School of Computer Science
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Research Proposal — Comp Sci Honours, 2017

Improving Autonomous Vehicles in Parts-to-picker systems

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Contents

Abstract

The order picking process is the number one expense in warehouse systems. Here we look at parts-to-picker a type of order picking where the products are autonomously retrieved and given to the pickers. Previous research have focused on improvements in the multi-agent path finding but they often overlook simple adjustments or additions which may reduce complexity of the problem. This project will test the effect that these aspects have on improving order-picking. We will create a simulation and focus on the warehouse layout first. The results of this project will help identify how small adjustments may increase the efficiency of the order picking process.

1 Introduction

In warehouse management, Order picking is the process whereby a product is retrieved according to incoming customer orders. This process has been identified by De Koster et al. (2007) as the most costly process in operating a warehouse, estimated to take 55% of the warehouse operating cost.

Here we look at a type of order picking known as Parts-to-picker systems which deals with automating the movement of products from storage areas to picking stations, where workers will manually pick the orders. (Wurman et al. (2008)). Part-to-picker systems often employ the use of automated vehicles when retrieve the orders from where they are stored. AutoStore (2015) is a recent system where products are organized in a grid of stacked bins. Robots move around the top of the grid, lifting bins and delivering them to a human picker. Benefits of the AutoStore system include high storage density and expansion capability. While not much literature is published about the specifics of AutoStore, we suspect some downsides of this system to be similar to conveyor belts with high operational and maintenance costs as well as high retrieval cost.

In this project we look at Kiva Systems (now known as Amazon Robotics). In Kiva systems, products are stored in shelves known as storage pods. Robots known as drive units are responsible for picking up and carrying storage pods to picking stations (see Fig 1 and 2).

Figure 1: A worker picking an order from a storage pod. The orange robot underneath is the drive unit. (Al Dekin (2014))

The process for a drive unit is as follows:

1. Unit is told to retrieve a product
2. Unit moves to the storage pod containing the product and picks up the pod
3. Unit carries the pod to a picking station
4. Human worker picks the product from the pod and packs it
5. Unit returns the pod back to where it was picked up
6. Unit waits until it is told to retrieve another product

Kiva systems do not require a complex infrastructure to operate hence solving issues found in alternative solutions: maintenance and operational costs. When a unit malfunctions it can be easily accessed and replaced, moreover the system remains operational. The initial setup for a warehouse is cheap and fast as a warehouse needs only storage pods, a picking station and a number of drive units to operate.

1.1 Need for the study

HALF-DONE Kiva Systems deal with a number of problems, in this project we will be focusing on the cooperative multi-agent pathfinding (MAPF) problem. MAPF aims to find a path from for each agent (drive unit) so that they can reach their goal while ensuring that no path conflicts with another. Kiva systems are cooperative as agents need to work together to resolve path conflicts? (**Is this correct?**).

Finding an optimal solution to multi-agent pathfinding is an NP-hard problem (Yu and LaValle (2013)), has applications in systems containing few agents. This is not an option as Kiva systems deal with hundreds of agents, for example the Office Supply company, Staples uses 500 robots in their $30000m^2$ center (Guizzo (2008)).

There is a trade-off with

1.2 Research Aims

In this project we aim to answer two major questions:

- Can we reduce the complexity of Cooperative MAPF by adjusting aspects specific to Kiva systems?
- How much faster will the pathfinding search run by using a path oracle to pre-compute paths?

What more should I say here?, I feel if I talk about more specifics I am overlapping with the research methods section

1.3 Review of the literature

HALF-DONE There are a number of problems in Warehouse Automation, some of these we will be looking at in this project include: multi-agent pathfinding, order sequencing and warehouse design.

In multi-agent pathfinding, Cohen and Koenig (2016) uses highways.

Gu et al. (2010) provides a comprehensive review of warehouse design and performance. It covers 5 major aspects, overall structure, sizing and dimensioning, department layout, equipment selection and operation strategy selection.

De Koster et al. (2007) provides a survey on order picking

Wurman et al. (2008) provides an in depth overview of Kiva Systems, describing their benefits, usages and research areas.

Ma and Koenig (2016) presents a Conflict-Based Min-Cost-Flow algorithm which is correct, complete and optimal. It implements it on Kiva Systems looking at hundreds of agents split into dozens of teams.

De Koster et al. (2007) overview of picking

Boysen et al. (2017) looks at the batching and sequencing of inventory orders which are given to units. Their study found that only half the units is needed when orders are optimized optimized picking allows

2 Research Context/Background

2.1 What is Cooperative Multi-Agent pathfinding

I think I am missing a lot here. Not exactly sure what other background to give besides expanding on Coop MAPF

TODO Cooperative multi-agent pathfinding (MAPF) involves a number of agents in an environment moving to individual locations while avoiding collisions with one another.

Talk about:

- NP-hard
- Optimality has only been done with small number of agents. Not possible here.
- Completeness

3 Research Design

3.1 Path oracle

Strasser et al. (2015)
PLACEHOLDER Decentralised MAPF algorithms usually involve search. A typical problem solving process (e.g. FAR (Wang & Botea, ICAPS 2008)) involves each agent finding a path independent from all the rest (i.e. if there are k agents we solve k single-agent problems separately). When all agents have a path they each take turns moving one step at a time towards their goal. Conflicts are resolved locally choosing in favour of one agent over another in some way (e.g. assign a priority to each agent and always favour the agent with highest priority). We aim to improve efficiency by introducing a path oracle which removes entirely the need to search. The oracle is pre-computed up front and reused for every subsequent pathfinding query thereafter. Since the cost of the initial path searches tends to dominate runtime in MAPF we expect this approach will significantly improve performance. **PLACEHOLDER**

3.2 Warehouse layout

Usually the picking station is positioned on one side of the warehouse and the pods are laid out in rows (Fig. 2).

Wilt and Botea (2014) looked at identifying zones by areas which are bottlenecks and assigning a controller, for that zone which manages any agents who need to travel through the bottleneck. Inspired by this and assuming pickup stations, we plan to split the warehouse into two halves and introduce an intermediate zone (See Fig 3). Delivering pods which are situated in the far zone is a two step process:

1. Units in the far zone move pods to the intermediate zone instead of a pickup station
2. Units in the delivery zone will pickup pods in the intermediate zone

These zones will have their own controller which handles any agents within the zone and tells them what behaviour should occur.

3.3 Order picking

As pods can be dynamically move around the warehouse, the layout pods can be changed to suit incoming orders. Storage pods containing popular orders may be placed next to a

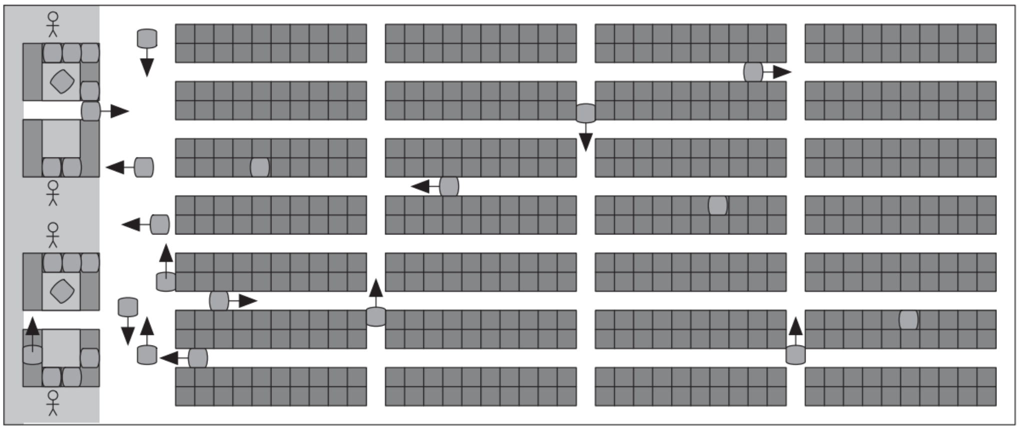

Figure 2: A Small Region of a Kiva Layout (Wurman et al. (2008)). Picking stations located on the left and storage pods laid out in rows.

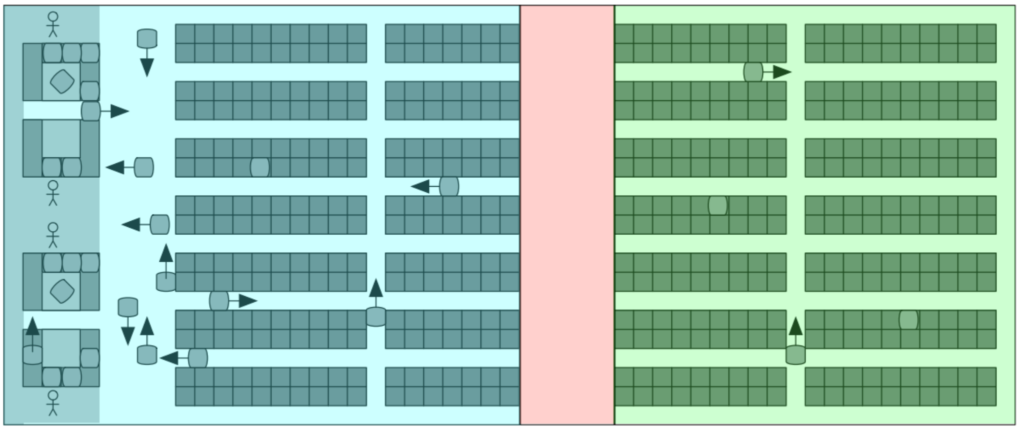

Figure 3: Intermediate zone in red, delivery zone in blue and far zone in green

picking station so a drive unit can readily access it and unpopular orders will be placed further away. Vice-versa the distribution of orders can be re-ordered to suit the current layout of the warehouse. Here we may take inspiration from Robin-hood hashing and apply it to sorting the inventory pods. Boysen et al. (2017) covered both of these aspects in detail and revealed that after optimizing orders, the total number of drive units can be cut by half and retain the same supply to picking stations.

3.4 Allowing for movement underneath storage pods

As drive units are capable of moving underneath pods when carrying them, this means that with small adjustments to the dimensions of storage pods it is possible to allow drive units to maneuver underneath the pods. With this the only obstacles in the environment are other drive units.

3.5 Timetable/plan

HALF DONE

Semester 1

Week(s)	Plan
7	Model warehouse and simple A* pathfinding
8	Add multiple agents with A* assigned random pods (no picking station) arsasarsa
9	Implement Cooperative A*
11	Add simple scheduler which assigns agents a location to fetch a random pod and return to the picking station
12	Focus on Interim Presentation
13	Focus on Literature Review
14	Focus on Examinations
Holidays	Implement Path Oracle with Compressed Path Databases

Semester 2

Week(s)	Plan
1	Add more complex scheduler, distributing requested inventory and allow agents dynamically sort pods according to popularity. Agents dynamically sort pods according to popularity. Decide on the focus for the rest of the project.
2-4	Implement Path Oracle with Compressed Path Databases
3	
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11	
12	Finish Final Thesis
13	Additional tasks
14	Focus on Final Presentation
15	Focus on Final Thesis

4 Significance / Expected Outcomes of the study

TODO

Contributions

- A Warehouse Automation simulation
- A better understanding of the effects of Warehouse Configurations
- An improved MAPF solution utilizing a path oracle

We should have a better understanding of how the aspects described in Section 3 affect the performance of Warehouse Automation.

Increased inventory supply for the picking stations. Decreasing speed for MAPF calculations.

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