Iterative Method of Labor Division for Multi-Robotic Systems

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Abstract

Labor division in multi-robotic systems allows distributing tasks between agents in order to increase the efficiency of performing the global task. Collective decision-making methods allow agents to form the “agent-task” pairs. In this paper, we consider the case when the number of tasks significantly exceeds the number of agents. We propose an iterative method of labor division in multi-robotic systems. It uses collective decision-making to assign a cluster of subtasks to an agent. The paper examines different ratios between cluster size, number of clusters, and number of agents in order to find ratios that provide minimal average global task execution time and minimal average energy consumption.

Keywords: Multi-robotic systems, swarm robotics, task allocation, division of labor, collective decision making.

1. Introduction

Robotic technologies are being implemented into all spheres of human activity: when performing routine tasks, space exploration, performing work in response to natural and man-made emergencies, in the agricultural industry, in exploration, geology, in the fight against terrorism, and much more. At the same time, the intensive development of microelectronics has led to the miniaturization of robots. Thus, it became possible to use groups of numerous robots - multi-robotic systems (MRS). The advantages of their use are high mobility, low maintenance costs, the ability to perform many tasks, and the ability to scaling[1].

The problems of constructing an autonomous control system for MRS groups caused by the complexity of objectively existing systemic connections between the agents of the group, the patterns of interaction of the elements of the groups in an uncertain environment and possible instable elements. MRS groups are usually stochastic, nonlinear, so building mathematical models to test and optimize control models is difficult. The lack of methods for the transition from the specific behavior of the agent to the universal behavior of the group does not allow building an effective control system for groups of robots[2].

In this regard, a huge class of tasks appears for managing MRS groups. One of these tasks commonly known as the division of labor task.

Analysis of work[3] suggests a large variety of theoretical methods for solving this problem, especially with an equal number of agents and subtasks. In terms of popularity, one can single out heuristic algorithms, analytical, based on market economy models, potential fields, probabilistic approaches; methods based on machine learning and ANN, fuzzy logic, ant algorithms, dynamic and integer programming, genetic algorithms, mixed algorithms.

Many of the presented methods show good productivity with an equal number of agents and tasks, while in the literature the application of these methods is not widely described for cases when the number of tasks exceeds the number of agents by more than 5-20 times. In this case, an important criterion for performing tasks is the energy efficiency of the method of division of labor to perform the largest number of possible tasks.

2. The proposed method

The essence of the iterative method of division of labor in a group of multi-robotic systems when solving multiple problems is to carry out iterative procedures for establishing relationships of the "cluster-agent" type[4].

The algorithm for performing a global task using the iterative method of division of labor shown in Fig.1.

Decomposition and clustering of a global task into local tasks performed on the equipment of the control center. The input data for the decomposition is the data on the global task, the output data is the set of subtasks $\boldsymbol{Q}$ (2).

Clustering involves the formation of a set of clusters $W = \{w_1, w_2, \dots, w_{n_w}\}$ Clustering involves the formation of a set of clusters[5].

It assumed that in a three-dimensional environment, clustering performed by dividing a zone into cubes of the same size. The scale of the partition made experimentally and given in the results section.

To establish relationships of the "cluster-agent" type, the work considers three variations of the method of distributing clusters between agents: the choice of near clusters (1M), the choice of distant clusters (2M) and the uniform choice of clusters (3M). The difference between the methods is in the order in which the clusters defined for the selection of agents. In the case of a variation of the 1M method, the clusters considered from the closest to the most distant from the place of launch of the MRS agents, in the variation of 2M, from the most distant to the nearest clusters. The 3M method selects several evenly distributed clusters in the target field equal to the number of agents. The choice of clusters starts from the farthest from the MRS launch point to the closest one. In the first round, only the clusters included in the list of selected clusters are considered.

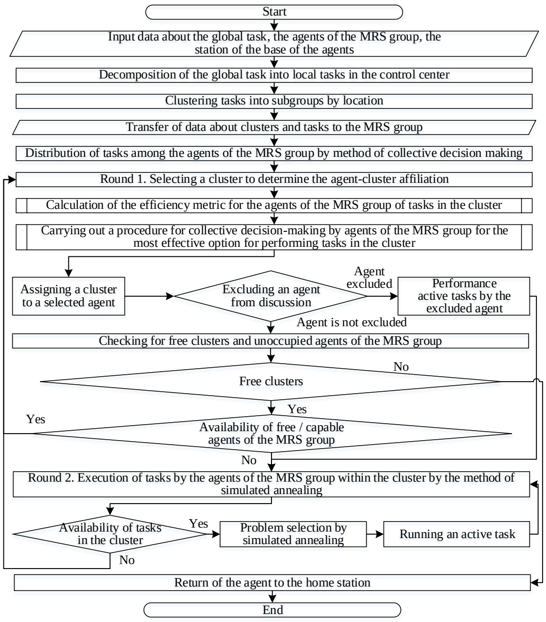

Fig. 1. Algorithm for performing a global task using the iterative method of division of labor.

Information about the clusters is transmitted to the agents of the MRS group, after which the agents proceed to the distribution of tasks (division of labor), which is carried out in two iterative rounds.

Round 1. Initially, all data about the set of subtasks $\boldsymbol{Q}$ and clusters $\boldsymbol{W}$.

Depending on the chosen method (selection of near clusters (1M), selection of distant clusters (2M) and uniform selection of clusters (3M)), a group of agents receives a certain cluster w_i,

Agents calculate performance metrics and the ability to perform tasks in the cluster. After calculating performance metrics, agents begin collective decision-making. Steps of Round 1 are repeated until there are free clusters and unoccupied agents.

Round 2. When assigning a cluster to an agent, the agent starts the 2nd round - performing tasks within the cluster. The sequence of tasks execution in the cluster determined by the simulated annealing method.

This procedure carried out until there are no free tasks or agents. If there are tasks and agents, the procedure repeated; if there are no tasks, but there are free agents, they sent to the base station. If there are no clusters at all, the agent starts moving to the home station.

3. Result

The software simulation carried out in the CoppeliaSim system. To assess the effectiveness of the proposed solutions for the distribution of tasks in the MPC group, 20'000 computational experiments carried out. The following methods implemented in the simulation:

- iterative task distribution algorithm, variation with distant clusters,
- iterative task distribution algorithm, variation with the nearest clusters,
- iterative task distribution algorithm, variation with distributed clusters,
- analog, greedy task distribution algorithm with collective decision-making.

In the simulation, 100 tasks generated by a uniform distribution, a group of MRSs of 5, 7, 10, and 15 agents performed tasks in clusters. For the purity of the experiment, the division into 18, 32 and 50 clusters checked. The results summarized for each generated map. A total of 250 cards were generated for one set of agents and clusters. The results of the study of the average distance traveled by all agents of the MRS group presented in Figures 3.

Based on the results of the study, the following conclusions drawn: with the average dimension of the clusters, the average distance traveled by the agent's decreases.

Because the distance traveled correlates with the expended energy in direct proportion, we can draw the following conclusions:

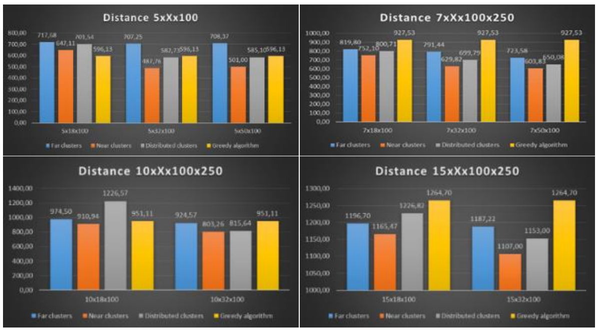

Fig. 2. Average distance traveled by 5, 7, 10, 15 agents in 18, 32, 50 clusters 100 tasks.

- for a group of 5, 7, 10, 15 agents with the ratio of tasks as to 20, to 14, to 10, to 7, respectively, it is optimal to use the iterative distribution method with variation of nearby clusters;
- depending on the size of the cluster, the algorithms show different results. For five agents, the best result shown by the distribution over 32 clusters. For 7 agents - 50 clusters, for 10 agents - 32 clusters, for 15 agents 32 clusters;
- for a different number of agents in comparison with the greedy algorithm, the results improved by 18% for 5 agents, by 35% for 7 agents, by 15% for 10 agents, by 12% for 15 agents.

The gain in energy efficiency in completing tasks offset by the time it takes to complete them. The best time indicator provided by the greedy algorithm.

4. Conclusions

This article proposes an iterative method for the division of labor in an MRS group in the case of an excess of the number of tasks over the number of agents by 5-20 times. The method is based on an iterative procedure for selecting task clusters and collective decision-making by agents of the MRS group. Three variations of the iterative method were proposed, with a difference in the order of selection of clusters for performing tasks by agents. The analogue of the method was a greedy algorithm for the division of labor with collective decision-making. According to the simulation results for a different number of agents, compared to the greedy algorithm, it was possible to achieve an improvement in the results by 18% for 5 agents, by 35% for 7 agents, by 15% for 10 agents, by 12% for 15 agents with a different number of task clusters.

References

1. A. Zakiev, T. Tsoy, E. Magid, "Swarm Robotics: Remarks on Terminology and Classification", Lecture Notes in Computer Science, Vol. 11097, pp. 291-300, 2018.
2. E. Magid, R. Lavrenov, M. Svinin, A. Khasianov, "Combining Voronoi Graph and Spline-based Approaches for a Mobile Robot Path Planning", Informatics in Control, Automation and Robotics, 14th International Conference on Informatics in Control, Automation and Robotics (ICINCO), pp. 475-496, 2017.
3. V.H. Pshihopov, V.V. Soloviev, A.E. Titov, V.I. Finaev, I.O. Shapovalov, "Group control of moving objects in uncertain environments", Fizmatlit, 2015. (In Russian)
4. A.R. Gaiduk, I.A. Kalyaev, S.G. Kapustyan, A.P. Kukharenko "Models and methods of control of large groups of robots: a tutorial", SFedU Publishing House, 2014. (In Russian)
5. F. Tebueva, V. Antonov, N. Svistunov, "Labour division algorithm for a group of unmanned aerial vehicles in a clustered target field", E3S Web of Conferences, Vol. 270, No. 01035, pp. 1-9, 2021.

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