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An Extended Simulation of Complex Task Partitioning Method in a Self-organized Robotics Swarm

Mehrdad Jangjou[1], Alireza Bagheri[2], Mohammad Mansour Riahi Kashani[3], Koosha Sadeghi Oskooyee[4]

[1] Department of computer engineering,
Islamic Azad University, U.A.E. Branch, Dubai, Emirates

[2] Department of computer engineering and IT,
Amirkabir University of Technology, Tehran, Iran

[3, 4] Department of computer engineering,
Islamic Azad University, North Tehran Branch, Tehran, Iran

[1] Mehrdadjangjou@live.com, [2] ar_bagheri@aut.ac.ir,
{[3] M_Riahi_Kashani, [4] K_Sadeghi_Oskooyee}@iau-tnb.ac.ir,

ABSTRACT

Interference and specially one of the most common kinds of it which is also known as physical interference, is among the most critical problems in terms of multi-robot co-operation.

A simple way reducing interference is to make robots remain in unique work areas and move the objects to the next robot as soon as they intersect their areas' borders. The problem of interference reduction, in this article, was investigated using complex task partitioning in the self-organized robotic swarms.

The presented method is simulated, which eliminates some of the previous simulations' limitations in many domains including the number and robots' speed. These developments contribute to a more real impression of the natural world problems. The results show improvements in terms of operation cost.

KEYWORDS

Interference, Self-organized task allocation, Robotics swarm, Foraging problem, Complex task.

1 INTRODUCTION

Interference is an important problem which limits the development of a swarm in the collective robotic science; Voiding the barrier increases too when each robot performs the only one task through irrelevant behaviors and as the capacity of individuals increases [1].

Operation of the task which is in trouble, though physical interferences may usually be improved using spatial (environmental) partitioning; for instance, by keeping each robot in its own working area [2].

One of the conventional research areas of collective robots is the problem of foraging (or harvesting) the objects by a robots' swarm, because this problem can be easily modeled, has some variants in the nature and can be applied in a lot of scientific applications. The foraging problem can provide a useful and effective system of measurement [3], [4].

A swarm of robots, in simple foraging, have to collect one- kind objects, and they are commonly stimulated by an internal motive or stimulus, such as artificial hunger, energy balance and so on [5].

Regarding self-organized task allocation, there are rarely few studies. This area is at its initial stages because most of the studies try to solve simple problems without tasks being dependent on each other. The self-organized task allocation studies are, mostly, based on edge-based methods, inspired by the division of labor in swarm oriented-insects [6].

There is one central robot in self-organized systems, which determines, autonomously, the time, which have been allocated for a task, to a robot.

Task partitioning is not a well-known concept, although it can be seen in most insect societies. Sometimes, it has been defined as a division of a single task among workers [7] and it is called so because several individuals divide a large task among themselves; it mainly allows tasks to be allocated not only to individuals but also to the swarms.

Division of labor explains division of workforce through many sorts of tasks, with which a swarm is opposed. It is essential through task processing and parallel operating, and it is a basis for training specialized individuals. Because of such a specialization, division of labor can increase efficacy, and promotes special training comparing to the operations, in which they have been specialized. Division of labor, therefore, may result in heterogeneous populations, in terms of behaviors.

These concepts are elaborated in the present paper as follows: Task partitioning is explained as the problem of dividing a general task to smaller (atomic) sub-tasks, which can be solved by an individual or a group of individuals.

We aim to find ways to implement task partitioning, effectively, (at least, minimally) in an automatic and self-organized mode. In this case, Pini's researches had been considered as a well formed foundation of our study [8]. The Pini's had ran the experiments using ARGOS simulator, which faced considerable limitations including the robots' population and speed. In this work, it is attempted to eliminate aforementioned limitations through creating a more realistic impression of the natural world events.

2 INTERFERENCE IN MULTI-ROBOT SYSTEMS

For a longtime, Interference had been known as one of the most critical problems of multi-robot co-operation field [9], [10]. Based on mathematical foundations, a logical strategy has been designed which makes possible determining the amount of interference and its effect on the efficacy of the swarm. In this way, a simple way reducing this kind of interference is to make robots remain in unique work areas and moving the objects to the next robot, as soon as they intersect the borders of areas which they are located in [11].

Therefore, the partitioning and task allocation problems revealed that they have to face the tasks division complex methods and task allocating to a swarm of robots. The proposed approach can promote the performance and decrease costs, through reducing the number of physical interferences.

2.1 The Recommended Method

Solving complex task by the sequential dependence, foraging problem is used which is one of the conventional areas of research in the collective robots field [12]. In this article, implementing the problem, a swarm of robots should pick up target objects from the source area and move transit them to the nest area. Employing spatial partitioning of the environment, the general foraging task will be devided into two sub-tasks:

1. Harvest target objects from an area (known as source).
2. Store them in an area (known as nest).

The robots, which work on the first sub-task, pick up target objects from the source and transit them and deliver them to the robots which work on the second sub-task and which store the objects in the nest. These sub-tasks are sequentially dependent on each other, in the sense that the operations should be performed one by one, in order to, immediately, complete the general task: delivering a target object to the nest area [8].

2.2 Interference Reduction through Sequential Task Partitioning

Interference is an important problem, which limits the of swarm development, in the science of collective robots; prevention from barrier increases, too, when each robot performs the task with irrelevant behaviors, as the density of people increases [1]. The task performing trend, which faces troubles because of physical interferences, can be usually improved by spatial (environmental) partitioning; for example, by keeping each robot in its own working area.
The method which is presented here is such that robots deliver the objects to other robots, which work in the next area and transit the objects to the defined destinations. This method effectively limits the robots population, which should be applied in the task. Robots apply a simple, absolute and edge-based model in order to decide on the time of changing the status of a task. When the time, t_w, is over, a robot changes its sub-task. This strategy was compared with the strategy which did not include task partitioning and the way it helped in interference reduction was analyzed. In this study, these two strategies are called divided and undivided sequences [8].

3 OPERATION ENVIRONMENT

The sections to which the environment is divided are those which include the source and are situated on the left and those which include the nest are situated on the right area. These two sides of the area are referred to as pick-up area and storage area, respectively. The exchange area is situated between these two areas. The robots working on the left are called harvesters which collect the target objects in the source area and transit them to the exchange area. Objects, in this area, will be delivered to the robots, working in the other side, the storers, whose role is transiting the target objects to the nest and to store them over there [13], [14].

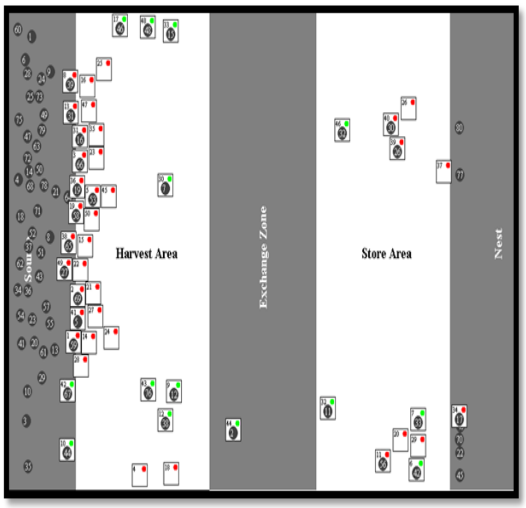

Figure 1. A graphic representation of the undivided strategy.

Undivided strategy's graphical representation is presented in Fig. 1 at time t = 0. All the robots are located in the harvest area. After picking up each object, each robot, enters the exchange area and, without hesitation (i.e. the value of edge is considered to be zero) enters the store area and places the object in the nest.

Graphical representation of the divided strategy in the problem operation is presented in Fig. 2. After picking up each object, each robot enters the exchange area and waits there until the arrival of the other robot from the store area for three seconds, in order to deliver the object to that robot; otherwise, the same robot enters the store area and performs the task of storer.

As shown in Fig. 3, the experiment is performed employing 10, 20, 30, 40 and 50 robots, respectively and the threshold of zero. Increasing the number of robots raised the physical interference among robots, because of the undivided complex tasks of the robots, and, in result, the system performance decreased.

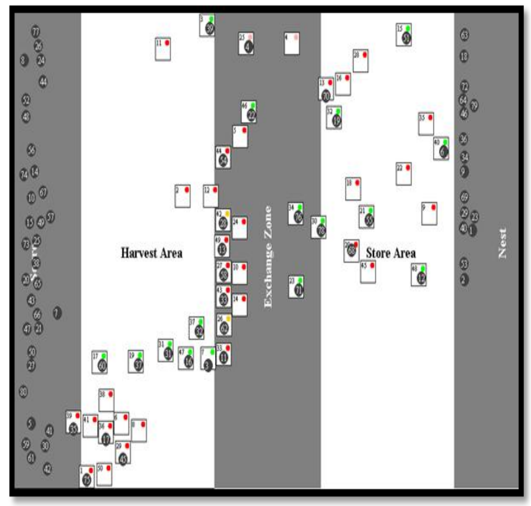

Figure 2. A graphic representation of the divided strategy.

In this experiment, the performance of the system is measured by 10, 20, 30, 40 and 50 robots, as shown in Fig. 4. Inference rate increment among robots and lack of specialization decreases the system performance. As it can be seen in Fig. 5, the experiment is performed employing 10, 20, 30, 40 and 50 robots at the threshold of 3 (i.e., each robot remained in the exchange zone for 3 seconds until the robot on the other side reached the zone to deliver the prey and take it to the nest). Unlike the undivided strategy, the cost did not increase, exponentially, in the undivided strategy.

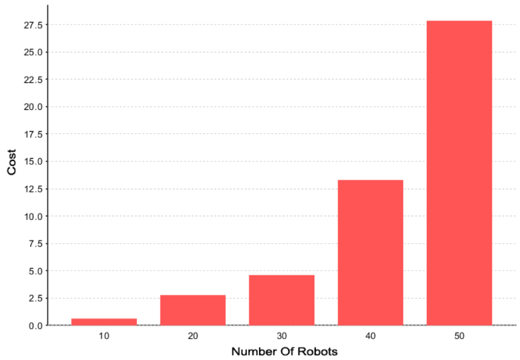

Figure 3. Graphical representation for attained cost, through the undivided strategy

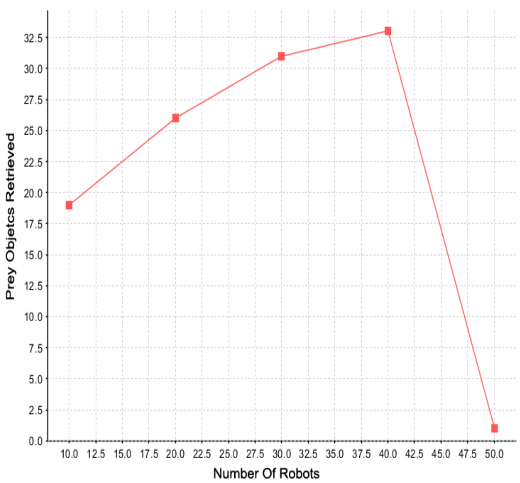

Figure 4. A graphic representation of performance in unpartitioning strategy

Moreover, decreasing the inferences in the divided strategy had increased the system performance. The system performance through this experiment (Fig. 6) employing 10, 20, 30, 40 and 50 robots was measured. As can be seen in Fig. 6, dividing the general task into two subtasks of harvester and storer increases the performance of the system. Each robot, in this case, was specialized for its sub-task. Consequently, the performance of the divided strategy increased, compared to the undivided one.

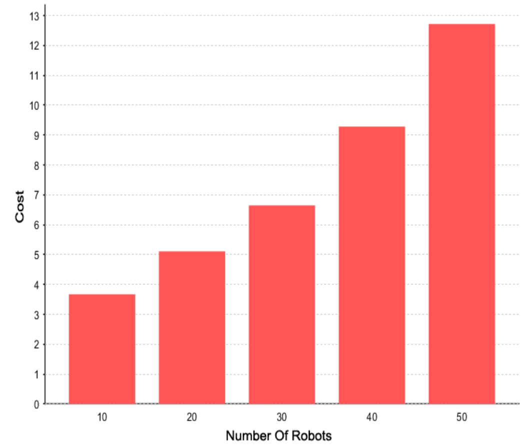

Figure 5. A graphical representation of attained cost in the divided strategy

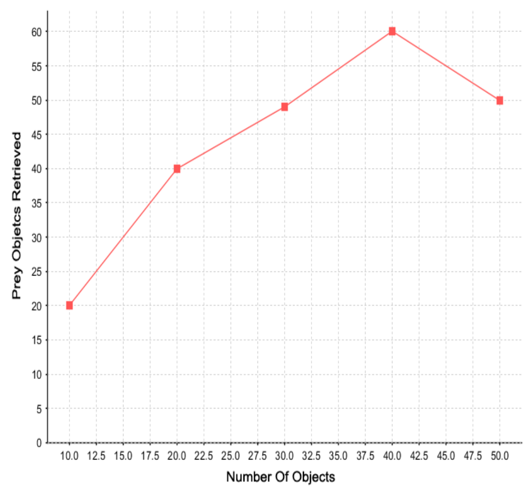

Figure 6. A graphic representation of performance in partitioning strategy

In Fig. 7, the blue column is in relation with undivided strategy and the red column is related to divided strategy. By increasing the number of robots, According to the diagram, the cost of undivided strategy increased, exponentially. While in divided strategy cost of performing tasks decreased. In Fig. 8, the red curve demonstrates the divided strategy, the blue curve demonstrates the undivided strategy. By increasing the number of robots, the performance of divided strategy increased, according to the diagram, compared to the undivided strategy.

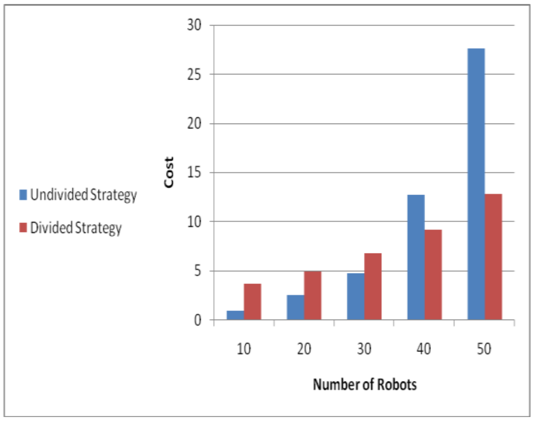

Figure 7. A graphical representation of cost differences between Undivided and Divided strategies

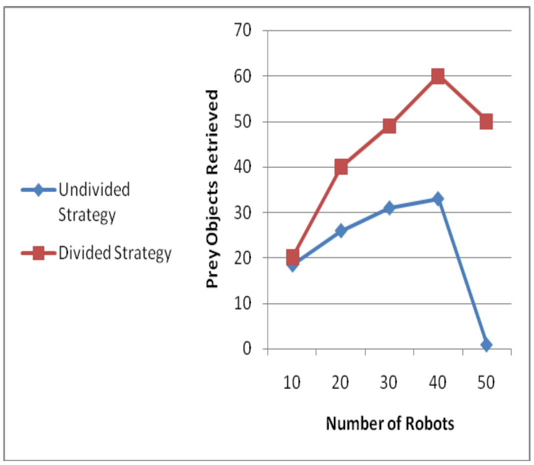

Figure 8. A graphic representation of performance for Undivided and Divided strategies

The divided strategy's performance was increased, because each robot was specialized for its subtasks.

4 CONCLUSION

The article aims to investigate whether task partitioning can reduce interference through critical task areas in crowded environments or not, and also examines the allocating a robotic swarm to the divisions. Interference is related to the number of individuals of the system. In addition, physical interference among robots is a function of the environment, in which the robots worked.

The larger the size of the swarm, the higher was the capacity and rate of physical interference. It can be concluded that, according to the conducted experiment, the amount of cost increases in the undivided strategy because of physical interference or contacts of robots against each other. In contrast, the divided strategy's efficacy and also the amount of performed work will decrease. Finally, the results showed that the employed method is more efficient in environments which contain robots' great population and higher probability of interferences.

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