Distributed coordination of a "society" of autonomous mobile robots in industrial environments: from collision avoidance to task assignment

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I. Extended Summary

In traditional factory automation there is a fixed hierarchy for communication, control, and decision making. On the other hand, the future manufacturing industry will have to find a difficult tradeoff between productivity and flexibility, quality of the production and costs reduction. As a consequence an agile organisation of production sites and logistic areas should be designed. One of the challenges in this contest is to bring more intelligence in the factory and to open the doors to a "society" of cooperative autonomous robots. Multi-vehicle robotic systems provide competitive advantages versus the single-agent solutions e.g. in terms of task speed-up and robustness to failures. While a high level of autonomy of single mobile robots is already a reality, the coordination of multiple robots is still a challenge and lead to several still open problems. For example: automatic task assignment, collision avoidance and conflict resolution requiring fast and reliable negotiation of shared resources and energy management. Those aspects play a crucial role in case of large industrial scenarios in which a high number of robots are deployed.

Moreover, while designing solutions for large distributed control systems the choice over whether to introduce distributed paradigms (with their scalability and flexibility advantages) or to rethink the centralised and hierarchical control solutions (with their strength in optimising the performance) must be carefully considered. In our opinion the solution stays in the middle: a balanced blend of the two ideas. In this work we propose .

In this contest we focus in particular on two distributed coordination protocols to address such issues in case of a "society" of autonomous vehicles: a collision avoidance and a task assignment protocols. The collision avoidance algorithm is based on a modified graph representation (time expanded networks) of the space-time in which the robotic vehicles operate. The basic idea behind the proposed approach is to coordinate agents even in traffic areas while diminishing as much as possible the necessity of the vehicles to stop. The approach is suitable for both structured and unstructured environments and, e.g., for urban traffic. Robots can make and exchange accurate predictions on their planned routes and speeds, so as to prevent and solve possible collisions. The algorithm has been formally proved to provide collision free paths.

On top of the coordination and planning protocols, the problem of assigning tasks to a set of mobile and heterogeneous robots based on their ability and their costs to accomplish a task has been considered. The challenge is that the dynamics of the robot and their private cost functions must be optimized together with the assignment. A distributed approach based on the subgradient method has been proposed. Thanks to the chosen approach different types of kinematic vehicles with different motion constraints can be taken into account.

Preliminary results on the proposed approaches can be found in [1] and [2].

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II. Collision avoidance protocol

Collision avoidance protocols for the robots coordination have been of large interest in the past years, see e.g. references in [1]. Although inspiring, approaches usually do not take into account the energy cost that an agent incurs in when it stops to re-plan its path by applying its collaboration algorithm. When a vehicle (a forklift, a car, etc) brakes, its kinetic energy is converted to heat by the friction of the brake pads. The total amount of energy loss depends on how often and how hard the vehicle brakes. Indeed, based on the analysis results of the papers, fuel consumption is mainly affected by extreme acceleration or deceleration rates (as long as vehicles are driving below 80 Km/h). From those studies, we can state that the sudden deceleration/stop/acceleration behaviour will result in negative influences on fuel consumption. Under the assumption of not traffic jammed scenarios, that usually occurs in warehouses and multi-robot scenarios, the proposed approach can also be used as a pilot decision support in semi-autonomous systems.

The novelty of the proposed coordination protocol is that it allows the agents to keep moving while coordinating/communicating to avoid collision or planning their routes. Indeed, in the proposed framework, an agent stops only in case of exceptional events (such as unsolvable conflicts) which are handled with exceptional behaviours (i.e. stopping agents in the neighbourhood and using a fall-back behaviour). The approach is based on the distributed use of a normalized and augmented time-expanded network for the computation of the vehicle's speed and is proven to be deadlock free under given conditions on the number of agents while reducing energy consumption due to "stops&go".

For the sake of simplicity, we consider a structured environment with associated topological graph where nodes represent intersection points and arcs represent streets. The idea it to design a distributed protocol that ensure a time-space separation of robots in the intersection points and along the streets. This is done considering a time expanded network from the topological graph. The obtained network is first normalized and then augmented to represent the possibility of robots to move between nodes ad different speeds. The agent will hence coordinate in a distributed fashion and based on priorities setting the travel speed to avoid collisions. Refer to [2] for more details and references.

A video on the simulation results for different scenarios can be found at https://www.youtube.com/watch?v=9QonesVe-rM

III. Task assignment and optimal control

The Task Assignment Problem is a common problem in every environment that includes different units and tasks. In this work we consider the problem of distributed and dynamic assigning tasks to a set of mobile and heterogeneous robots based on their ability and their costs to accomplish a task, together with the dynamics of the robot and private cost functions to be optimized.

In our distributed scenario we suppose robots to have a complete knowledge of the environment and tasks (positions, deadlines, etc.) while communicating with other robots to share local information. The assignment to tasks is based on the cost of the robot in reaching the task position and in accomplishing the task. Moreover, the motion of the robot is based on private costs and goals. For example, a robot may want to move far from others while moving fragile or dangerous material while other robots may need to move in formation to deploy large objects. In order to take into accounts those aspects, our approach is not to simply assign tasks to generic units, but we also consider robots' physical and physics characteristics. Moreover, we want to focus on the general case of heterogeneous robots in which each robot may have different dynamics constraints, movement typology, goals and cost functions. Furthermore, we consider an industrial scenario where tasks are not just simply "something to do" but they may have a time variant position, must be executed within a certain time and have execution time and periodicity.

We solve the problem, in a distributed framework, through a distributed dual decomposition method based on the sub-gradient method, which allows us to deal with a possibly high number of tasks and robots. With the proposed approach, a local dynamic optimal control and a task assignment problem are solved based on the information exchanged through a communication network. In the proposed framework different types of kinematic vehicles with different motion constraints and private costs can be taken into account together with different type of task to be accomplished. Details and related literature can be found in [2].

We consider a *cost matrix* C and an *assignment matrix* A:

$$C \in \mathbb{R}^{n\times n} \quad A \in \{0;1\}^{n\times n}, \tag{1}$$

where the element $c_{i,j}$ is the cost of task T_j for robot R_i while with $a_{i,j} = 1$ ($a_{i,j} = 0$) we denote that robot R_i is (is not) assigned to task T_j. Consider the n^2 dimensional column vectors:

$$c^T = \left[c_1^T, \dots, c_n^T\right] \qquad x^T = \left[x_1^T, \dots, x_n^T\right], \tag{2}$$

where each component c_i of c is a row of matrix C, i.e. $c_i^T = [C_{i1}, \dots, C_{in}]$, and each component x_i of x is a row of matrix A, i.e. $x_i^T = [A_{i1}, \dots, A_{in}]$.

Given a local cost function $J_{OC_i}(z_i, u_i)$, the overall optimal control for the assignment problem is:

$$\begin{cases} \min\limits_{z,u,x} \left[J_{OC}(z,u) + J_{TA}(z,u,x)\right] \\ \left.\begin{array}{l} \dot{z} = f(z,u,t) \\ u \in [u_l, u_u] \end{array}\right\} D \\ \underline{\mathbf{1}}_n^T x_i = 1 \quad \forall i = 1,\dots,n \\ \sum\limits_{k=1}^{n} e_j^T x_k = 1 \quad \forall j = 1,\dots,n \qquad (*) \\ x \in \{0;1\}^{n^2} \end{cases} \tag{3}$$

with $J_{OC}(z,u) = \sum\limits_{i=1}^{n} J_{OC_i}(z_i,u_i)$ and $J_{TA}(z,u,x) = \sum\limits_{i=1}^{n} J_{TA_i}(z_i,u_i,x_i)$. Moreover, with the notation $(z,\, u) \in D$ we denoted the dynamical system consisting in the robots dynamical equation $\dot{z} = f(z,u,t)$ and the input constraints $u \in [u_l, u_u]$.

The proposed model has several advantages in terms of representation of realistic robotics scenarios. Indeed, it allows us to consider heterogeneous robots with different dynamics and dynamical constraints, represented by $(\tilde{z}_i, \tilde{u}_i) \in D_i$. The local *optimal control loss function* $J_{OC_i}(\tilde{z}_i, \tilde{u}_i)$ can be considered to be as the standard forms of an optimal control problem, and it depends on the shared variables with the task assignment problem $\tilde{z}_i$, $\tilde{u}_i$. This private loss function can obviously be different for each robot and may have various forms such as minimum time to reach a task, minimum or maximum distance between robots, minimum energy consumption etc..

On the other hand, the *task assignment loss function* $J_{TA_i}(z_i,\, u_i,\, x_i)$, which has $c_i^T x_i$ as standard form, has been modified as follows in our approach:

$$J_{TA_i}(z_i, u_i, x_i) = \left(c_i + v_i(z_i,u_i)\right)^T x_i.$$

This new form has some advantages since it gives us the possibility to introduce local costs on which the assignment is going to depend. For example, we can use v_i to introduce:

- **agent's constraints**: battery, position, etc.
- **scenario's constraints**: task distance from robot, task deadline, task duration, task periodicity, etc.
- **supervisor's constraints**: task priority, task configuration, etc.

Hence, while c_i is generally a static cost, $v_i(z_i, u_i)$ can change over time (such as distance between robots and tasks) and can better capture the dynamic nature of the scenario. For example, the following cost function v_i has been used:

$$v_i(z_i, u_i) = d_i - \delta_i,$$

where d_i is the vector of the distances between robot R_i and the tasks and δ_i is a vector that represents the decreasing costs of expiring tasks. In other cases $d_i \in \mathbb{R}^n$ may indicate the distance vector between the robots and the tasks and it is updated over time. Depending on the robot kinematics and motion constraints we may consider non Euclidean distances. In case of non-holonomic vehicles such as Dubins ones (unicycle with constant speed and minimum turning radius), d_i will be the minimum Dubins path length for the agents toward the tasks. As another example, in case of differential drive vehicles, the time to turn on the spot may also be considered in the distance d_i.

Due to the coupled nature of the assignment problem and the coupling of the assignment problem with the optimal control one, we use the decoupling method known as *Dual Decomposition* jointly with the *Subgradient Method*, see details and references in [2].

A video on the simulation results of two robots, to allow visualization of the whole evolution, can be found at https://www.youtube.com/watch?v=aWFrc5z6EyY

REFERENCES

[1] Ferrati, M. ; Pallottino, L., "A time expanded network based algorithm for safe and efficient distributed multi-agent coordination", *Proc. 2013 IEEE 52nd Annual Conference on Decision and Control (CDC)*, DOI: 10.1109/CDC.2013.6760308, pp. 2805-2810, 2013.

[2] Settimi, A. ; Pallottino, L., "A subgradient based algorithm for distributed task assignment for heterogeneous mobile robots", in *Proc. 2013 IEEE 52nd Annual Conference on Decision and Control (CDC)*, DOI: 10.1109/CDC.2013.6760447, pp. 3665-3670, 2013.