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ASOC-3637; No. of Pages 11

ARTICLE IN PRESS

Applied Soft Computing xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Robust distributed spatial clustering for swarm robotic based systems

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ARTICLE INFO

Article history:
Received 9 March 2016
Received in revised form 9 May 2016
Accepted 2 June 2016
Available online xxx

Keywords:
Clustering
Swarm robotics
Swarm intelligence
Multi-robot systems

ABSTRACT

This paper proposes and formally evaluates a distributed clustering strategy of swarm of robots into any predefined number of classes. The strategy is an extension of an existing work that is applicable for two classes only [9]. It is implemented and experimentally tested on a swarm of a real swarm of Kilobots. Based only on the local information coming from neighboring robots and the disposition of virtual tokens in the system, the robots of the swarm can be clustered into different classes. The proposed strategy acts in a distributed manner and without need of any global knowledge nor any movement of the robots. Depending on the amount and weight of the tokens available in the system, robots exchange information to reach a token homogeneous disposition. The clustering strategy is inspired by the settling process of liquids of different densities. Using information gathered from neighboring robots, a token density is computed. As a result, the tokens with higher weights cluster first, shifting those of lower weight, until they form differentiated bands for each group, thus completing the clustering process of the robots.

1. Introduction

Multi-robots systems provide advantages over one individual robot when a task that requires higher execution speed, higher precision and fault tolerance is performed [3,4,11,12]. When there are two or more tasks to be performed and the set of robots is heterogeneous, it is possible to group them according to their functionalities [16]. In case the set of robots is homogeneous, the grouping can be implemented according to the distance between the robots and the places where the tasks must be performed [14].

Clustering is the term given to a group of computational methods for classifying elements in groups, based on their characteristics or some degrees of similarity [2,21]. The basic idea consists of putting individuals, that are similar according to some predefined criteria, in the same group [19]. Groups in a system must be described in terms of internal homogeneity and external separation. That is, the elements of the same group must be mutually similar yet distinct from those included in other groups. Clustering in swarm robotics has two main purposes, depending on the elements to be grouped: (i) the token clustering, which deals with passive elements, distributed throughout the environment; (ii) the clustering of the robots themselves.

For token clustering, the behavior of swarm robots, that have the ability to move tokens from one point to another, is studied. The robots, programmed with simple rules, can gather homogeneous elements in only one cluster and, depending on the sensing characteristics of the robots, can gather heterogeneous elements in different clusters.

One aspect that has to be taken into account, in token clustering, is the movement physics of the passive element, as well as the physics of the robot movement itself. In [23], an approach called *non-physical system* is described, where the behavior of token clustering, done by the robots, is considered, without taking into account the physical structure of the robots or that of the tokens. In other words, the robots are represented only by the manipulation of the tokens. As a result of this research, it was concluded that the increase in the number of clustered elements leads to a considerable increase in the clustering speed.

Multi-robots systems consist mainly of many simple robots, that generally have low computational capacity, due to cost restrictions [4]. However, working together, robots can solve complex problems. In order to get the best efficiency in solving problems, the original problem needs to be divided into many sub-problems, which will be distributed among individual robots or groups of robots. Robot's clustering attempts to manage the division of a large group of robots into many smaller groups, in order to allocate the tasks.

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http://dx.doi.org/10.1016/j.asoc.2016.06.002
1568-4946/

Please cite this article in press as: N.B. Cruz, et al., Robust distributed spatial clustering for swarm robotic based systems, Appl. Soft Comput. J. (2016), http://dx.doi.org/10.1016/j.asoc.2016.06.002

In this work, a spatial clustering method, based on [9], is used. Considering the work described in [9], only two classes are allowed. Through message passing among neighboring robots, this method allows clustering without robot movement. Based on token clustering method, the proposed method employs virtual tokens, denominated as *loads*. Exploring the characteristics of a load, it is possible to determine to which class a robot belongs. The main contribution of this work is the generalization of the method proposed by [9] for $\zeta \geq 2$ classes. All definitions introduced in [9] are generalized so as they apply to more that any number of classes. The proposed method also takes into account the problem of information loss, in order to minimize the impact of the original load losses. A formal description of the algorithms of the implemented solution are described and explained. It is noteworthy to point out that a first version of the proposed algorithm and some preliminary results appeared in [15]. The algorithm as it is detailed here solves many open problems in the first version. Moreover, new experiments and results are presented and discussed thoroughly, establishing the effectiveness and efficiency of the up-to-date complete version of the proposed algorithm. Furthermore, the computational complexity of the algorithm is formally evaluated.

The rest of this paper is organized in six sections. First, in Section 2, related works are discussed. After that, in Section 3, the main steps of the distributed algorithm, proposed herein, for robots clustering into $\zeta \geq 2$ classes is described. Subsequently, in Section 4, some aspects of the implementation are detailed. Then, in Section 5, experimental results are analyzed. In the sequel, in Section 6, we compare the proposed algorithm to the existing one. Finally, in Section 7, some conclusions based on the proposed algorithm are presented, along with some directions for future work.

2. Related work

One of the pioneer works developed for token clustering was published in [17]. The employed robots were equipped with a claw that enables disc movement, aiming at gathering discs of similar characteristics. It is noteworthy to point out that clustering in swarm robots generate similar problems as when clustering in wireless sensor networks [1,8].

In [23], the behavior of robots while performing token clustering, is studied. In order to understand this behavior, first it was simulated without taking into account the physical structure of the robots or that of the tokens. The simulation results led to the conclusion that the increase in the amount of elements already clustered facilitates the clustering of the remaining elements. In [23], only simulation has been carried out. In contrast, the strategy proposed in this work is implemented in a swarm of real robots.

Based on the tokens clustering existing work, other studies were carried out, aiming at robots clustering themselves. In [7], robots clustering behavior was performed. In this work, robots could perform two initial actions: stay still, waiting for another robot to arrive, in order to start a cluster, or keep in movement until finding still robots that already clustered. After starting the first clusters, robots could move in search for a better cluster. The evaluation of the found cluster is implemented through the robot vision, where most dense cluster is considered the best.

Based on another perspective, in [18,10], a robot's segregation method is proposed, based on the effect of *Brazilian Nuts* (*Castanhas do Brasil*) [5]. The simulation of this effect is reached through the random movement of the robots, with a common attraction point, and the repulsion between neighbors. This last parameter depends on a virtual radius defined by the communication range. Robots with the same virtual radius are grouped. Unlike the work described in [18,10], the clustering in this work occurs without the need for robot movement, which saves a big deal of the energy available in the robot's battery.

In [22], an adaptive cruise control suitable for a vehicle platoon is applied allow for robot clustering. For the platooning robots based on the adaptive cruise control, a reactive clustering method using local information among neighboring robots is proposed. Adjacent robots are clustered into small platoons considering several changing circumstances. Once more, the control strategy reported in [22] use simulation to validate its effectiveness while in this work, the effectiveness and efficiency of the clustering strategy is proven in a real robotic swarm of Kilobots.

After collecting information from different clustering methods, in [9] a robot's spatial clustering method is developed, where robots need a local knowledge of the system. Through virtual tokens exchange, robots can gather into clusters. This strategy provides an increase in clustering speed and a decrease in energy spent, due to the fact that robots need to communicate only for information exchange and do not need to move. In [9], only one kind of token is implemented and, hence, the algorithm works only when two clusters are required. In contrast, the algorithm described herein allows any number of classes.

3. Proposed clustering algorithm

The proposed algorithm is an extension on the spatial clustering algorithm developed in [9]. In its original form, the algorithm was designed to cluster the robots into 2 classes only. It is distributed and allows the swarm robots to form clusters, exchanging information with neighboring robots. Here, the algorithm is extended and generalized to be applicable for clustering the robots into $\zeta \geq 2$ classes.

The clustering algorithm is mainly based on tokens movements, called *loads*, by the robots. For ζ classes, there will be $\zeta - 1$ types of *loads*. These loads can be dynamic or static. A robot can have only one static load, but may receive any number of dynamic loads. The static load determines the robot's class, while the dynamic loads represent the movement of the token within the system. If a robot has a static load, independently of its class, it is called *loaded*. On the other hand, if a robot does not have any static load, it is called *unloaded*. A local variable u_i indicates that robot i has a static load, with $u_i \in \{0, 1, 2, \ldots, \zeta - 1\}$. Note that robot i is unloaded when $u_i = 0$. This variable is also used to indicate the class weight.

Fig. 1 shows an illustrative diagram of robot i that holds a static load and some dynamic ones. In the illustration, ℓ represents the identifier of the dynamic load with $\ell \in \{1, 2, \ldots, d_i\}$, d_i is the number of dynamic loads held by robot i and $c_{i\ell}$ represents the class of the dynamic load ℓ with $c_{i\ell} \in \{1, 2, \ldots, \zeta - 1\}$, $f_{i\ell}$ is the phase

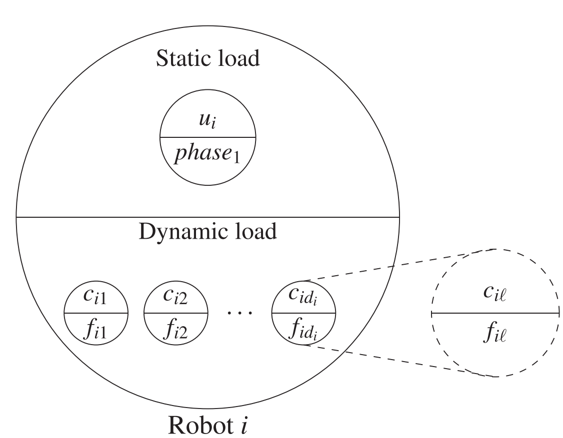

Fig. 1. Illustrative diagram of a robot and the included static and dynamic loads.

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