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Multi-robot coalition formation in real-time scenarios

José Guerrero *, Gabriel Oliver

Universitat de les Illes Balears, Mathematics and Computer Science Department, Palma de Mallorca, Spain

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ABSTRACT

Task allocation is one of the main issues to be addressed in multi-robot systems, especially when the robots form coalitions and the tasks have to be fulfilled before a deadline. In general, it is difficult to foresee the time required by a coalition to finish a task because it depends, among other factors, on the physical interference. Interference is a phenomenon produced when two or more robots want to access the same point simultaneously. This paper presents a new model to predict the time to execute a task. Thanks to this model, the robots needed to carry out a task before a deadline can be determined. Within this framework, the robots learn the interference and therefore, the coalition's utility, from their past experience using an on-line Support Vector Regression method (SVR). Furthermore, the SVR model is used together with a new auction method called 'Double Round auction' (DR). It will be demonstrated that by combining the interference model and the DR process, the total utility of the system significantly increases compared to classical auction approaches. This is the first auction method that includes the physical interference effects and that can determine the coalition size during the execution time to address tasks with deadlines. Transport like tasks run on a simulator and on real robots have been used to validate the proposed solutions.

1. Introduction

Multi-robot systems can provide several advantages compared to single-robot systems, for example: robustness, flexibility and efficiency. To make the most of these potential benefits, several problems have to be solved, specially when two or more robots can constitute coalitions to execute tasks. Of all the issues reported in the specialized literature, this paper focuses on the methods to select the best robot or set of robots to execute a task, which is commonly referred to as the 'Multi-Robot Task Allocation' (MRTA) problem.

In [1] Gerkey and Mataric, broke down the MRTA problem in three orthogonal axes: Multi-task robots (MT) vs. Single-task robots (ST) depending on whether multiple tasks can be assigned to the same robot or not; Single-robot tasks (SR) vs. Multi-robot tasks (MR), where SR means that only one robot can be assigned to a task, while MR means that several robots (a coalition) can concurrently execute a task; and finally, Instantaneous assignment (IA) vs. Time-extended assignment (TE) where in IA the allocation is made by not taking into account the future incoming tasks. In terms of this taxonomy, the present work is concentrated on the ST-MR-IA problem. Moreover, special attention is paid to the tasks that have to be fulfilled before a deadline, in which case the knowledge of how long the coalition will take to finish a task is essential in order to determine the proper alliances. The time needed to finish a task is frequently unknown. Thus, in general, anticipating if certain coalitions can meet the task's deadline or estimate their utility can be quite difficult. In this context, it is very arduous to accurately model the execution time of a task because it depends on many complex and dynamic factors, among which this paper will center its attention on the physical interference. Interference appears when some individuals of a community compete for a shared resource. In Multi-robot systems, a frequent situation occurs when two or more robots need to access the same point simultaneously. It has been demonstrated in different studies [2,3], that physical interference has an important impact on the system performance. This effect can be dramatic when the system has to address tasks with deadlines because interference increases the time needed by the coalition to finish the task and, therefore, diminishes the coalition utility. This paper proposes a new MRTA method for creating coalitions of mobile robots in real time scenarios, that is, in environments where the tasks must be executed before a deadline. When a coalition finishes a task before its deadline, the system obtains the maximum utility associated with that task. Otherwise, the utility decreases following some time function. The goal of the proposed method is to maximize the total utility obtained by the system. Auction methods have been thoroughly studied and they are frequently used as a task allocation solution. Furthermore, the current MR auction methods cannot predict the expected execution time of a task nor the

* Correspondence to: Universitat de les Illes Baleares, Departament de Matemàtiques i Informàtica, Cra. de Valldemossa, Km. 7.5, 07122, Palma (Balears), Spain. Tel.: +34 971171391; fax: +34 971173003.

E-mail addresses: jose.guerrero@uib.es (J. Guerrero), goliver@uib.es (G. Oliver).

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coalition size, thus, they are unsuitable for real time situations. To solve the stated problem, this work presents a new auction method, called Double Round auction (DR). The DR auction is used together with a model of the physical interference, based on Support Vector Regression (SVR) [4], to predict how long the task execution will last. This paper also analyzes the effect of the task progress' monitoring on the system performance. The experimental results presented here show that, using a correct interference model, the task execution time can be predicted and, therefore, the monitoring processes and their sensorial and communication resources, are not necessary. To test the proposed system a foraging-like task is used, where multiple robots can cooperate to transport the same object. The experiments have been obtained using both a simulator and a set of four real robots (Pioneer 3DX). The results prove that the new proposed method clearly outperforms those obtained with classical auction mechanisms. The main goals of this paper are:

- To present a new MRTA method that takes into account physical interference and uses this information to estimate the tasks' execution time.
- To describe a coalition formation procedure that can determine on-line the size of the workgroup required to meet the tasks' deadlines.
- To develop a new auction method, called Double Round auction, that improves the classical auction approaches in terms of total utility achieved in environments with deadlines.

This paper extends and analyzes in greater detail our previous work on MRTA algorithms explained in [5]. Although the double round concept was preliminarily introduced in [6], here we include a detailed description and analysis of the algorithm, an error recovery strategy and new experimental results, including tests on real robots.

The paper is organized as follows: Section 2 reviews the relevant work in MRTA with special attention paid to auction methods; Section 3 presents a formal definition of the problem to solve and details the real time foraging task; Section 4 explains the techniques used to predict the execution time; Section 5 introduces the Double Round auction task allocation algorithm; the experimental results are shown and analyzed in Section 6 and, finally, the conclusions and future work are presented in Section 8.

2. MRTA related works

Nowadays, swarm intelligence and auction based methods are the MRTA methodologies mostly used. Swarm methods are inspired by insect colonies' behavior, such as bees or ants, where a global action emerges from the interaction between very simple entities. In general, the swarm systems do not need communication protocols to coordinate the robots, but the complexity of the tasks they can carry out is strongly limited. Most swarm systems can only deal with SR problems with homogeneous robots. This restriction is superseded in the swarm system proposed by Ducatelle et al. [7] dealing with tasks without deadlines. The Low's et al. swarm method [8] also allows the coalition formation to execute a task, but with very complex communication protocols. Moreover, very few swarm methods address time restricted tasks; an exception being the work by Oliveira et al. [9], where only a robot can be assigned to each task. Some swarm methods have tried to reduce the physical interference effect dividing the environment into several areas which only some of the robots can access simultaneously [10,11], but none of these approaches gives a quantitative value of the interference effect for calculating the expected tasks' execution time.

Due to the swarm method limitations, this work is focused on auction-like mechanisms, based on an explicit communication protocol to coordinate the robots' actions. In these kind of systems, the robots act as selfish agents bidding for the tasks. The bids are adjusted to the robots' interest (capacity) to carry out the goal. Thus, the robot with the highest bid, that is the best robot, wins the auction process and gets the task. A lot of works have been done to address SR problems with auction based methods [12–19], some of them partially adapting ideas originally conceived in the computer engineering context to solve the task allocation problem. The Jones' et al. study [18] takes into account time restrictions within an auction process where only a robot can be assigned to each task. The Jones' method uses a learning SVR model to obtain the bid value, but does not estimate the execution time. Lemaire's auction method [17] allows soft deadlines with a single robot per task. Other auction like approaches [20,19] can deal with deadlines but with many restrictions regarding the execution time or the kind of tasks to execute.

A few auction strategies, such as [21–25], allow us the addressing of MR problems, but none of them is able to deal with time restrictions associated with the tasks. Acebo and de la Rosa propose in [26] a swarm based method, with many characteristics from auction strategies, that solve MR problems with deadlines, but assume the execution time to be known in advance. Thus, not one of the referred methods takes into account the physical interference nor predicts the execution time of tasks. The MR auction method proposed in this paper overcomes these limitations and increases the number of finished tasks compared to the classical MRTA auction approaches.

In [27] Paquet proposes a method to estimate the size of an agents' coalition for the Robocup rescue competition. Due to its computational complexity Paquet's method cannot be applied online, so the number of robots in each group has to be calculated before executing the mission. Moreover, this method has not been executed on robots and, therefore, it does not take into account the physical effects. Other authors use learning algorithms to fit the number of robots of each group, for example Dahl et al. in [28] implement a Q-learning method but with neither deadlines nor making time execution estimations. Several methods, such as [29] or [30], make predictions about the time required to finished a mission in scenarios with only one robot. For multi-robot systems, Sellner and Simmons in [31] can predict the execution time with kernel techniques that are similar to the SVR methods shown in Section 4.2.1, but only for SR scenarios. Thus, to the best of our knowledge, the method presented in this paper is the first auction-like algorithm that includes time predictions and physical interference to address MR problems.

3. Definition of the problem and complexity analysis

This section introduces the general MR problem to be solved and defines the transport task used to verify the proposed MRTA methods.

3.1. Problem statement

The task allocation problem is defined as follows: Let $T = \{t_1, \ldots, t_m\}$ be a set of m tasks and $R = \{r_1, \ldots, r_n\}$ the set of n robots to carry them out. Each task t_j has the following characteristics: the amount of work needed to finish it ($taskWorkLoad_j$), a deadline ($DL_j > 0$), that is the time instant before which the task must be finished and, finally, a utility function $U_j(fT_j) > 0$, where fT_j is the time passed since the task t_j started. If the execution time of a task exceeds its deadline, U_j decreases. The Fig. 1(a) shows an example of a hard deadline utility function, where U_j is constant and equal $U_{\max_j}$ while $fT_j < DL_j$ and abruptly drops to zero if the