Task decomposition and distribution method for heterogeneous multi-robotic systems

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Abstract. This article presents a method for decomposition and distribution of tasks in a multi-robotic system (MRS). The proposed implementation of the method of elementary operations distribution is based on maximizing the expected efficiency of each agent and collective decision making (CDM). To compare the effectiveness of various methods, computational experiments were carried out. According to the results, the implementation of the CDM mechanisms allows reducing the time for performing a global task by MRS agents by more than 10%. For the initial conditions described in the work, the use of the proposed method for maximizing the individual efficiency of an agent in combination with the CDM algorithm allows reducing the average execution time of a global operation by 21% in comparison with the method of minimizing the individual execution time without CDM.

Keywords: Multi-robotic systems; Decentralized control; Task decomposition; Tasks distribution; Collective decision making.

1. Introduction

Currently, methods of constructing complex adaptive systems based on multi-agent methods are being actively developed. These technologies can be used to control multi-robotic systems (MRS) capable of performing complex composite tasks in uncertain environments. Robotic devices for various purposes, called agents or group members [1-3], are used as executive elements of the MRS.

The taxonomy of MRS is given by Iocchi, Nardi, Salerno in [4]. The proposed taxonomy was used and developed in [5]. MRS in this context is a system containing several robots that can be combined into heterogeneous groups consisting of homogeneous subgroups.

The main research areas of MRS are centered around modeling and management, planning and decision-making, technological and methodological issues [6].

The intensive growth in the number of publications and projects in these areas of research indicates the high popularity and relevance of this topic among researchers [7-11]. The main issues of the development of MRS, described in these works, are summarized in the topic of implementing a decentralized control system for a complex heterogeneous MRS.

According to the research [7-11], a number of problems can be identified in the construction of MRS control systems:
- a complex hierarchy of interrelationships among MRS agents;
- requirements for a high level of autonomy of MRS;
- limited communication range of agents;
- limited agents' sensory capabilities;
- insufficient optimization depth of subtasks distribution;
- high computational complexity of control algorithms;
- lack of a system for evaluating and optimizing time parameters for performing complex tasks.
- the complexity of organizing a centralized control system, which is associated with a number of the above factors and the need to solve complex optimization problems for the distribution of tasks between agents, etc.

The difficulties can be partially solved by modifying the design of agents, increasing their computing power, which will affect their cost, or by building a decentralized group management system and a system for collective decision making.

This article deals with the problem of constructing a scenario for performing tasks by agents of MRS with a decentralized control system.

Decentralized control can be roughly divided into two groups:
- control systems, where each element of the MRS is not controlled by other agents, but at the same time random interactions lead to global positive effects, which is a manifestation of the emergence effect;
- control systems, which assume the presence of a control action that “directs” the MRS agents and is the source of some of the input data. Moreover, control signals can come both from a control system external to the group and from a “local” leader (agent) within the group [12].

The main problems of decentralized management arise at the stage of building such a system in view of the particular complexity of the structure of interaction of all elements.

Diagrams of the processes of performing tasks of the centralized and decentralized control systems of the MRS are presented in figure 1 [8-11].

Data from the control center is transmitted to the MRS agents for further distribution. In turn, the agents collect information about the environment and send the data directly or through a connected element for processing to the control center.

In this case, the control center decides to perform a complex composite task, for which it is necessary to decompose it into a group of elementary subtasks.

Analysis of external data on the environment and available information on the state of the MRS allows you to divide a complex task into groups of simple subtasks.

The MRS agents receive a set of subtasks and perform the procedure for their distribution within the group in such a way as to minimize or maximize the values of one or several selected optimization criteria (time, energy consumption, path length, etc.).

Each MRS agent orders an individual chain of subtasks, which are then recursively decomposed to elementary operations.

In this system, there is a complex hierarchical structure of relationships when performing global complex tasks, taking into account the non-determinism of the environment and the instability of the elements of the group. Consider the classic and modern systems of decomposition and distribution of tasks between the MRS.

2. Materials and methods

According to the results of the analysis of some works devoted to the methods of decomposition and distribution of tasks in multi-agent systems, some drawbacks of the existing approaches were revealed.

The paper [15] describes a method for multi-agent assessment of the state of moving objects based on a cyclic search algorithm of stochastic approximation. The disadvantages of the described approach include insufficient optimization depth of the choice of subtasks during their distribution, as well as high computational complexity, since the regulation of the search cycle must perform a large number of passes to obtain an optimal solution.

The project [16] uses algorithms for simultaneous localization and mapping for a heterogeneous group of robots in a natural disaster. However, according to the specifics of the project, in the proposed system, the MRS group is the results of the formation of several swarms, underwater, ground and air.
Thus, task groups for each swarm are identical and cannot in any way be distributed among agents of another swarm.

In [17], a hybrid approach to controlling a swarm of robots is implemented, in which a part of the swarm acts as a control object, evaluating global information in order to influence the behavior of the remaining agents and increase the performance of tasks. At the same time, adding a control object leads to centralization and requires additional mechanisms to ensure the stability of communication.

As an analogue in this article, we will consider the classical analytical method of task distribution for a group of MRSs. The distribution of tasks is based on the principle of choosing the nearest points of location of tasks. And the process of agreeing a solution between agents consists of comparing the distances between the agent and the task.

Further, a simplified model of the MRS agent, working environment and elementary subtask is introduced.

Let the MRS consist of a set of agents \( A = \{A_1, A_2, ..., A_n\} \). Every agent \( A_i \in A \) is characterized by:

- coordinates on the plane \((x_{A_i}, y_{A_i}) \in \mathbb{R} \times \mathbb{R}\);
- a set of types of performed operations \( O_{A_i} \subseteq O \), where \( O \) is a set of possible operation types;
- performance \( P_{A_i} \) of performing operations of various types, reflecting the amount of work performed by the agent per unit of time:

\[
P_{A_i} = \{p_{A_i}(a) \forall a \in O\},
\]
where $p(a)$ – performance on operation type $a$:
\[
\forall a \in O_a, p_A(a) \in R_+,
\forall a \not\in O_a, p_A(a) = 0;
\]

- the speed of movement $v_A$ (within the framework of the simplified model, we take the speed of the agent to be constant in any direction and not dependent on external factors).

The working environment is a two-dimensional plane. Each elementary subtask $m_j$ from the set of subtasks $M'$ is characterized by:

- coordinates in the environment $(x_{m_j}, y_{m_j}) \in Z \times Z$;
- operation type $o_{m_j}$;
- job volume $V(m_j) \in R_+$;
- status $S_m$ ($S_m = 0$ – subtask is free, $S_m = 1$ – subtask is seized).

Since the subtasks are located at integer points of the work plane, such a model corresponds to dividing the global task by territoriality into square areas of $1 \times 1$ size. At the same time, the regions of several elementary subtasks of the same or different types can be located at the same point. At a given moment in time, an agent is able to perform only one subtask of one type, however, subtasks located at one point can be simultaneously executed by different agents. Within the accepted model, collisions between agents are not possible and are excluded from consideration.

As an analogue algorithm, we consider a greedy subtask distribution algorithm, which consists in the choice by each agent with the least labor input of a subtask from the free:

1. Initial state:
\[
\forall m_j \in M' \ S_{m_j} = 0, \ 0 \leq x_{m_j}y_{m_j} < C_{\text{max}},
\forall A_i \in A \ S_{A_i} = 0, \ 0 \leq x_{A_i}y_{A_i} < C_{\text{max}},
\]

where $C_{\text{max}}$ is environment size constraint.

2. For each agent $A_i \in A$ and every subtask $m_j, m_k \in M'$ sets of work intensity metrics are calculated:

2.1. $H_{0,A_i} = \left\{ h_{A_i,m_j} = \frac{l(A_i,m_j)}{v_{A_i}} + \frac{V(m_j)}{p_{A_i}(o_{m_j})} \right\}$ is time for agent $A_i$ to reach and complete task $m_j$ from the initial position,

where $l(A_i, m_j) = \sqrt{(x_{m_j} - x_{A_i})^2 + (y_{m_j} - y_{A_i})^2}$ is distance between two points on a plane;

2.2. $H_{A_i} = \left\{ h_{A_i,m_j, m_k} = \frac{l(m_j, m_k)}{v_{A_i}} + \frac{V(m_k)}{p_{A_i}(o_{m_k})} \right\}$ – time of reaching and execution by agent $A_i$ task $m_k$ from the position of subtask $m_j$.

If the operation of a specific subtask $m_j$ cannot be performed by the agent $A_i$, then $h_{A_i,m_j} = \infty$.

3. At the initial stage, each agent $A_i$ chooses the task $m_{A_i, \text{min}}$ with the smallest value of the work intensity metric, declares it busy and heads to execute it:
\[
m_{A_i, \text{min}} \leftarrow \arg \min_{m_j \mid S_{m_j} = 0} h_{A_i,m_j},
\]
\[
S_{m_{A_i, \text{min}}} \leftarrow 1.
\]

Agents select subtasks sequentially, thereby ensuring the absence of collisions.

4. When the current subtask $m_{A_i, \text{min}}$ is executed, the agent announces its exclusion from the list, then it selects the following subtask with the minimum metric of work intensity relative to the current position:
\[
M' \leftarrow M' \setminus \left\{ m_{A_i, \text{min}} \right\},
\]
\[
m_{A_i, \text{min}} \leftarrow \arg \min_{m_j \mid S_{m_j} = 0} h_{A_i,m_{A_i, \text{min}},m_j},
\]
\[
S_{m_{A_i, \text{min}}} \leftarrow 1.
\]
5. Step 4 is repeated by different agents while $M' \neq \emptyset$.

This algorithm does not guarantee the optimality of the distribution of elementary subtasks in terms of minimizing the total execution time. Although the efficiency of the greedy algorithm may be sufficient for practical use, its disadvantage is the dependence of the resulting distribution of tasks on the order in which agents select tasks for execution.

The proposed method is an effective and reliable method for finding a feasible solution when distributing tasks between agents. It should be noted that the method is analytical, and when refined, it can search for an optimal solution. Since the system is decentralized, an increase in the number of agents in proportion to the number of tasks does not affect the computational complexity; however, with an increase in the number of tasks in relation to the number of agents, the computational complexity of the problem selection algorithm will grow exponentially.

To reduce the dependence of the computational complexity of the algorithm on the number of tasks, artificial neural networks (ANNs) operating on the equipment of each agent can be used. ANN preparation is carried out in the process of simulating the functioning of the MRS and is based on the methods of machine learning with reinforcement. The advantages of this approach are the absence of a training sample prepared in advance, as well as the absence of the need to explicitly define the control algorithms of agents.

3. The proposed subtasks distribution method

The proposed solution to improve the efficiency of the global task execution by the MRS agents is an algorithm based on collective decision making by the MRS agents.

The metric $r_{A_i}(m_j)$ is used as a metric of the potential reward of the agent $A_i \in A$. It estimates the performance of the subtask $m_j$ execution:

$$r_{A_i}(m_j) = \frac{\nu(m_j)}{h_{A_i,m_j}},$$

(7)

where $n_0$ is a number of subtasks from $M' \setminus m_i$.

Since with a large number of subtasks calculating $R_{A_i}(m_j)$ in real time can be difficult, it is proposed to use an ANN to form the expected reward, the input of which is information about the current state of subtasks and the agent, and the output is the value of the expected reward (figure 2).

![Artificial Neural Network](image)

Figure 2. Artificial neural network usage scenario for efficiency metrics generation
Algorithm (2) for the distribution of tasks using collective decision making consists of the following stages:

1. Based on information about the state of the environment, each agent $A_i \in A$ determines the set $R_{A_i}$ of potential reward values $r_{A_i}(m_j)$ for each subtask, sorted in descending order:

$$R_{A_i} \leftarrow \left\{ R_{A_i,k} = \left( m_j, r_{A_i}(m_j) \right) \right\}_{k} \forall m_j \in M'$$

where $k$ is the number of element in $R_{A_i}$.

2. For $n \in 1, M' \bar{M}'$ the sequence of actions is repeated:

2.1 Agent $A_i$ chooses the subtask $m_{A_i} \in R_{A_i,n}$ as a candidate for execution and informs the rest of the agents about the choice.

2.2 If a response of the form $(m_{A_i}, r_{A,x}(m_j))$ comes from at least one agent $A_x \in A$ and $r_{A,x}(m_j) > r_{A_i}(m_j)$, then $n \leftarrow n + 1$ and transition to 2.1.

3. If all subtasks were distributed with the best values of the efficiency metric, i.e. $n = (n_{M'} + 1)$, agent $A_i$ stops working on the current subtask, both in the case of its completion ($V(m_{A_i}) = 0$), and in the case of displacement by another agent with higher performance metric value.

Algorithm (2) is launched with a certain periodicity $t$, and also every time when agent $A_i \in A$ stops working on the current subtask, both in the case of its completion ($V(m_{A_i}) = 0$), and in the case of displacement by another agent with higher performance metric value.

The use of an ANN of reinforcement learning makes it possible to use this method in the absence of a training sample prepared in advance, and also in the absence of the need to explicitly define the control algorithms of agents.

4. Computational experiment

On the basis of the considered algorithms, the following decision-making methods by MRS agents can be formed:

- selection of a free task with the minimum expected execution time;
- selection of a free task with the maximum expected efficiency;
- selection of a task with the minimum expected execution time using the CDM method;
- selection of a task with the maximum expected efficiency using the CDM method.

Computational experiments were carried out to compare the effectiveness of these methods.

For each experiment, size of the working field is 15x15 cells, number of agents is 8, number of tasks is 100, number of task types is 3.

Using a pseudorandom number generator (PRNG) with a uniform distribution, the following are generated (figure 3):

- initial positions of agents and tasks in range $[0; 14]$;
- types of tasks (1, 2 or 3 – presented in red, green and blue, respectively);
- volumes of tasks in the range $[100; 255]$ units of work;
- the performance of each agent when executing a task of a specific type in range $[0; 10]$ units of work per time tick;
- the speed of movement of agents in range $[2; 6]$ units of distance per tick (the unit of distance is equal to the side of the cell).

To obtain statistics characterizing the speed of task execution when using each method, 1000 tests were carried out with the preliminary PRNG initialization with a constant.

Examples of modeling the four described algorithms for selecting subtasks by MRS agents are shown in figure 4.
The greatest differences in decisions made by agents using a method based on maximizing individual efficiency and collective decision-making in comparison with analog methods are observed at the final stages of the experiment, when the areas corresponding to local problems are not densely located.

5. Results

Based on the results of 1000 experiments with identical initial conditions for each method, statistical characteristics were obtained (table 1 and figure 5).
The use of the CDM algorithm allows reducing the average execution time of a global task by 11% for the method based on minimizing the individual time of subtask execution, and by 16% for the method based on maximizing the individual efficiency of each agent. In addition, CDM increases the stability of the global task execution time, decreasing the standard deviation of its execution time from the average value. The use of the CDM algorithm and the method of maximizing individual efficiency can reduce the average time to complete a global task by 21% in comparison with the method of minimizing the individual time to complete a subtask without CDM.

6. Conclusion
In this article, a method has been developed for distributing tasks between agents of multi-robotic systems, based on maximizing the individual performance of each agent and using a collective decision-making approach.

The paper considers the basic problems of the development and use of MRS. Emphasis is placed on the decomposition and distribution of tasks in the MRS. The well-known methods for the implementation of these tasks are presented. Analogs of the proposed method are considered.

Based on the results of the computational experiments, it has been established that the implementation of collective decision-making mechanisms can reduce the time for performing a global task by MRS agents by more than 10%; The use of the method of maximizing the individual efficiency of an agent in combination with the CDM algorithm for the considered initial conditions allows reducing the average execution time by more than 20% in comparison with the method of minimizing the individual execution time without CDM.

The prospect for the development of the method lies in the use of ANN not only for the formation of the value of the reward, but also for the distribution of tasks between agents, as well as increasing the depth of the calculation of the next steps; adaptation of the algorithm to more complex models of agents and environments.

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