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International Conference on Information Resources Management (CONF-IRM)

5-2018

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DEVELOPMENT OF AN INDUSTRIAL INTERNET OF THINGS (IIoT) BASED SMART ROBOTIC WAREHOUSE MANAGEMENT SYSTEM

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Abstract:
According to data of Census and Statistics Department, freight transport and storage services contributed to 90% of the employment of logistics sector in the period from 2010 to 2014. Traditional warehouse operations in Hong Kong are labor-intensive without much automation. With the rapid increasing transaction volume through multi-channel, the preference for next-day delivery service has been increasing. As a result, 3rd party logistics providers have realized the importance of operational efficiency. With the advent of Industry 4.0 emerging technologies including Autonomous Robots, Industrial Internet of Things (IIoT), Cloud Computing, etc., a smart robotic warehouse management system is proposed as it redefines the warehouse put-away and picking operations from man-to-goods to goods-to-man using autonomous mobile robots. This paper aims to develop and implement an IIoT-based smart robotic warehouse system for managing goods and autonomous robots, as well as to make use of the autonomous mobile robots to deliver the goods automatically for put-away and picking operations. The significance of the paper is to leverage the Industry 4.0 emerging technologies to implement the concept of smart warehousing for better utilization of floor space and labor force so as to improve logistics operational efficiency.

Keywords:
Robotic System, Industrial Internet of Things, Industry 4.0, Swarm Robot, Collision Avoidance

1. Introduction

The rapid development of the Internet innovates the traditional commercial shopping mode. Online shopping has offered new marketing and distribution channel for enterprises all over the world. China-based e-commerce giant Alibaba earned 168.2 billion yuan (US$25.3 billion) in 24 hours of the Double 11 shopping festival last year. JD.com, Chinese's second-largest e-commerce platform, also reported 127.1 billion yuan (US$19.12) in orders on Double 11. As a recent report by Statista (2017) indicates, the retail e-commerce sales in China will increase to $840 billion by 2021.

Driven by the overwhelming growth of the retail e-commerce sales, express delivery plays an important role in China's logistics and supply chain industry. According to statistics from iResearch, it is expected that the China express delivery market will grow at a CAGR of 22.8% from 2016 to 2021, which is shown in Fig. 1. To meet the delivery demand, more employees has to be hired in logistic companies. However, the monthly minimum wages in major cities such as Beijing, Shanghai and Shenzhen have doubled to over 2000 yuan, which puts a heavy burden on the Logistic Service Providers (LSPs). Meanwhile, the labor force aged from 15 to 24 years old keeps declining since 2010 because of the sluggish economic growth and the one-child policy. Less young people choose to engage in the logistic industry.

Facing the enormous challenges, the labor-intensive industry is eager to search for a novel method to solve this problem.

Fig 1. 2011-2021E China Express Delivery Market [Source: U.S. Securities and Exchange Commission, 2017]

In response to the severe labor shortage in manufacturing and supply chain, an IIoT-based Smart Robotic Warehouse Management System is proposed in this paper. Swarm of autonomous unmanned ground vehicles (UGVs) is applied to relieve man of monotonous and repetitive logistics operations. With the conversion from man-to-goods to goods-to-man picking and replenishment process, the system aims to enhance the efficiency and effectiveness of the order fulfilment process. As the UGVs are responsible for the fatigued and repeated picking and replenishment process, operators only work in a specific workstation, which is more comfortable, safe and attractive compared with the warehouse storage area. Comparing with human beings, robots do not need bright lights and comfortable air conditioning to perform operations such that the LSPs can save electricity cost and protect the environment.

Although there have been some practitioners equipping their warehouse with material handling devices such as trucks, conveyors, carousels and cranes to facilitate the picking process, the inherent property of these devices makes it difficult to expand and any changes of floor plan needs a lot of effort for renovation. Moreover, it takes a long time for operators to be familiar with the layout of the whole working area and the locations of the goods in the traditional material handling system (MHS). The emergence of automatic guided vehicles (AGVs) saves LSPs from the quandary, since the use of automatic robots supports fast expansion and short training time so as to improve enterprises' competitiveness. However, in some traditional warehouses, the AGVs should move on fixed lanes such as wired and magnetic, resulting in low flexibility. In most distribution centers, the guided vehicles can only move on aisles by using QR code, but the utilization of space is not efficient enough. The proposed system solves these problems by allowing UGVs to pass under the racks, which maximizes utilization of space, labor and resources. The transformation from traditional, labor-intensive and low technology warehouse to modern, unmanned and high technology fulfilment center helps the LSPs to satisfy the customers' needs and expectations.

The rest of the paper is organized as follows. Section 2 mainly reviews the related research on the path planning and motion controlling problem of mobile robot for material handling. Section 3 presents the design of the whole system and describes each component in detail, followed by a case simulation to illustrate the implementation of the system in Section 4. Finally, a short conclusion of the study and the future works are summarized in Section 5.

2. Related Studies

A typical warehouse includes inbound and outbound management. On one hand, the inbound process like order receiving and restocking is to receive products and to stock materials until they are requested. On the other hand, the outbound procedure like order picking and packing, and order delivery is directly in response to the customer demands. Amongst the order handling operations in a distribution center, order picking is the most labor intensive process and hence accounts for 55% of the overall expense (Accorsi et al., 2014). With the development of wireless communication and embedded computing, robots are deployed to automate the logistics warehousing system. For example, a large quantity of AGVs are used to enhance the effectiveness and efficiency of the warehouses procedure in Amazon, DHL and Alibaba (Kehoe et al., 2015).

A warehouse with a number of AGVs can be viewed as a multi-agent system (MAS). As Stone and Veloso (2000) defined, a MAS is consisted of problem-solving agents working together to solve complicated problems that are beyond the limit of individual entity's capability. In the autonomous warehouse system, each vehicle represents an agent and cooperatively works with each other to fulfil orders. To be more exact, the warehousing system is actually a kind of swarm robotic system. Sahin (2005) stated that swarm robotics studies the design of the collective behavior from local agent-agent and agent-environment interactions. Three properties (robustness, flexibility and scalability) inspired from the observation from social insects are desirable in the system. Robustness indicates fault tolerance such that the robot swarm is able to continue working even if some individuals fail. The robots are flexible if their role can be assigned based on the needs of particular moment. As for scalability, it requires that the swarm can complete tasks in different group sizes from small to large.

The advantages of MAS attract practitioners to penetrate AGVs in the distribution centers. Nevertheless, since there are plenty of vehicles working in the same area, interferences such as blockages, collisions, conflicts and deadlocks may occur. It is a complicated issue for the industry to coordinate the motion of AGVs so as to resolve the problem mentioned above. Abundant issues of the control of vehicles are discussed in the literature.

In practice, AGV systems usually build upon a centralized control architecture where various tasks are performed by a central unit to schedule mission, plan path and coordinate motion. Each vehicle in the system has to communicate with the central unit, so its location can be known and action can be carried out. Depending on the amount of information gathered, centralized control can be further classified as coupled and decoupled. The coupled method treats the coordination as a whole and composite system (Vivaldini et al., 2010; Nishi et al., 2005; Gawrilow et al., 2007), while the decoupled one breaks it into path planning and motion coordination (Zhang et al., 2017; Wu & Zhou, 2007; Klimm et al., 2011). However, the centralized control relies on considerable communication demands and heavy computation loads, which gives rise to a relatively low level of fault tolerance. Decentralized methods are developed to distribute computation (Purwina et al., 2007; Draganjac et al., 2016; Demesure et al., 2017). But different unpredictable situations may occur in the decentralized methods.

Author	Year	Control Architecture			Routing			Conflict-free routing		Collision Control Method					Solution Method				Kinematics	Penalty Cost	Shortest Path			Priority
		centralized		decentralized	offline	online		predictive	reactive	Petri net	Zone control	Time window	Rule-based	Optimization	Exact method	heuristic	simulation	Dynamic programin			Dijkstra	A^*	Unknown	
		couple	decoupled			static	dynamic																	
Purwina et al.	2007			✓		✓			✓		✓				✓	✓			✓	✓			✓	✓
Draganjac et al.	2016			✓		✓			✓		✓				✓				✓			✓		✓
Zhang et al	2017		✓			✓			✓				✓		✓				✓				✓	✓
Wu & Zhou	2007		✓		✓			✓		✓					✓								✓	
Demesure et al.	2017			✓			✓		✓					✓		✓			✓				✓	✓
Saidi-Mehrabad et al.	2015	✓			✓			✓						✓		✓							✓	✓
Vivaldini et al.	2010	✓					✓	✓				✓						✓			✓			
Nishi et al	2005	✓			✓			✓				✓		✓	✓					✓	✓			
Klimm et al.	2011		✓			✓		✓					✓	✓	✓								✓	
Maza & Castagna	2001		✓				✓		✓			✓	✓		✓		✓						✓	
Smolic-Rocak et al.	2010	✓					✓	✓				✓			✓								✓	✓
Vivaldini et al.	2010	✓					✓	✓				✓				✓	✓	✓			✓	✓		✓
Gawrilow et al.	2007	✓					✓	✓				✓			✓								✓	
Herrero-Pérez et al.	2010			✓		✓			✓	✓	✓				✓		✓		✓				✓	✓
Krishnamurthy et al.	1993		✓			✓		✓						✓		✓							✓	
Ours	2018		✓			✓			✓			✓	✓		✓		✓		✓	✓	✓			

Table 1. Summary of literature review

The dominant methodology to find shortest path is Dijkstra's algorithm (Vivaldini et al., 2010; Nishi et al., 2005), although A^* is gradually proposed in the pathfinding literature (Draganjac et al., 2016). There are two types of routing method offline and online. The offline routing assumes that all requests are known at the beginning, while the online method allows requests appear sequentially. In terms of the domain to determine route, the online approaches are prevailingly divided into static and dynamic routing in the literature. Static routing focuses on the spatial dimension (Purwina et al., 2007) and dynamic routing determine paths in time-space domain (Smolic-Rocak et al., 2010). Predictive and reactive manners are used to solve conflict. Unlike reactive method solving collision in real time (Wu & Zhou, 2007), predictive approach provides paths without collision (Krishnamurthy et al., 1993).

Various methods by considering time window are studied by researchers to control conflicts. Vivaldini et al. (2010) used dynamic programming to solve the time window based method, but they solved collisions by rerouting vehicles. Heuristic function was applied to optimize number of maneuvers so as to generate conflict-free path in the time window, as Vivaldini et al. (2010) proposed. Optimization is another method of controlling collision which is often solved by heuristics. Saidi-Mehrabad et al. (2015) adopted an Ant Colony Algorithm (ACA) to minimize the make-span. Moreover, zone control and petri net methods are also accepted in some research. Herrero-Pérez and Martínez-Barberá (2010) employed a topological map to represent the large workplace and petri net formalization to model AGVs' behaviors. Apart from the above methods, collision control can be rule-based as well. Zhang et al. (2017) suggested three cars following rules such that the vehicles avoid collisions without stopping.

Additional parameters are also taken into consideration in the research. Penalty cost is added to prevent vehicles from choosing the same route as others. Priority is another factor to value different tasks. Some researchers also think about kinematic constraints to be feasible to apply their methodology in practice. Because of restrictive security issues, centralized structure still dominates the logistic industry. Therefore, in this research, a decoupled control architecture with static routing is adopted. Taken UGV dynamics and penalty cost into consideration, the system bases on rules with time window helps to solve conflict and provides a simulation interface to validate the solution.

3. IIoT-based Smart Robotic Warehouse Management System

To improve the overall performance of the LSPs, the IIoT-based Smart Robotic Warehouse Management System redefines the business model of fulfilment center from labor-intensive to unmanned. The overview of the system is illustrated in Fig. 2. The implementation of the proposed system relies on material handling devices such as vehicles and workstation, the core control unit and their communication. There are three main components in the system, including autonomous UGVs, the robotic picking and replenishment workstation and the cloud-based swarm robots control system. The detailed description for each part are as follows.

3.1 The Autonomous Unmanned Ground Vehicle (UGV)

The autonomous vehicle is the main component of the whole system. Different from traditional manufacturing robots, the employed UGV carries the rack by lifting instead of dragging. There is no need to install sensors in the environment to locate the UGV, since the UGV automatically locates itself by scanning the QR code stuck on the ground. The heartbeat signal is sent and control commands are received via wireless communication. In addition, the robot is capable

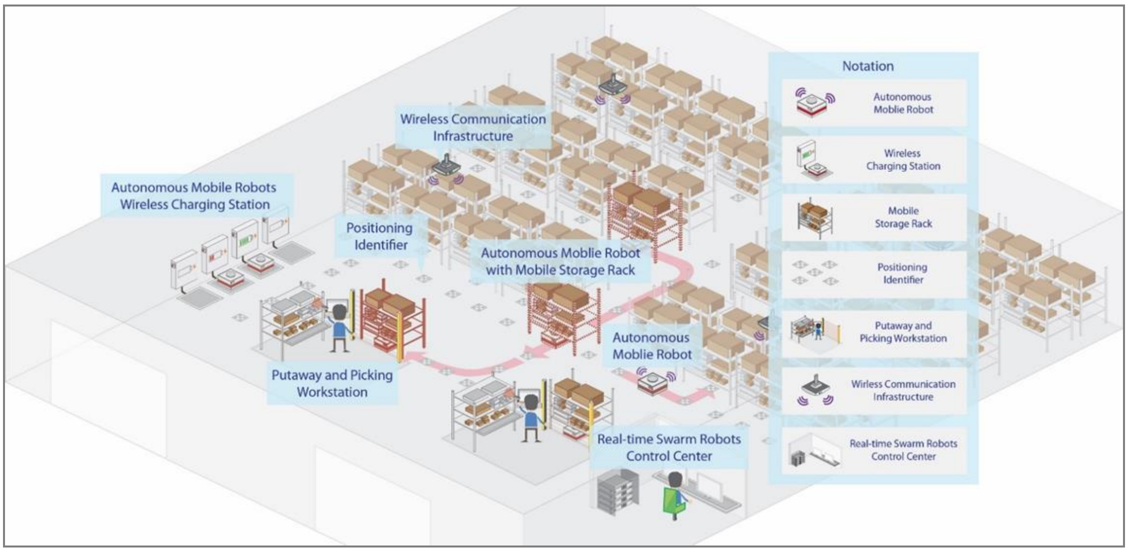

Fig 2. The overview of the IIoT-based Smart Robotic Warehouse Management System

of detecting obstacles at three different distances by laser and hence slows itself down to avoid crash. The physical appearance of the UGV is shown in Fig. 3. The autonomous UGV lifts racks to workstations for picking and put-away process. It enables operators to achieve a consistently high order picking and replenishment performance, and optimize warehouse utilization.


Fig 3. The autonomous UGV

3.2 The IIoT-based Robotic Picking and Replenishment Workstation

The IIoT-based Robotic Picking and Replenishment Workstation is designed for efficient and accurate picking and replenishment activities. When the mobile storage rack is delivered to the workstation using autonomous UGV, workers can pick or replenish the goods simply by referring to the delivery order instruction shown on screen, and recognize the rack position and the required number of goods by referring to the Pick-Put-To-Light (PPTL) Guiding Devices. The devices are installed on the frame at the workstation together with the safety light curtain. The PPTL Guiding Device indicates the correct picking and replenishment location, and the appropriate order bin for that goods. Once worker picked and put the goods into the appropriate bin, they press the button of guiding device to confirm the act. The device can guide workers and prevent wrong picking and replenishment of goods. The safety light curtain is designed to protect workers from dangers. Warnings will be sent to the control center if objects reach out the curtain before the rack arrives. All the information is exchanged and monitored in real time with the swarm robot control system to ensure accuracy. The surface of the workstation and interface of sample order for picking and replenishment are shown in Fig. 4.

Fig 4. The surface of the workstation and the interface of sample order picking

3.3 The Cloud-based Swarm Robots Control System

The Swarm Robots Control System acts as the brain of the whole system, which is the most important and highlighted feature of the proposed system. It is responsible for controlling the collaboration between autonomous UGVs and the operations in Picking and Replenishment Workstation. The system applies a Robot-as-a-Service (RaaS) model, which integrates autonomous UGVs into a cloud computing environment. Autonomous UGVs are offered as a service rather than a product. The Cloud links up the robots control system and vehicles to allow communications and data exchanges via wireless infrastructures. RaaS is not only effective in providing consistently high service quality, but also elastic to deal with various service demand. There are four major sections of the cloud system, which are discussed in the following part.

3.3.1 Swarm Robots Strategy

The Swarm Robots Strategy proposes two modes of UGV role assignment, which is illustrated in Fig. 5. The first mode is a common one in most robotic warehouse. That is, all UGVs are assigned the same role and are responsible for delivering mobile racks from the storage area to the workstation and reversely to the storage area. In the second mode, labor is divided up among UGVs in peak periods. One group of autonomous vehicles named storage robot is in charge of moving racks to the buffer zone and back to the storage zone, while the other group named operation robot focuses on delivering racks to the workers for picking and replenishment according to rack’s arrival time. The division of labor is beneficial to increase productivity and efficiency of the fulfilment center. However, the setting should be pre-set carefully for the second mode. For example, the size of the buffer zone is assumed to be 8 and the queue size in each workstation is preset as 3. If there are 6 storage robots and 2 operation robots, sometimes the storage robot waits for the operation robot to move the rack back to buffer zone and sometimes the operation robot waits for the storage robot to move the needed rack from the storage area. Therefore, assigning the right number of robot to perform specific role is crucial for the overall system performance.

3.3.2 Conflict Resolution with Collision Avoidance

The control of UGVs is decoupled into path planning and motion coordination. The route selection is based on the Dijkstra’s algorithm with dynamic cost table, so the chosen paths can be dispersed to avert conflicts. The penalty cost associated with every grid is predefined as $\sum_{n\in N}\alpha * \beta^{Dist_n}$, where α and β are the coefficient constants; $Dist_n$ is the distance from UGV n 's current gird to the calculated grid; and N denotes the total number of UGVs. If there are more robots passing the grid, the cost will be increased such that the UGV assigning new tasks can be arranged a route without going through this grid. The dynamic cost table is updated every five seconds, so the real-time information can be fetched for efficient allocation.

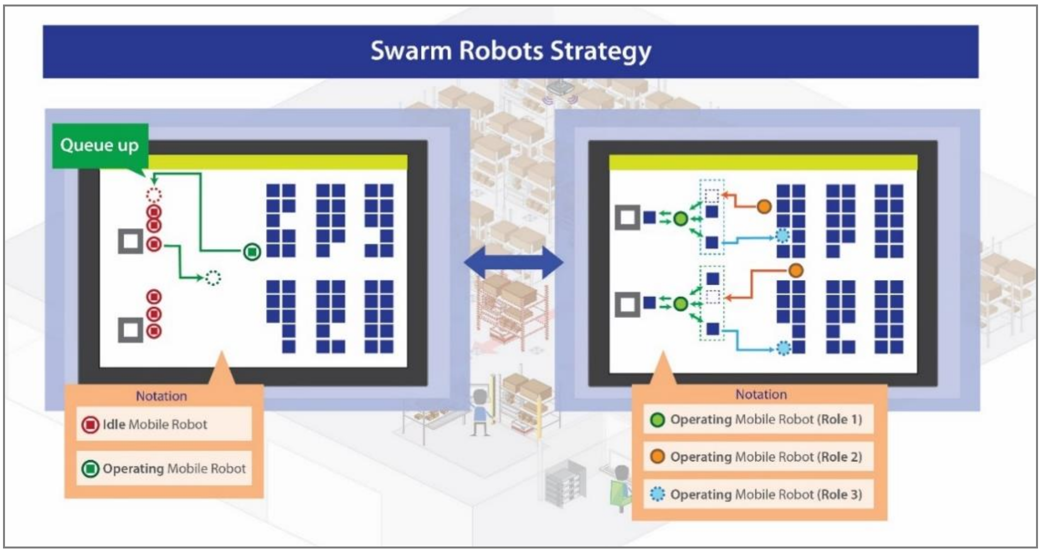

Fig 5. The conceptual diagram of Swarm Robots Strategy

During the motion coordination step, the foresee path associated with time window t_m for vehicle i $Path_{i,t_m} = \{Node_{i,k}, Node_{i,k+1}, Node_{i,k+2}, \ldots, Node_{i,k+n}\}$ is used to predict possible collisions, where $Node_k$ is the current position of the vehicle and n is the length of the foresee path. The length of the foresee path should be long enough to ensure that UGV with highest speed can make a full stop before crashing into other UGVs. At the same time, the length cannot be too long. Otherwise, the robot will frequently receive unnecessary stop command. From our experimental results, it is indicated that the minimal length should be set as 4 for safety assurance if the maximal speed of UGV is 1 m/sec. The collision detection is processed pair by pair. If the two paths $Path_{i,t_m}$ and $Path_{j,t_m}$ intersects on at least a node $Node_n$, conflict may occur.

The decision tree for collision avoidance is shown in Fig. 6. The collision evaluation step is processed per second. Firstly, the four main branches are developed by the UGV status which could be running, staying and stopping. There are various conditions to be considered when both robots are running, such as the standing flag $StandFlag_i$ indicating whether UGV_i stands on the intersection node, the lifting flag $LiftFlag_i$ indicating whether UGV_i carries a rack, the turning flag $TurnFlag_i$ indicating whether UGV_i need to turn before arriving the intersection node and the overlapping position $OverlapPos_{ij}$ indicating whether the two paths $Path_{i,t_m}$ and $Path_{j,t_m}$ have more than one intersection node and the position of the additional overlapping nodes. Basically, three different types of conflicts including same-direction collision, opposite-direction collision and cross-direction collision can be found in the two dimensional space. It is a normal catch-up conflict case when $StandFlag_i$ or $StandFlag_j$ is true and directions at this node $D_{i,n}$ and $D_{j,n}$ of UGV_i and UGV_j are the same. In this situation, the collision avoidance relies on laser detection or a compulsory stop command. When $StandFlag$ is true, the control command depends on $LiftFlag$ and $TurnFlag$ respectively for the opposite-direction collision and cross-direction collision. For example, laser avoidance is efficient enough if the turning flag of either vehicle is true for the cross-direction collision. Otherwise, stop command will send to the UGV at a longer distance. For opposite-direction conflict, a UGV without rack will always give way to UGV carrying rack. As for the opposite-direction conflict with $StandFlag$ be false, apart from the lifting flag, the overlapping flag is also taken into consideration. Cases are more complicated for the cross-direction collision detection with $StandFlag$ be false. When both vehicles do not lift a rack, the control decision is related to $TurnFlag$. Otherwise, the position of the additional overlapping node $OverlapPos$ will affect the selection of vehicle to be stopped. Rules based on the conflict type and the occurrence of UGV on the intersection point effectively detect and eliminate collisions and conflicts in advance.

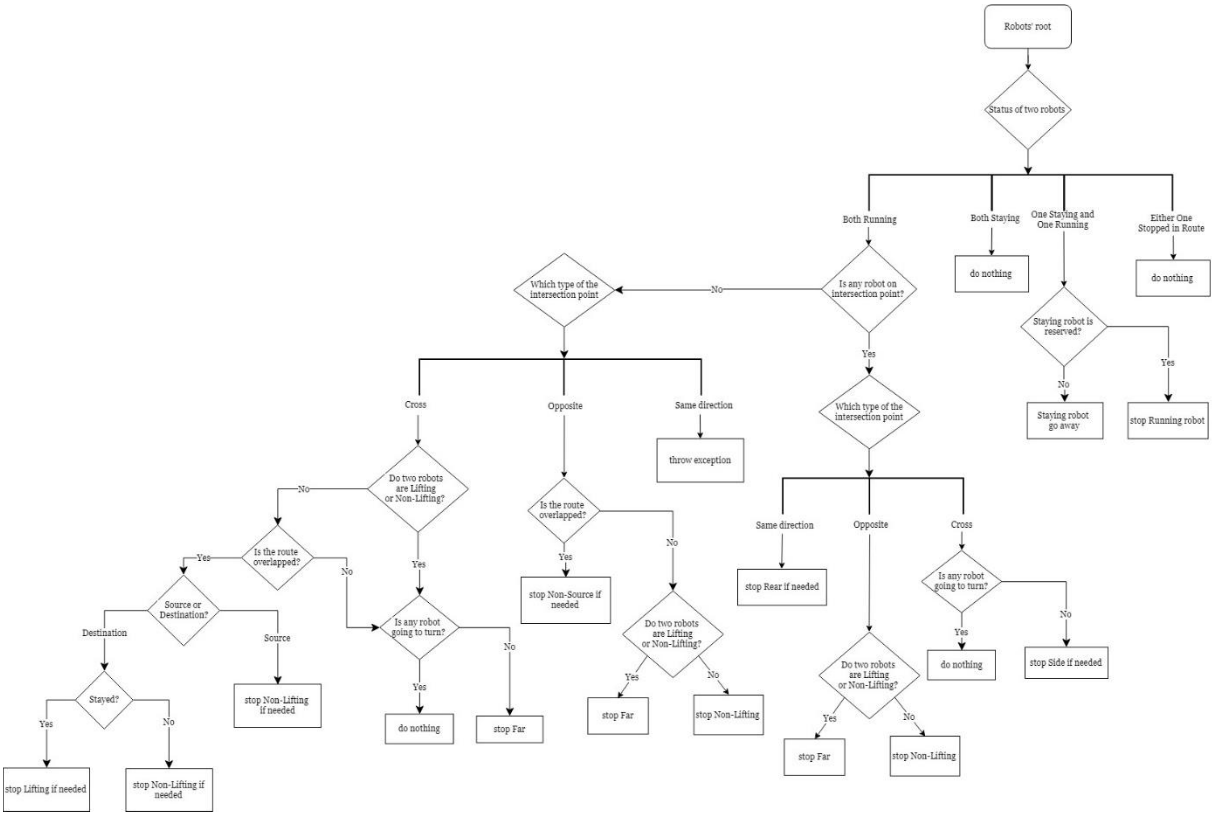

Fig 6. Decision tree for collision avoidance

3.3.3 Warehouse Slotting and Re-slotting Optimization

Pre-organization of racks' location is optimized to minimize the delivery distance of goods from rack to workstation in peak times and increase service rate. The control system re-slots the racks according to existing orders in system, goods turnover and the past delivery records during the midnight such that the efficiency can still be guaranteed. Every grid is associated with a priority, according to the grid type and its location in the floor plan. A grid closer to the workstation gets a higher priority, so idle autonomous UGVs can move racks with goods to be delivered in the next few days near to the picking and replenishment workstation. As a result, shorter distance and less time will be required for autonomous UGVs to deliver goods on the next working day which can balance workload and reduce peak power. The optimized resource allocation can improve the productivity and fulfilment rates, so the total cost can be reduced and the profit can be increased. The concept of the re-slotting optimization is demonstrated in Fig. 7.

3.3.4 Robotic Warehouse Simulator

The system offers a "Simulation Mode" for top-management to model, analyze, plan and predict future situation and supports decision making on investment of spaces, labors and equipment for fulfilment center. Users can see the difference in the performance of operations by entering different parameters. The user interface of Robotic Warehouse Simulator is shown in Fig. 8.

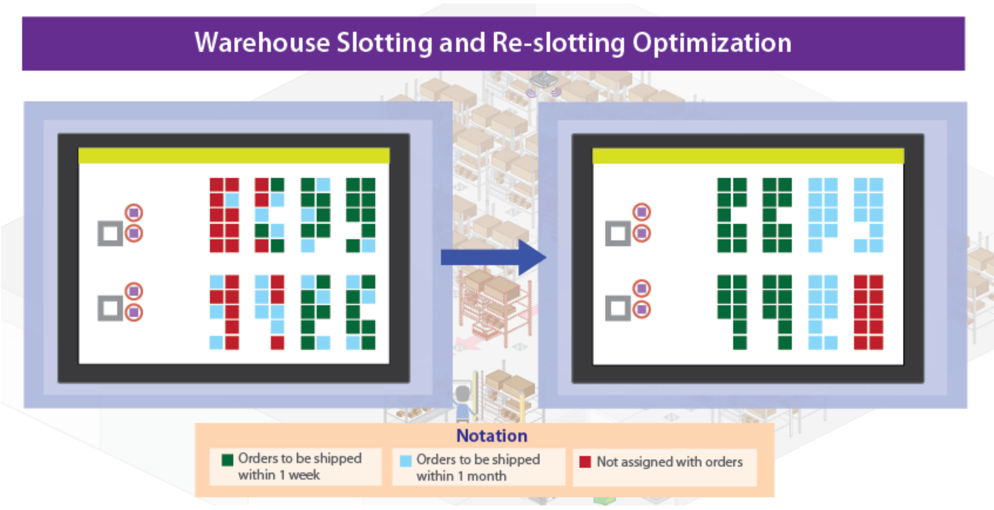

Fig 7. The conceptual diagram of the Warehouse Slotting and Re-slotting Optimization

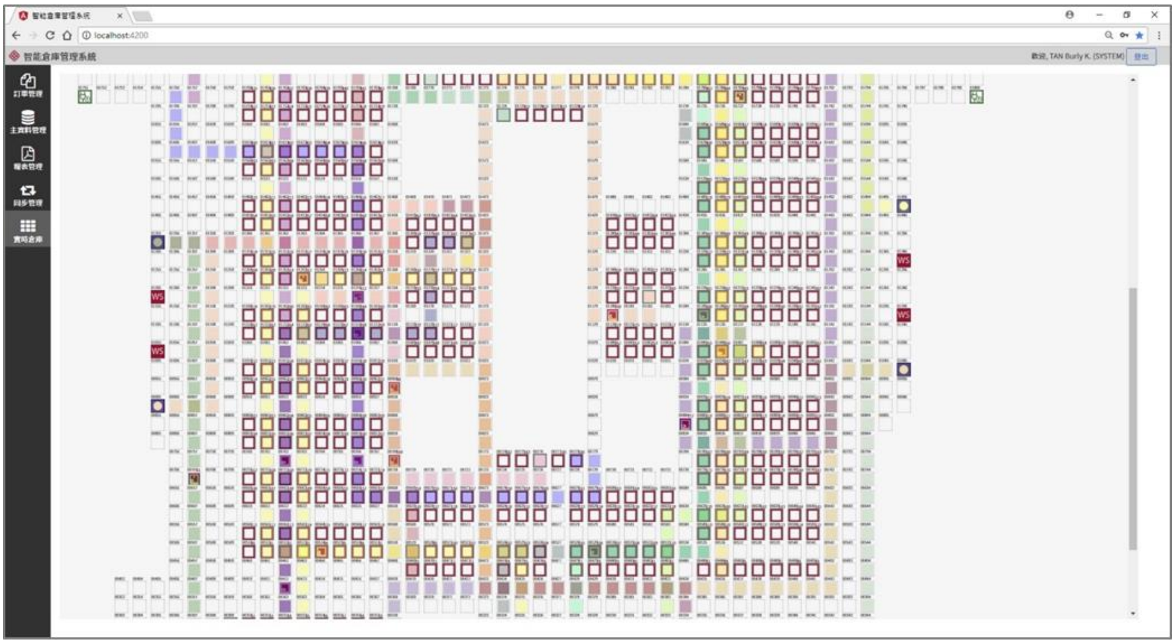

Fig 8. The user interface of Robotic Warehouse Simulator

4. Case Simulation

Hong Kong is one of the main trans-shipment hubs from / to China. In recent years, the rapid growth of ecommerce at China has generated the demand of cross-border logistics service. To commit logistics service demand, lowering delivery cost, high delivery efficiency and visualizing traceability are the keys to sustain the competitiveness of Hong Kong third party logistics. It is expected that there will be a huge potential for smart robotic warehouse management system to increase the efficiency and accuracy of logistics operations.

As requested by a local trading company named as WT, the pilot simulation experiments are mainly conducted based on a floor map covering an area of 2500 square meters, as shown in Fig. 9. The travelling time is approximately 51% of the time of picking orders in a traditional warehouse, therefore the operators do not need to remember the merchandise location or the slotting category and spend most of the time for walking and searching the goods to fulfil orders. The tasks done by 6 operators in the traditional distribution center can be finished by 1 to 3 operators in the autonomous warehouse, which means 50% to 80% reduction in manpower. As the pick-put-to-light guidance and the on-screen instructions are given clearly, the workers are able to pick one item per second. If there are 8 opening workstations and 24 active UGVs, it takes nearly 23 minutes to complete 133 order lines. The productivity in a conventional shelf warehouse is 100 lines/hour, while the productivity can be improved to 3 to 4 times in the smart warehouse.

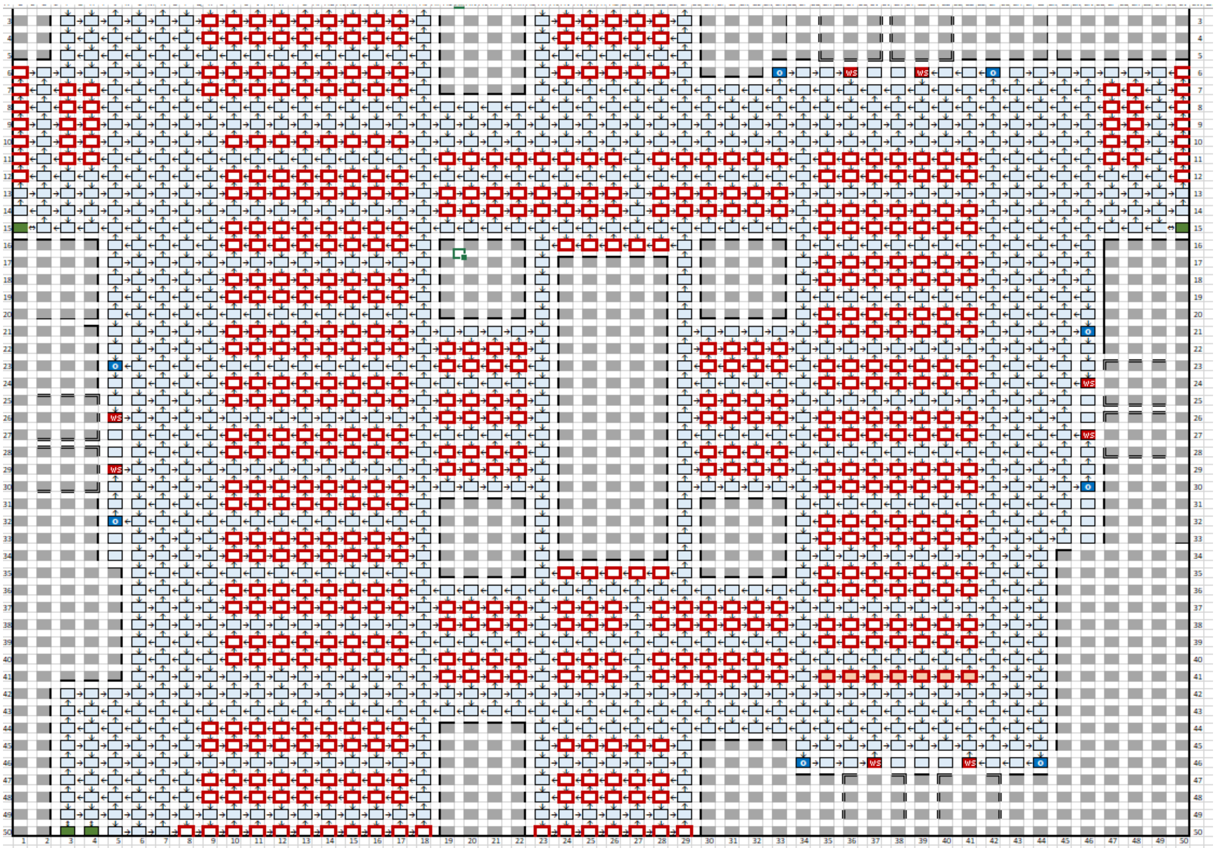

Fig 9. A floor plan with a size of 50 meters X 50 meters

Additional experiment was done to analyze the impact of robot size on the productivity. Assuming the size of order lines to be replenished is 150 and the size of opening workstations with queue size be 3 is 2, the robots are in proportional growth. When the UGV size is 4, it takes 2 hours to complete all tasks. As the robot size is increased to 6 and 8, the completion time is decreased to 1.5 hours and 68 minutes respectively. Although the robot size is further expanded to 10 and 12, the completion time remains to approximately 63 minutes. Since the queue size is fixed and the worker's picking speed has limitation to be further reduced, the efficiency is not directly proportional to the robot size. The optimal number of robots can be investigated by using the simulator.

5. Conclusion

Logistics service providers realized that there is a lack of labor for warehouse operation and the efficiency to fulfill the increasing e-order demands is low. An Industrial Internet of Things (IIoT) based Smart Robotic Warehouse Management System is proposed in this paper to solve the labor shortage problem and increase the competitiveness of the logistics company. The autonomous UGV is deployed to participate in the repetitively tedious picking and restocking process, so the operators can work in a comfortable and safe place instead of walking around to find goods. The Pick-Put-To-Light device in the picking and replenishment workstation clearly guides the workers to pick and put goods correctly, which reduces the order error rate and thus increase the customer satisfaction. By applying intelligent strategy and optimization methodology, the system allocates different tasks to UGVs and re-slots the inventory racks to balance the workload. A simulator is implemented to model and evaluate the overall performance under different parameters settings. Useful suggestions can be achieved from the simulator such that the effectiveness and efficiency can be further increased.

Despite of the remarkable benefits obtained by the system, there are areas for further improvement. Currently, the UGV can move at a speed of 1 m/s and its permissible maximum load is 500 kg, the loading and the travel speed of the vehicle can be adjusted to improve the system performance. Advanced collision avoidance strategies and order sorting methods may be studied to enhance the overall efficiency. More real-life experiments will be carried out in the future to investigate the possible problem encountered for different warehouse layouts.

Acknowledgement

This work is supported by the Hong Kong Polytechnic University. Our gratitude is also extended to the research committee and the Department of Industrial and Systems Engineering of the Hong Kong Polytechnic University for support in this project (K-ZM25) and RV Automation LTD for supporting the equipment for pilot run. Thanks for the technical staff, Burly K. Tan and Gabriel Lee for supporting software design and development.

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