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Development of a reduced human user input task allocation method for multiple robots

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ABSTRACT

Task allocation mechanisms are employed by multi-robot systems to efficiently distribute tasks between different robots. Currently, many task allocation methods rely on detailed expert knowledge to coordinate robots. However, it may not be feasible to dedicate an expert human user to a multi-robot system. Hence, a non-expert user may have to specify tasks to a team of robots in some situations. This paper presents a novel reduced human user input multi-robot task allocation technique that utilises Fuzzy Inference Systems (FISs). A two-stage primary and secondary task allocation process is employed to select a team of robots comprising manager and worker robots. A multi-robot mapping and exploration task is utilised as a model task to evaluate the task allocation process. Experiments show that primary task allocation is able to successfully identify and select manager robots. Similarly, secondary task allocation successfully identifies and selects worker robots. Both task allocation processes are also robust to parameter variation permitting intuitive selection of parameter values.

1. Introduction

There are numerous applications for multi-robot systems such as search and rescue, exploration and object manipulation. Benefits such as robustness to failure and increased efficiency can be achieved in multi-robot systems by distributing the group task across the team. Many multi-robot systems employ task allocation and coordination mechanisms to achieve these benefits. Task allocation mechanisms distribute tasks between different robots [1]. Coordination mechanisms allow individual robots within a group to take each others' actions into consideration such that the team operates coherently [2]. Coalition formation [3,4] employs task allocation methods that allow multiple robots to collectively achieve the objectives of a task that the individual robots are incapable of executing.

In multi-robot systems, a group task that is to be executed by the team is defined (or specified) as a set of tasks that must be completed. Tasks can be further divided into independent or interdependent subtasks in many applications. The challenge of task allocation is to find a suitable mapping of robots to tasks (or subtasks) [5].

A hierarchical heterogeneous multi-robot system for urban search and rescue (USAR) is currently under development [6]. This specific multi-robot system has three categories of robots labelled grandmother, mothers, and daughters. At the top of the hierarchy, the grandmothers are physically the largest and most powerful computationally. Grandmother robots are generally employed to manage the operation of a group task (managers). The lower tiered robots (mothers and daughters) are smaller in size and less computationally powerful. They are also more specialised in their sensing and actuation abilities. This enables them to be deployed for searching the environment (workers).

Ideally the coordination of all of these robots should not be the domain of a few expert human users since it may not always be possible for such experts to physically travel to the disaster site quickly. This can have negative consequences for a search operation. It is preferable to have a robotic system that can allocate tasks, coordinate itself, and dynamically monitor its efficiency to ensure the allocation has been optimised, based on inputs provided by non-expert human users.

Allocating tasks to robots in a heterogeneous multi-robot system such as [6] requires a strategy that takes into account the physical capabilities (such as processing, communication, sensing, and actuation) of the different robots. However, a non-expert human user may not be able to precisely specify the type of mobile robot required for a task. For example, it may be difficult to specify the exact quantity and type of sensors required for an exploration task. In such situations it is often better to let the

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non-expert user input a grading for a sensor type (or the sensing resource/capability) and let the task allocation process choose the best robot for the task.

Let n be the number of tasks t_i in set T that need to be executed by single robots (1). Based on the hierarchical nature of the multi-robot system, there is a subset of manager tasks T_1 and a subset of worker tasks T_2 within the task set T (2), (3). Let there be n_1 manager tasks and n_2 worker tasks. These tasks are specified in terms of the minimum physical capabilities (processing, communication, sensing, and actuation) expected of a robot to execute the task (4). Let this task specification be denoted as a Vector of Task Requirements (VOTR). It consists of graded inputs representing a resource capability score (RCS) for each capability type. Section 3 provides more details on task specification.

$$T = [t_1, t_2, \ldots, t_i, \ldots, t_n] \tag{1}$$

$$T_1 = [t_1, t_2, \ldots, t_{im}, \ldots, t_{n1}] \tag{2}$$

$$T_2 = [t_{n1+1}, t_{n1+2}, \ldots, t_{iw}, \ldots, t_{n1+n2}] \tag{3}$$

$$t_i = [t_iRCS_{proc}, t_iRCS_{comm}, t_iRCS_{sense}, t_iRCS_{act}]. \tag{4}$$

Similar to the tasks, the robots need to be specified in terms of their physical capabilities (processing, communication, sensing, and actuation). Let p be the number of robots r_j available in the set R (5). The resource capability score (RCS) for each physical capability category of robot r_j (6) needs to be derived from verbose resource capability (RC) data (7). Eq. (7) assumes there are q sub-resource capabilities. Let the verbose robot resource capability information be denoted as a Vector of Merit (VOM).

$$R = [r_1, r_2, \ldots, r_j, \ldots, r_p] \tag{5}$$

$$r_j = [r_jRCS_{proc}, r_jRCS_{comm}, r_jRCS_{sense}, r_jRCS_{act}] \tag{6}$$

$$r_jRC_{type} = [r_jrc_{type1}, r_jrc_{type2}, \ldots, r_jrc_{typek}, \ldots, r_jrc_{typeq}] \tag{7}$$

$$\text{type} \in [proc, comm, sense, act]. \tag{8}$$

After specifying tasks as VOTR and robots as VOM, the task allocation process involves finding a mapping of robots to tasks such that the minimum capability requirements for the tasks are met. A function f_{type} is required to map the verbose VOM information into a simplified resource capability score for each capability type (9). Following this, another function (or algorithm) is required to map the simplified VOM data to the VOTR data. This depends on a utility [1] parameter denoted as a Vector of Task Suitability (VOTS). Section 4 provides more details on the verbose VOM information and its simplification. Section 7 provides more details on the mapping of the simplified VOM data to VOTR data.

$$r_jRCS_{type} = f_{type}(r_jRC_{type}). \tag{9}$$

Fig. 1 illustrates an overview of the proposed task allocation process. It is proposed to utilise fuzzy systems [7] to map the verbose VOM information into a simplified form. Fuzzy systems mimic non-binary human logic, thus potentially enabling an initial selection of robots based on non-expert human user input.

2. Related work

Various methods for coordination and task allocation in multi-robot systems have been discussed in [1,2,5,8,9]. Whereas [2] focuses on coordination, [1,5,8,9] address task allocation.

Of the classifications based on coordination identified in [2], the weakly centralized systems [10–12] are of particular interest since they can be utilised in hierarchical heterogeneous systems. In these systems, a leader robot is selected dynamically during task execution based on the situation of the team and the environment. The method proposed in [10] intends to take into account the physical capabilities of robots using detailed specifications but has not been fully implemented. In [11] the robots are heterogeneous and a leader is selected from a pair of robots based on specific (detailed) sensing or actuation capabilities. A three layer hierarchical structure is proposed in [13]. The high-layer robot is responsible for task feature synthesis and task level matching. Low-layer robots are responsible for task decisions within their troops (bottom layer robots). In a simulated multi-robot hunting task, tasks are specified with detailed information.

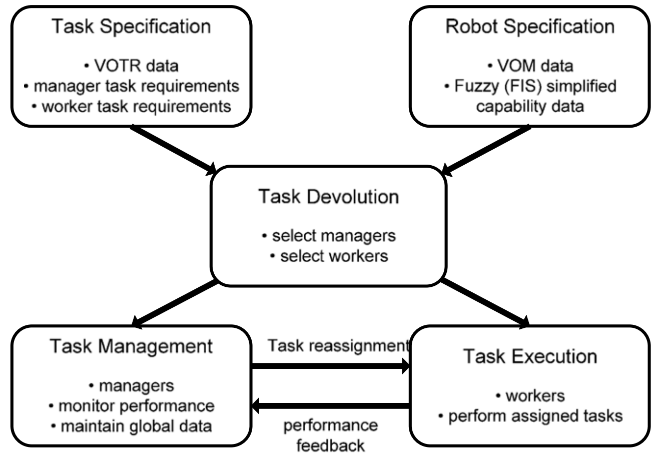

Fig. 1. Overview of task allocation process.

In [1,5] a taxonomy has been developed for the multi-robot task allocation problem, differentiating robots as either single-task (ST) or multi-task (MT), tasks as either single-robot (SR) or multi-robot (MR), and assignment types as either instantaneous (IA) or time-extended (TA). Representative approaches to multi-robot task allocation are classified (behaviour-based or market-based) and analysed. It has been shown that developing an optimal mapping of tasks to robots is NP-hard [14]. Hence, many existing approaches employ heuristic greedy methods to achieve this mapping. This can produce suboptimal solutions.

ALLIANCE [15] and BLE [16] are examples of behaviour-based approaches to multi-robot task allocation. ALLIANCE uses motivational behaviours to monitor and dynamically reallocate tasks thus achieving fault tolerance and adaptive behaviour. In the BLE system, each robot has a corresponding behaviour that is capable of executing each task. The robots select a task to execute by continuously broadcasting locally computed eligibilities followed by determining the most eligible task using a greedy algorithm. A behaviour-based approach to multi-robot task allocation that uses the concept of vacancy chains is presented in [17]. This approach is demonstrated in groups of homogeneous robots where vacancy chains emerge through reinforcement learning.

Market-based task allocation methods [12,18,19] have also been widely utilised in multi-robot systems. These approaches can divide a task into subtasks for the robots to bid and negotiate. An auctioning mechanism utilises a task to revenue/cost mapping function to greedily assign subtasks to the highest bidders. TraderBots [20] is a market-based approach for resource, role, and task allocation in multi-robot coordination. Building on the success of market-based multi-robot coordination techniques, an approach to complex task allocation is presented in [21] where a complex task is represented using task trees. The S + T approach [22] solves market-based task allocation based on the concept of service where robots ask for help if they cannot execute tasks by themselves. By using the Hungarian method [23] the efficiency of trade-based task allocation for a multi-robot exploration task has been improved [24]. A drawback of market-based methods is that