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Design and Implementation of Multi-Function Logistics Robots for Intelligent Warehousing

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Abstract. The collaborative task of logistics robots is a very big challenge for the intelligent warehousing industry. In order to improve the effectiveness of task deployment for intelligent warehousing, this paper proposes a novel strategy of collaborative tasks for logistics robots, which includes three different functional robots, named transport robot which is used for transportation tasks, mobile manipulator used for sorting goods, and pick-and-place robot. All of these robots have an omnidirectional mobile base, which allows them to move in any direction, rotate in place, and navigate with the artificial potential Field (APF). Finally, the experimental verification proves clearly that the logistics robot cooperates well to complete the tasks of outbound and inbound goods and shows great flexibility under an unstructured environment.

Keywords. logistics robots, warehousing industry, mobile manipulator

1. Introduction

Today, the growing demand for robotic automation across various industries has led to the deployment of low-cost logistics robots in factories and warehouses [1]. This has effectively reduced the need for manual labor and increased operational efficiency, allowing for less or even unmanned management. Notably, companies such as Amazon and Google have introduced automated delivery systems using unmanned air vehicles (UAVs) and robots in their fulfillment warehouses. In Amazon's distribution centers, over 30,000 Kiva robots have been deployed, contributing significantly to warehouse operations. These robots stand at a height of 40cm and can travel at speeds reaching 1.3m per second. Impressively, they can carry loads up to 340kg. Compared to traditional logistics methods, Kiva robots demonstrate an efficiency improvement ranging from 2 to 4 times. Furthermore, they boast an accuracy rate of 99.99%.

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The operational mechanism of the Kiva system is underpinned by a resource allocation algorithm managed by its control system. Once this algorithm determines tasks, it dispatches instructions to the Kiva robot. Following these guidelines, the robot identifies and navigates towards specific shelves using its planned path. These shelves are equipped with sensing capabilities, allowing them to communicate with the Kiva robot. Upon recognizing that items on a particular shelf are to be dispatched, the Kiva robot lifts the entire shelf and transports it to a designated picking location. Mobile manipulators, which integrate a robotic manipulator and a mobile robot, offer task flexibility and robotic mobility that can be useful in logistics tasks such as transporting parts between workstations and storages or loading components into feeders and machines [2, 3]. The logistics tasks cover the process of transporting parts between workstations and storages. Mobile manipulators that integrate a robotic manipulator and a mobile robot in a single platform can be useful in such tasks. [4] presents a search–based algorithm for generating time-optimal trajectory for picking and transporting parts using a mobile manipulator between workstations and storages, and the process of loading components (several or one at a time) into feeders and machines. [5]. In order to give full play to the potential and efficiency advantage of the robotic system and split the cost, practical robotic warehousing systems usually contain a large number of mobile robots. Multi-robot path planning and motion coordination become an issue. At present, Many algorithms have been presented in the literature for multi-robot path planning and motion coordination to optimize the efficiency of robotic systems [6-10]. For example, Liu [11] proposed a traffic flow prediction algorithm to predict the evolution of the robot density distribution in a future horizon and estimate the future traffic heat value of each sector. Based on the characteristics of A* algorithm, Zheng et al. [12] optimized the node search mode and search speed, and add the angle evaluation cost function to the cost function of A* algorithm to find the path with the least inflection point. [6] describes a new approach for robot online navigation in static and dynamic environments, eliminates local minima, and finds a practical trajectory for path planning with low computing time that lines up with the standard A* method.

The main objective of this paper is to address the challenges associated with designing and coordinating logistics robots for use in unstructured environments, such as warehouses with narrow spaces and fixed shelves. To achieve this objective, the authors have developed a system that incorporates transport robots, mobile manipulators, and pick-and-place robots. In Section I, the authors provide a brief overview of the software and hardware design of the system. This includes a description of the various sensors and actuators used by the robots, as well as the software architecture used to coordinate their actions. Section II introduces the software construction of the system. This paper proposes a front-end and back-end system based on the Spring+Vue framework, which can effectively manage robots and perform reasonable scheduling. In Section III, the authors present the results of their experiments, which were conducted to validate the feasibility of the proposed strategies. Section IV presents conclusions.

2. Design and Implement

2.1. Robot Design

Based on the different types of logistics robot tasks, we classify the task execution process into three stages: picking up, transporting, and placing. For those stages, we have developed and designed three distinct types of robots: the transport robot, the mobile manipulator, and the pick-and-place robot as shown in Figure 1. These robots are specifically tailored to efficiently carry out their respective sub-tasks within each stage, ensuring smooth and seamless operations in the logistics industry

(a)pick-and-place robot (b) mobile manipulator (c) AGV robot

Figure 1. Three different types of robots

(a) An pick-and-place robot capable of freely handling both inbound and outbound items. (b) A mobile manipulator equipped with a monocular camera that employs a deep neural network model trained for classification to achieve a 98% accuracy rate in sorting specific items. (c) A transport robot that performs the transportation of goods, replacing conveyor belts, and reducing the cost of setting up an intelligent warehouse.

Specifically, each robot in the system is equipped with a unique functional execution mechanism, seamlessly integrated into an omnidirectional mobile platform. The composite robot system encompasses a range of functionalities, which can be described using the following formula:

$$f(x) = base + g(x) \tag{1}$$

In this formula, the first term represents the mobile robot base, which is equipped with an omnidirectional drive system. This allows the robot to move in any direction and perform turning operations without a turning radius, even in narrow spaces. This greatly improves work efficiency and increases system flexibility when all of those robots do collaborate tasks assigned the inbound or outbound items. The parameters of the mobile base are shown in Table 1; The second term g(x) varies with the change of the independent variable, where x ∈ {sort, transport, pick, and place}, and the corresponding function F(x) ∈ {mobile manipulator, transport robot, pick-and-place robot}.

Table 1. The parameters of the mobile base

Translational velocity	1m/s
Rotational velocity	0.45rad/s
Diameter	50cm
Drive methods	Omnidirectional

2.2. The localization algorithm

The challenging part of localization is estimating the robot's position and orientation of which this information can be acquired from sensors and other systems [12-14], Though UWB and RFID have been successfully used for forklift localization, we find the approach with visual sensors more appropriate for our case since visual features that already exist for the robot localization. Thus, the AprilTag algorithm was employed in our case for logistics robot localization. AprilTag is a type of 2D barcode that is designed to be easily detectable by computer vision algorithms [15]. The odometer on a mobile platform can provide accurate readings in the short term, but over time, system errors and slippage can cause inaccuracies in the readings. To solve this issue, a visual-aided approach to odometer localization has been proposed. This method utilizes AprilTag as visual aids to precisely determine the spatial coordinate relationship between the camera and the reference frame. By using vision-based information to correct the parameters of the odometer, we can improve the accuracy of the mobile platform's motion estimates.

Another challenging part of localization is the determination of the initial position. The initial position inside the warehouse is defined as the origin of the robot, and when the robot is powered on, it needs to accurately locate this initial position and adjust its odometer to complete the initialization process. In the algorithm design, as shown in figure 2, a series of ordered AprilTag codes are attached to the initial position, with IDs 1, 2, 3, 4, and 5. Upon powering on the robot, the control system gradually moves it forward to search for the first random location with an ApriTag code and continues until it is located. Once the first location is found, the robot rotates to align its angle with the spatial position of the set AprilTag code. After this step is completed, the algorithm begins to compare the detected AprilTag code with the surrounding codes. If the code number is smaller than the set value, the robot moves slowly to the right. If the code number is greater than the set value, the robot moves slowly to the left. When the robot detects the correct code number, it stops moving, initiates another rotation to align its angle with the code, and completes the initialization process. The pseudocode for this process can be represented as follows:

```
algorithm 1 search the initial position
input: ImageArray
output: x,y,z,w
function ALIGENED(set_x, set_y, set_w)
    v_x ← 0.1
    if ApriltagID has been detected then
        v_x ← 0
        while δ_x ≠ set_x and δ_y ≠ set_y andδ_w ≠ set_w do
            v_x ← 0.1
            v_y ← 0.1
            v_w ← 0.1
        end while
    end if
    return AprilTagID has been aligened
end function

function INIT POSITION(Array, x, y, w)
    ALIGENED(0,0,0)
    while ID is not the target id  do
        if ID < id then
            v_y ← −v
            aligend(ID+1,0,0,0)
        else
            v_y ← v
            aligend(ID-1,0,0,0)
        end if
    end while
    return result
end function
```

Figure 2. The pseudocode of the initial position algorithm

2.3. Navigation strategy

The potential field method (PF) was introduced by Khatib [16] for a configured space. The main idea of the method is to establish an attractive potential field around the goal position, as well as to establish a repulsive potential field force around obstacles, by this idea the potential field method uses attractive and repulsive forces to guide a robot to its goal while keeping it away from obstacles.

The designed system comprises three distinct categories of robots, and the quantity of each category is indeterminate. During practical operation, the selection of path planning and navigation methods becomes critically important for the robots, since different categories may necessitate diverse strategies for these tasks. The present study employs the artificial potential field (APF) method as the navigation strategy for the robots, due to its advantages such as low computational complexity, fast obstacle avoidance response, and ease of hardware implementation. The artificial potential field method involves the creation of a virtual "repulsive" potential field around obstacles and a virtual "attractive" potential field around the target object.

$$U(x,y)=U_{att}(x,y)+U_{rep}(x,y) \tag{2}$$

Where $U_{att}(x,y)$ represents the goal's potential, U_{rep} the obstacle's potential and $U(x,y)$ the total potential. This potential is only computed in the vicinity of the robot (x, y). Through the combined effect of the "attractive" and "repulsive" potential fields, the robot gradually avoids the high potential energy fields of obstacles and reaches The attractive potential energy formed by the target point varies with the distance between the moving robot and the target point. In the artificial potential field, the magnitude of the attractive potential energy is proportional to the distance between the robot and the target point. The farther the distance, the greater the attractive potential energy generated by the target point. The representation of the attractive potential field function is as follows:

$$U_{att}(x,y)=\frac{1}{2}\varepsilon\rho(q,q_{goal}) \tag{3}$$

Where $\rho(q,q_{goal})$ is the distance between the robot and the target point, expressed as $\sqrt{(x-x_g)^2+(y-y_g)^2}$. ε is a constant that determines the strength of the attractive force.

The repulsive potential field function can be expressed as follows:

$$U_{req}(q)=\begin{cases}\frac{1}{2}\eta[\frac{1}{\rho(q,q_{obs})}-\frac{1}{\rho_0}] & if\,\rho(\mathrm{q},\mathrm{q}_{obs})\le\rho_0\\ 0 \quad if\,\rho(\mathrm{q},\mathrm{q}_{obs})>\rho_0\end{cases} \tag{4}$$

Where $U_{req}(q)$ represents the repulsive potential field created by obstacles around the current position of the robot; η is repulsive potential field gain function;

$\rho(q, q_{obs})$ represents the Euclidean distance between obstacles and the current position of the robot; ρ_0 represents the influence radius of the obstacle, which indicates the effective range of the repulsive potential field. When the relative distance $\rho(q, q_{obs})$ between the robot and the obstacle is greater than ρ_0, the obstacle no longer exerts a repulsive force on the robot. Figure 3 depicts the navigation method based on the APF algorithm.

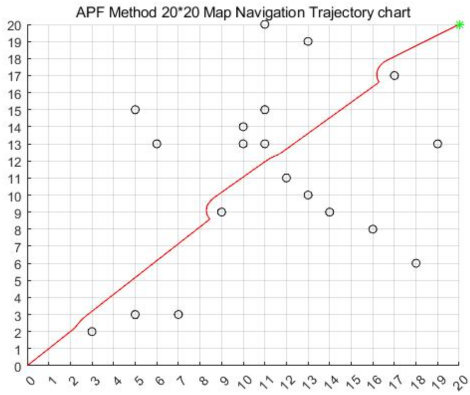

Figure 3. APF algorithm demo

2.4. Management System and Robot System

A management system consisting of a front-end and a back-end based on the Spring Boot and Vue frameworks, which allowed for the development of a robust and efficient system that can meet the needs of various applications, has been designed and the system's interface is shown in the figure below, with a modern and responsive layout.

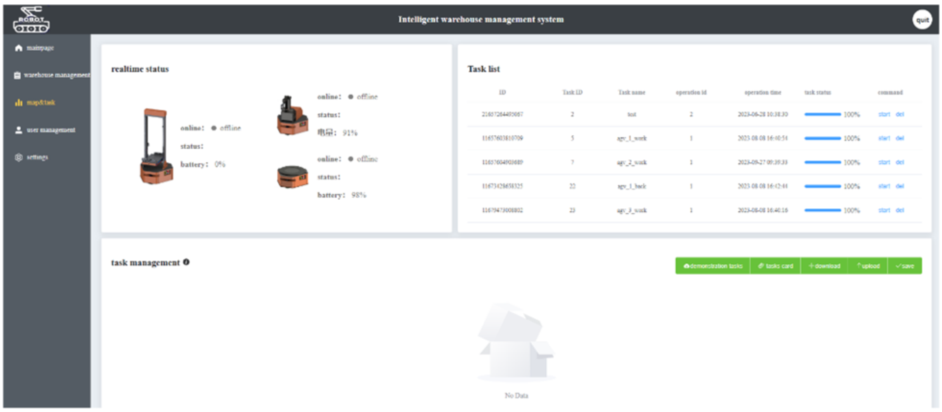

Figure 4. The interface of the management system

From Figure 4, it can be seen that the system includes pages for managing robots, managing goods, and configuring robots. The interface dynamically displays the status, like power and task, and usage of the designed robots. The system can be extended to support the coordination and scheduling of multiple robots for collaborative processing. Through this system, tasks can be assigned to a single robot multiple robots working together in coordination.

The topological structure of the logistics robots and system is shown in Figure 5. The three types of robots interact with the management system through a local area network (LAN) for information exchange.

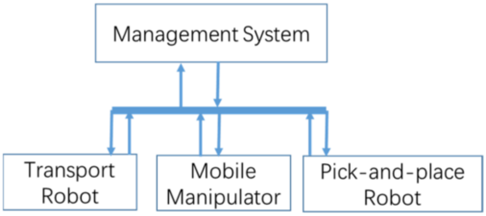

Figure 5. Scheme of the system

The state machine diagram for the internal system of the logistics robot is depicted in Figure 6. Upon power-up, the robot enters the idle state, during which it is unable to perform its tasks effectively. It requires further initialization to locate the reference point. Once the reference point is successfully identified, the robot's status transitions to the ready state. In this state, the robot can receive assigned tasks from the system and execute them until completion, while updating its status in the background system. If insufficient battery power is detected during this process, the robot needs to switch to the charging state and initiate the charging task.

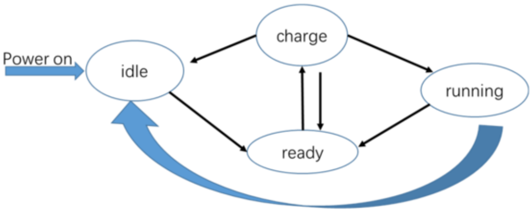

Figure 6. The state machine of the robot

3. Experiment

To verify the feasibility and task execution capability of the designed warehousing logistics robot, two sets of experiments were conducted. Figure 7 shows the robots described in Section II.

Figure 7. The logistics robot designed

3.1. Single task

In the first set of experiments, the focus was on assessing the robot's performance in fulfilling various tasks related to warehousing and logistics operations. The following aspects were considered:

(a). Collision avoidance: The robot's ability to navigate through the environment without colliding with obstacles or other robots was evaluated. This ensured the safety of both the robot and its surroundings.

(b). Path planning: The effectiveness of the robot's path planning algorithms was tested. The robot should be able to determine an optimal or efficient path to reach its target location, considering factors such as distance, obstacles, and any specified constraints.

(c). Task execution: Each type of robot was evaluated based on its specific task requirements. The tasks are shown in Table 2, for example, a sorting robot's ability to identify and correctly pick up objects from a designated location, an AGV's capability to transport goods over long distances while maintaining stability, and a placement robot's accuracy in storing items in the correct locations were all assessed.

(d). Performance metrics: Quantitative metrics were used to measure the robot's performance, such as the time taken to complete a task, the accuracy of object recognition and grasping, the efficiency of transportation, and the precision of item placement.

Table 2. Sub-task lists

Name	Task assigned	Completion rate
Transport robot	Transporting goods to a specified location and returning along the same path after placing them	100%
Mobile manipulator	Using a visual system to recognize the goods, the robotic arm is capable of accurately gripping the detected items and transferring them using the chassis.	98%
Pick-and-place robot	The robot is capable of autonomous navigation to move to the front of the shelving unit, locating the position of the goods, and using its own mechanism to perform the functions of picking up and placing the items.	100%

3.2. Collaborative task experiment

To validate the collaborative task completion of multiple robots, we designed a collaborative inventory task involving three robots

The process includes the following steps:

(a) A transport robot transports the goods close to the mobile manipulator.

(b) The robot updates its own state, and the backend system synchronizes the state with the mobile manipulator.

(c) Upon detecting the transport robot's state, the mobile manipulator starts searching for the transport robot's pose and adjusts its position relative to the transport robot, using its chassis to achieve an optimal pose relationship.

(d) The mobile manipulator utilizes its 3-axis robotic arm to accomplish the grasping task.

(e) The mobile manipulator updates its own state, and the backend system synchronizes the mobile manipulator's state with the pick-and-place robot.

(f) Upon receiving the command, the pick-and-place robot autonomously navigates to the vicinity of the mobile manipulator.

(g) The mobile manipulator transfers the goods onto the gantry of the pick-and-place robot, and they collaborate in this process.

(h) The pick-and-place robot then navigates to the vicinity of the shelving unit based on the desired storage location for the goods.

(i) The pick-and-place robot lifts the goods to a certain height and, relying on the corresponding mechanism, pushes the goods into the specified position.

(j) Finally, the pick-and-place robot returns to its initial position and stands by.

Through the front-end system, 10 inbound tasks and 10 outbound tasks were designated, and the task completion rate reached 100%.

4. Conclusion

The paper introduces a novel strategy for logistics robots in which inbound and outbound tasks are categorized into separate subunit modules based on their characteristics. Warehouse logistics robots with the ability to perform these subtasks are designed. Through the coordinated and sequential collaboration of these robots, including the execution of outbound and inbound tasks, complete warehouse operations can be achieved. Experimental analysis validates the individual robot's capability to accomplish specific subtasks. When integrated with a task allocation and scheduling system, the combined efforts of three types of robots enable the successful completion of comprehensive warehouse tasks, such as outbound and inbound operations. This approach offers the advantages of lower deployment costs and enhanced flexibility in the intelligent deployment of warehouses, thereby providing practical value for small-scale warehouses and warehouse automation upgrades.

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