, simulator ants are dispatched toward a random direction and the probability of the consecutive step’s direction in the two-dimensional space is random initially. As the ants discover routes that take less effort (shortest distance), pheromone concentration (the reward) on those paths will increase and intervene in the decision that the next generation of ants will make. Quoting Zeinab E et al. again [7], “the continuous ACO is based on both local and global search. Local ants have the capability to move toward the latent region with the best solution with respect to transition probability of region \( k \).” (According to the formula below)

\[ P_k(t) = \frac{t_k(t)}{\sum_{j=1}^{n} t_j(t)} \quad (2) \]

Where \( t_k(t) \) the total pheromone at region \( k \), and \( n \) is the number of global ants [7].

However, this algorithm will not only accumulate pheromone but have them evaporate through time, fostering the ants to find the optimal path that requires the lowest number of steps. The pheromone concentration updates under the guide by the following formula:

\[ t_i(t + 1) = (1 - r)t_i(t) \quad (3) \]

Where \( r \) is the pheromone evaporation rate [7].

3.3. Incorporating ACO with the robot

According to the theory of ACO [8-10], traversing through this process, the best route will converge since the ant descendants will tend to move on the paths that contain more pheromones.

Since our robot mainly conducts activities in hospitals and bio-laboratories, the map that this algorithm will be tested on should best simulate the environment with obstacles included see Figure 8).
4. Path planning simulation methodology

The objective of this simulation is to investigate the effectiveness of the ACO algorithm in terms of obstacle avoidance, so our robot can work in the environment safely. Three pairs of predefined coordinates indicate the starting point and the ending point (target) that the robot must approach. Figure 8 illustrates 1 pair, and Figure 9 illustrates all three, respectively labeled in red with a circle indicator, blue with a square indicator, and green with a triangular indicator. Their optimal routes through manual calculations are the following:

![Diagram](image1.png)

**Figure 8.** Overview of the environmental simulation map (Photo credit: original).

![Diagram](image2.png)

**Figure 9.** Three target routes for simulation (Photo credit: original).

Note that the sensors (laser radar and ultrasonic sensors) equipped the robot will aid the robot when it comes to obstacle detection. In the following program simulation, it has been idealized that the sensor does not contribute to any action that the ant chooses.

5. Result evaluation

5.1. Displaying data.

Route 1 is technically the most challenging route for the algorithm to discover an optimal path since the distance between the starting and ending points is the furthest among all three pairs, hence yielding more possibilities for the ants according to the formula above. It could be seen the green line in Figure 10b — the performance analysis of route 1 shown in Figure 10a — was fluctuating and never converged. Therefore, several experimental parameters involved in the algorithm were altered to achieve a satisfactory result:
Ant number per generation = 75  
Pheromone evaporation rate = 0.7  
Pheromone weight = 1  
Distance weight = 10  
Initial pheromone concentration = 8

*These are only values for reference.* From those parameters, the ant number per generation was independently adjusted from 75 to 135, resulting in a converging optimal route at around 40 generations of ants (see Figure 11b). Consequently, Figure 11a, demonstrating the optimal path, is ideally close to the pre-calculated one in Figure 9.

In terms of simplicity, route 2 and route 3 are relatively neat to approach if setting route 1 as the standard difficulty. Therefore, the two routes were both run under the default settings according to the bullets. Due to the routes’ simplicity, the optimal path of routes 2 and 3 (especially route 2) converged at 20 and 60 iterations respectively.

### 5.2. Data analysis

Through the results displayed, ACO performed sufficiently in terms of path planning under the scenario of an isolation ward in a hospital setting. Although the default values of the parameters are sufficient for discovering the shortest path in simple maps like the one above, more adjustments to the parameters could be made to achieve higher functionality. For instance, the effect of evaporation rate (one of the experimental parameters) on the speed at which the result is converged is significant. According to the comparison shown in Figure 12 and Figure 13, it takes 20 more iterations for the sample, which ran with the evaporation rate \( r \) of 0.9 compared to 0.7. \((0 < r < 1)\)
For future referencing, the parameters can be set to a set of new values as a default, then adjust the numbers until the optimal route of a relatively complex landscape. If the robot can discover the optimum (or an approximated) pathway, then the algorithm is suitable for the robot to set its basis on.

Figure 12. Optimal path of Route 2; ants per generation = 75; evaporation rate = 0.7. And performance report yielded for the left (Photo credit: original).

Figure 13. Optimal path of Route 2; ants per generation = 75; evaporation rate = 0.9. And Performance report yielded for the left (Photo credit: original).

6. Conclusion

ACO, compared to the prevailing path planning algorithm such as Dijkstra’s, RRT, or A* (heuristic), is comparatively flexible since it includes a variety of variables. It obtained significant success in reading hospital maps and devising an optimal route for robot path planning. For further extensions to take place, those parameters in the ACO algorithm could be altered to achieve a self-suiting algorithm for each type of landscape. Environmental simulations could be done, for example on a Gazebo simulator, to enhance the robot’s adaptivity in practical situations. Further flaws in details could be better examined through such a process. In addition, the prospected 3D map constructing technology - LiDAR can be merged into the robot by comprehending the laser radar and ultrasonic sensors into a sensory system.

Although ACO performed well in this preset scenario, numerous challenges exist for it to become a fortified and concrete algorithm that can be applied to autonomous robots involving route anticipation and real-time navigation. Further investigations on this algorithm must take place. It is also plausible that several attributes, including mechanisms such as reward evaporation mechanisms, could be incorporated into different existing algorithms. This will significantly enhance the performance of the algorithm with improved accuracy shown in our test records.
References


