Mission Assignment for Multi-Vehicle Systems in Industrial Environments ⋆

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Abstract: In this paper we introduce a methodology for mission assignment in multiple vehicle system exploited in industrial environments for logistics operations. We explicitly consider the model of the traffic, for performing an optimized dynamic mission assignment. Simulation results are provided for comparing the proposed methodology with state-of-the-art techniques, that do not consider the state of the traffic while allocating missions.

Keywords: Mobile robots and vehicles, Transport and delivery robots, Multi cooperative robot control

1. INTRODUCTION

As automatic warehouse systems are gaining increasing popularity, researches on the coordination of the fleet of Automated Guided Vehicles (AGVs), as a solution for addressing the problems of production efficiency and flexibility, are becoming more and more important (Sabattini et al., 2013; Oleari et al., 2014). A portion of a warehouse where AGVs are exploited is shown in Fig. 1.

Fig. 1. AGV system exploited in industrial logistics

The control of a group of AGVs for industrial logistics is a very complex problem: in fact, several aspects need to be addressed, such as navigation algorithms, path planning, coordination, creation of a roadmap, mission allocation, etc. AGV systems have been extensively studied in the literature: a comprehensive survey is presented in (Tsumura, 1994), where authors describe the main technologies adopted for localization and guidance of AGVs in industrial environments. The work in (Stouten and de Graaf, 2004) describes the use of multiple AGVs for cooperative transportation of huge and heavy loads.

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Thus, AGVs are generally exploited for goods transportation, that is for moving batches of goods (pallets or boxes) from one location to another one, according to the requests from the logistics system (Mahadevan and Narendran, 1990; Berman and Edan, 2002). As illustrated in (Vis, 2006), in the vast majority of modern automatic warehouses, AGVs are constrained to move along a set of (virtual) paths and this set is usually called roadmap, that is defined in such a way that all the locations of interest can be reached by the AGVs, as described for instance in (Digani et al., 2014a).

The AGVs need then to be coordinated along the roadmap itself, in order to be able to complete their tasks, and in order to avoid collisions among each other, as highlighted in (Parker, 2009; Zhang and Mehrjerdi, 2013; Hoshino and Seki, 2013). Several strategies can be found in the literature that solve the coordination problem. Generally speaking, main approaches for coordination of multi-vehicle systems can be divided into two categories: centralized and decentralized. With *centralized* strategies, a single decision maker determines the entire path plan for all the robots. The main advantage of centralized approaches is in the fact that they can theoretically find optimal solutions for multi-robot path planning problems (LaValle and Hutchinson, 1998). For this reason, fleets of AGVs in industrial applications are generally coordinated by a centralized supervisor (the control center) which manages all the information coming form the Warehouse Management System (WMS) and from the environment. The control center handles the coordination of the fleet, solving a multi-robot path planning problem (see e.g (Olmi et al., 2011; Simeon et al., 2002; Pallottino et al., 2007)). The dimension of the multi-robot state space may be reduced using of a multi-layer structure to represent the world. As explained in (Park et al., 2012), the approach is to construct a hierarchical map which can abstract the traversable areas using the adequate number of nodes and edges of a graph. The path is searched using the graphs of the several layers. A hierarchical coordination strategy for AGVs in industrial application was presented in (Digani et al., 2014b). The combination of the coordination strategy with an automatic algorithm for roadmap creation was presented in (Digani et al., 2015b). An advanced coordination method was proposed in (Digani et al., 2015a), with the purpose of reducing the number of necessary negotiations among the AGVs.

Each transportation task is defined as a *mission*. The *mission assignment* problem consists then in assigning a mission to be completed to each AGV. Clearly, in order to optimize the overall performance of the system, it is necessary perform the assignment in an optimized manner, that means minimizing the overall completion time. Mainly utilized assignment methods consider the mission assignment problem in a *static manner*: roughly speaking, each mission is assigned to the closest AGV. This assignment method does not consider the dynamic effects due to the motion of the AGVs themselves: namely, traffic jams might decelerate the AGVs, thus making the assignment very far from the optimal solution. In this paper we explicitly consider the traffic model within the assignment problem: specifically, information on the state of the system is utilized to obtain a quantitative measure of the traffic, that is then exploited for an optimized mission assignment.

The paper is organized as follows. In Section 2 we describe some of the most relevant works that can be found in the literature related to the task assignment problem in multiple vehicle systems. Details on the scenario under consideration are given in Section 3. The proposed methodology is then described in Section 4. Section 5 describes the implementation of the proposed methodology in a simulated environment, and presents the achieved results. Finally, Section 6 contains discussion of the results and conclusions.

2. THE TASK ASSIGNMENT PROBLEM: RELATED WORKS

Without aiming completeness, in this Section we provide a brief review of the literature related to task assignment. Task assignment is a very well studied problem, in several domains: for a complete taxonomy of the task allocation problems, and a subsequent overview of the most relevant task assignment methodologies, the reader is referred to the survey papers (Gerkey and Matarić, 2004) and (Pentico, 2007).

Several strategies can be found in the literature that consider the task allocation problem in multiple vehicle scenarios: see for instance (Thunberg et al., 2009) and references therein. As highlighted in (van der Horst and Noble, 2010), task assignment algorithms for multi vehicle systems can be divided into two main categories: *centralized* and *decentralized*. In centralized approaches, a single computation unit has a complete knowledge of the state of the multi vehicle system, as well as of the list of tasks to be accomplished. The task assignment problem is then solved as an optimization problem, and the final assignment is communicated to the vehicles. Conversely, in decentralized approaches, vehicles perform the coordination exploiting only local knowledge, without a centralized computation unit.

As is well known, decentralized algorithms are inherently more reliable: in fact, in case of failure of the central computation unit, centralized task assignment cannot be performed. However, decentralized algorithms generally lead to sub-optimal solutions, as single vehicles do not have access to the full state of the systems. When considering industrial applications, optimality of the solution is a primary issue: in fact, sub-optimal design choices immediately relate to decreases in the efficiency, and therefore generate reduction in the income. Moreover, it is worth noting that, typically, industrial plants are equipped with a global communication infrastructure, that enables all-to-all data exchange. For these reasons, in this paper we will focus on centralized task assignment.

The Hungarian algorithm, first presented in (Kuhn, 1955) and subsequently refined in (Munkres, 1957), provides an optimal solution to the assignment problem in polynomial time. The original formulation of this algorithm was developed for the *static* task assignment problem: namely, a certain number of tasks need to be assigned to a certain number of actors. However, it is worth noting that, in industrial applications, new tasks are generated as the system evolves: as an example, every time a production machine has completed the production of a batch of goods, it is necessary to remove the products and place them in the appropriate location in the warehouse. For this purpose, we need to consider a *dynamic* assignment problem: namely, it is necessary to foresee *task re-allocation*. A dynamic version of the Hungarian algorithm was presented in (Mills-Tettey et al., 2007).

In multiple vehicle systems, task assignment is related to the path planning and coordination problems. In fact, once tasks have been assigned to the vehicles, subsequent path planning has to be performed to obtain the completion of the tasks themselves. The relationship between task assignment and the path planning problems have been extensively studied in (Panagou et al., 2014; Turpin et al., 2014). The main idea is that of solving an optimization problem whose solution globally optimizes the performance of the system, that is the global task completion time, taking into account both task assignment and path planning.

The contribution of this paper is in the definition of an enhanced mission assignment methodology for multiple vehicles in industrial environment. The problem is then modeled as a dynamic task allocation problem, where tasks are represented by missions to be accomplished by a multi-vehicle system for goods transportation in industrial environments. In particular, we consider the presence of a central computation unit, that constantly monitors the overall state of the system, and in particular the position of each vehicle. Information regarding the current position of each vehicle is exploited for defining a traffic model, that allows the system to identifying areas of the environment that are particularly crowded. Therefore, mission assignment is performed in order to optimize the overall completion time: vehicles are assigned to missions not only based on travel distance, but also on the state of the traffic. This gives a better estimate of the completion time, and leads to increasing the overall performance of the system.

3. SCENARIO

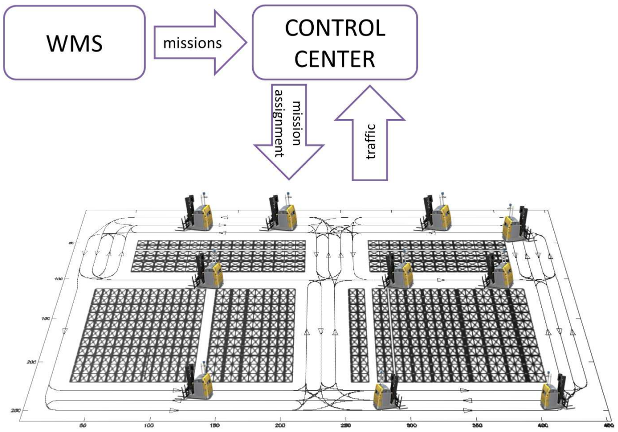

Fig. 2. Multi-vehicle system in industrial applications: architecture

In this paper we consider the mission assignment problem for multi-AGV systems used for factory logistics: the architecture of the system under consideration is depicted in Fig. 2.

In particular, we consider the case where AGVs are exploited for goods transportation inside a manufacturing plant. In this case, each *mission* to be accomplished consists in taking a particular batch of goods (e.g. a box or a pallet) to a desired location inside the plant (e.g. a rack). The motion of the AGVs is constrained along a *roadmap*, that is a a set of virtual paths that connect every location of the plant.

The fleet of AGVs is coordinated by a centralized supervisor, referred to as *control center*, that is in charge of assigning a mission to each AGV, and of coordinating the motion of the AGVs themselves. A communication infrastructure is exploited for putting the control center in communication with the AGVs: in this manner, the control center can control the mission assignment and the motion of each AGV, while monitoring each AGV position.

The list of missions to be accomplished is generated by the Warehouse Management System (WMS), that is integrated into the automatized logistic system of the plant. The list of missions is then sent from the WMS to the control center, for subsequent allocation to the AGVs.

4. PROPOSED METHODOLOGY

The proposed mission assignment methodology consists in exploiting the Hungarian Algorithm that, as is well known, represents the optimal algorithm for solving the assignment problem. Generally speaking, the Hungarian Algorithm solves the problem of assigning a certain number of *activities* to a certain number of *agents*. This assignment is based on a matrix of weights, whose element (i, j) corresponds to the cost of assigning the j-th activity to the i-th agent. The optimal assignment obtained after applying the Hungarian Algorithm has the minimum total cost among all possible choices.

In the scenario considered in this paper, *activities* are represented by *missions* to be accomplished, and *agents* are represented by *AGVs*. It is worth remarking that the objective is that of increasing the overall efficiency of the system: therefore, this implies reducing the overall completion time for all the missions.

Therefore, the cost for assigning each AGV to a particular mission should be proportional to the time spent by that AGV to complete that mission. Currently utilized solutions translate this idea defining the cost as a quantity that is proportional to the distance between each AGV and each mission location. In fact, assuming constant speed, travel distance is proportional to completion time. Define then $x_i(t)$ as the position of the i-th AGV at time t, and m_j as the location of the j-th mission. Therefore, the cost $c_{i,j}(t)$ is computed as follows:

$$c_{i,j}(t) = \delta(x_i(t), m_j) \quad (1)$$

where $\delta(\cdot)$ is the shortest path between $x_i(t)$ and m_j, computed using the Dijkstra's algorithm over the roadmap (see (Dijkstra, 1959) for details). In particular, a roadmap is a set of roads, that are defined as a sequence of elements referred to as *segments*. Once the roadmap has been defined, each segment s_h is characterized by its length $|s_h|$. Thus, let the shortest path between $x_i(t)$ and m_j be a sequence of $M_{i,j}$ segments, namely

$$\{s_1, \dots s_{M_{i,j}}\}$$

Subsequently:

$$\delta(x_i(t), m_j) = \sum_{h=1}^{M_{i,j}} |s_h| \quad (2)$$

One of the drawbacks of the definition of the cost given in (1) is related to the fact that assuming a constant speed for the AGVs is unrealistic, in particular in dense multi-vehicle systems. In fact, traffic jams can significantly slow down AGVs: this leads to the fact that the completion time is no longer proportional to the travel distance.

We will hereafter assume that the motion of the AGVs along the roadmap is coordinated exploiting the methodology presented in (Digani et al., 2014b). In particular, this coordination strategy consists of a hierarchical control architecture composed by two layers. The higher level performs the coordination over macro-areas of the environment, called *sectors*, while the lower level considers the coordination within each sector. A portion of the roadmap divided into sectors is depicted in Fig. 3.

We introduce the concept of *capacity* of a sector. Namely, based on its geometric and topological properties, each sector is characterized by its capacity, that is the maximum number of AGVs that are simultaneously allowed inside the sector itself. Namely, the k-th sector is characterized by capacity $C_k > 0$.

Subsequently, based on the hierarchical division of the roadmap, it is possible to introduce the definition of traffic model.

Definition 1. (Traffic model). Consider a multi vehicle system, where vehicles are constrained to move along a roadmap. Consider then a division of the roadmap into N sectors. Then, a *traffic model* is a function that assigns

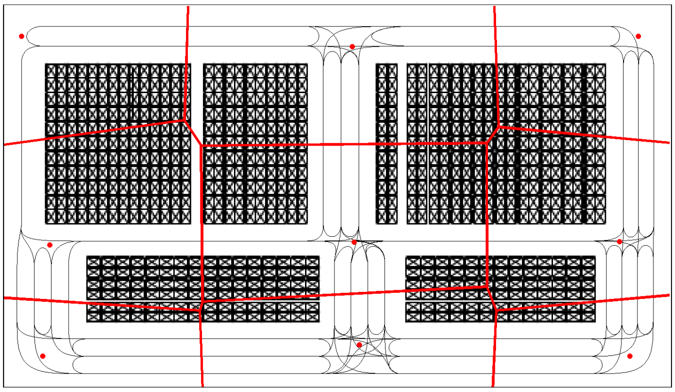

Fig. 3. Portion of a roadmap divided into sectors

a non-negative weight $w_k(t)$ that quantifies the traffic at time t inside the k-th sector. $\diamond$

Considering the definition of Traffic model, the main idea in this paper is that of modifying the definition of the cost (1) to take into account the traffic itself. Specifically, let segment s_h belong to the k-th sector. Then, define the *weighted length* of s_h, namely $l_h(t)$, as a function of both the segment length $|s_h|$ and the weight $w_k(t)$, namely:

$$l_h(t) = l_h(w_k(t), |s_h|) \tag{3}$$

Subsequently, the cost (1) is defined computing the shortest path $\delta(x_i(t), m_j)$ utilizing the Dijkstra's algorithm over the roadmap, where each segment s_h is characterized by the weighted length $l_h(t)$ defined as in (3).

It is worth noting that modeling the traffic in a multi vehicle system is still an open problem, that has been investigated by several research groups: see for instance (Wan et al., 2013; Li and Ioannou, 2004; Tonguz et al., 2009; Daganzo, 1994). However, the proposed methodology can be applied considering any traffic model that can be represented according to Definition 1.

5. IMPLEMENTATION AND EVALUATION

The proposed methodology has been implemented in a simulated environment, where a real industrial plant was represented. Due to confidentiality reasons, it is not possible to provide details about the industrial plant utilized for evaluation. Generally speaking, AGV plants can be characterized into three classes, based on their dimension. In particular:

- *small plants* include up to 10 AGVs
- *medium plants* include 10 to 30 AGVs
- *big plants* include more than 30 AGVs

We validated the proposed methodology with simulations performed on a medium size plant, characterized by:

- Number of AGVs: 30
- Number of sectors in the roadmap: 18

The traffic model utilized in the simulations is the following. We consider each sector to be characterized by the same value of capacity $C > 0$: namely, $C_k = C$, $\forall k$. Moreover, let $n_k(t)$ be the number of vehicles in the k-th sector at time t. Then, the weight was defined as follows:

$$w_k(t) = -\left(\frac{1}{\frac{n_k}{C} - 1}\right) - 1 \tag{4}$$

The weight function is depicted in Fig. 4 considering the capacity $C = 10$.

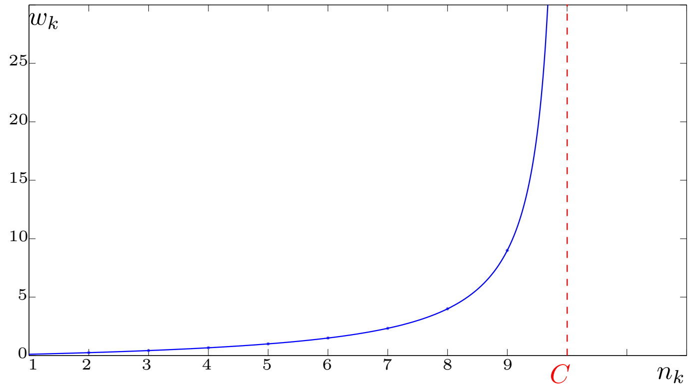

Fig. 4. Weight $w_k(t)$ computed as in (4), with capacity $C = 10$

Subsequently, the weighted length l_h is computed as follows:

$$l_h = k_1 |s_h| + k_2 w_k \tag{5}$$

where $k_1, k_2 > 0$ are design parameters. Simulation results are reported hereafter for $k_1 = 1$, $k_2 = 10$, for different values of the capacity $C \in [2, \ldots, 30]$. In particular, simulations were performed randomly generating missions to be accomplished by the AGVs. Then, we measured the average number of missions accomplished per hour, and we compared it with the current result: namely, computing the weights based on path length only, that is obtained with $k_2 = 0$. Fig. 5 depicts the percentage increase.

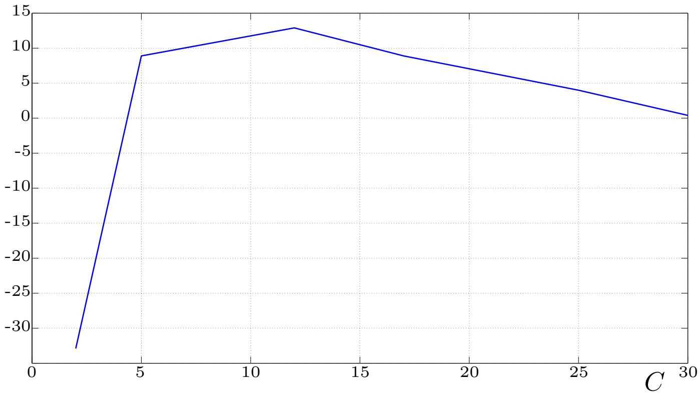

Fig. 5. Average number of missions accomplished per hour: percentage increase with respect to the nominal case, i.e. $k_2 = 0$, for different values of the capacity C

6. DISCUSSION AND CONCLUSION

In this paper we proposed an enhanced mission assignment methodology, for multiple AGVs used in industrial environments for logistics operations. Each missions to be executed consists in delivering a certain amount of goods from one location of a warehouse to another one. Missions need to be allocated to AGVs, that accomplish them traveling along a set of predefined roads, that constitute a roadmap.

Traditionally applied mission assignment methodologies consist in assigning missions based on the distance of each AGV from the destination, computed along the roadmap. While this is optimal in the ideal case, since it leads to minimizing the distance to be traveled by each AGV, traffic jams have great influence on the performance. On these lines, we introduced the idea of assigning missions taking into account the current traffic state. In particular, we introduced a heuristic method that considers the environment partitioned into sectors, each of which is characterized by a certain *capacity*, that is the maximum number of AGVs that are simultaneously allowed inside the sector itself. The weight of each path is then computed taking into account the state of occupation of each sector, together with the path length.

A critical design parameter is represented by the capacity of the sectors, which heavily influences the performance of the system. As detailed in Section 5, we performed several simulations based on data acquired on real plants, for variable values of the capacity. Results are depicted in Fig. 5, which represents the average number of missions accomplished per hour, in terms of percentage increase with respect to the nominal value (i.e. without considering the traffic state). Different values of the capacity were considered, ranging from $C = 2$ to $C = 30$, for a plant with 30 AGVs. Very promising results were obtained for medium values of the capacity, namely $C \in (10, 15)$: in these cases, the number of missions accomplished per hour increased by more than 10%.

It is worth noting that, for high value of the capacity, the performance is very similar to the nominal case. This is however expected, since it is very unlikely to have a high number of AGVs concentrated in the same sector. Therefore, traffic has only a small influence on the assignment procedure.

Conversely, for very small values of the capacity (i.e. $C < 5$) we observe a decrease in the performance: this is mainly due to the fact that a sector containing a small number of AGVs are identified as heavy traffic spots, that lead to a suboptimal mission assignment.

Current work aims at defining a more precise traffic model, that takes into account the geometric characteristics of each sector, as well as the logistics operations to be carried out, in order to better quantify the effect of the presence of a certain number of AGVs in a particular area of the environment.

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