APPLYING THE CONCEPTS OF MULTI-AGENT APPROACH TO THE DISTRIBUTED AUTONOMOUS EXPLORATIONS

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Abstract: The problem of development and application of the multiagent techniques for organizing mobile exploring agents' cooperative behavior is examined. The main problems related to design and operating of distributed decentralized homogeneous multi-agent systems with restricted local interaction between agents are analyzed. A number of collective behavior models (algorithmic, interpolational, entropic), which discover the problems of distributed decentralized exploration are proposed.

Keywords: multi-agent systems, distributed autonomous explorations, self-organization.

ACM Classification Keywords: I.2.11 Distributed Artificial Intelligence

Introduction

The basic scenario of distributed autonomous explorations is the following [[Ögren, Fiorelli, Leonard, 2004] - [Botchkaryov, Golembo, 2003]. The set of autonomous explorers is located in some environment. Then each of explorers starts gather information and transmits it to the center (the case of global user) or to some actuators located in the same environment (the case of local user). Together explorers form the system of distributed autonomous explorations, which main objective is to gather more precise and complete information by less cost. Main features of the distributed autonomous explorations' system are the following: 1) explorers are constructively and operationally autonomous; 2) system is spatially distributed; 3) explorers do in-situ measurements in environment; 4) system performs long-term explorations; 5) explorers are mobile. Examples of the systems of distributed autonomous explorations are 1) mobile wireless sensor networks [Ögren, Fiorelli, Leonard, 2004] - [Howard, Mataric, Sukhatme, 2002], 2) spatially distributed radar systems, 3) autonomous oceanographic sampling network [Turner, Turner, 1998] , [Curtin, Bellingham, Catipovic, Webb, 1993], etc.

The current state of the art in the area of organizing mobile explorers' cooperative behavior requires a fresh self-organization perspective look on the possibility to adapt the exploration instrument to the environment characteristics. Thus in our research work on distributed autonomous exploration systems in the Laboratory of Multiagent Systems at Computer Engineering Department of Lviv Polytechnic National University [Botchkaryov, Golembo, 2001] - [Botchkaryov, Golembo, 2003] we try to develop corresponding multiagent techniques. Here explorer station (sensor node, measuring device) is thought as mobile explorer (explorer agent) and corresponds to intelligent agent [Weiss, 2000] , [Wooldridge, 2002]. In addition, the distributed autonomous exploration system is thought as mobile explorers' team and corresponds to multiagent system [Weiss, 2000] , [Wooldridge, 2002] .

Problem statement

There are two main problems related to the operating of the distributed autonomous explorations' system. The first problem is the problem of placement. It can be described in the following way. The number of explorer agents located in environment (explored object space) is limited. This limitation naturally results from principle of minimization of exploration instrument's influence on explored object. Hence, explorer agents' team can obtain only the limited information about explored object at one moment of time. Based on this fact one can make the following statement: different placements of explorer agents in explored object space give us images with different amount of information about this object. Thus, the problem of placement arises: how one can place explorer agents in object space to achieve image with maximum amount of information?

The second problem is the problem of control. It can be described in the following way. The global (or local) user is usually remote from the explorer agents. The user also has no or has a little a priori information about processes in object under exploration. Hence, user cannot solve problem of placement precisely and in time. The quality of decisions generated by user will be always limited by uncertainty about real conditions of corresponding task. Based on this fact one can make the following statement: a user cannot eliminate the uncertainty because of its remoteness while the explorer agents potentially have such ability. Thus, the problem of control arises: how one can delegate the initiative in making rational decisions to the explorer agents?

Considering problem of placement and problem of control together, one can see that behavior of the explorer agents' team must be in some way strictly related to the processes in explored object. In other words we need to develop such a multiagent exploration system, which can autonomously (solving the problem of control) find the best according to the specified criteria way of exploration (solving the problem of placement). Here the most difficult case is non-linear dynamics of environmental processes (especially the so-called synergetic processes). Thus, we can state the following proposition: if synergetic environmental processes will be explored by self-organizing multiagent system, then we obtain the qualitative rise in autonomous explorations. Multiagent exploration system must be capable to assimilate "order" of environmental processes (this "order" in fact is the source of multiagent system's self-organization). In this way, multiagent exploration system obtains similar to the environmental processes dynamics eliminating corresponding uncertainty.

The main properties of multiagent exploration system under consideration are 1) homogeneity of explorer agents (all agents have the same structure (Fig.1) and embodiment and each agent perform the same set of control & AI algorithms), 2) decentralized control (each agent makes and implements decisions independently, the control center is absent), 3) local limited communication between explorer agents (each agent can detect and possibly communicate only with neighbor agents within limited detection range).

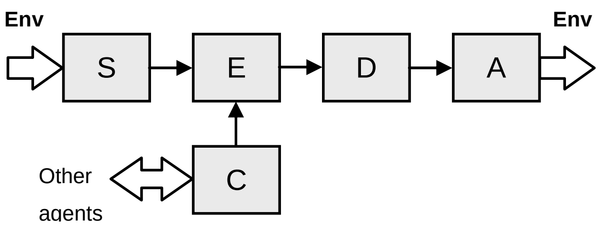

Figure 1. Functional structure of mobile explorer agent:

S – sense the environment state, C – communicate with other agents,
E – estimate the appropriateness of previous action, D – decide about next action, A – actuate decision

Under these conditions, we consider the main problem of multiagent systems' design: how one can transform the Global Utility Function of multiagent exploration system to local utility functions of agents? Or else how one can make the desired collective behavior emerges from individual agents' actions? In this case, the best way of exploration is equal to emergent collective behavior and corresponds to global extremum of the Global Utility Function (Fig.2).

Here the following problems arise. How one can decide which way of exploration is better? How one can estimate current success in finding proper way of exploration? How one can develop the effective algorithms of collective behavior of explorer agents?

Figure 2. The common framework

Research and Development

Our approach (Fig.3) consists in implementing key problems (problem of control, problem of placement, and eventually problem of self-organization) in designed task environments (models of collective behavior) and developing the algorithms of collective behavior (collective decision making, multiagent reinforcement learning, autonomous exploration heuristics) in framework of these task environments [Botchkaryov, Golembo, 2001] - [Botchkaryov, Golembo, 2003], [Wooldridge, 2002] - [Botchkaryov, 2002], [Botchkaryov, 2005], [Botchkaryov, Golembo, 2005]. Here we use the following theories and methods: real-time search [Ishida, 1997], learning automata [Tsetlin, 1973], and reinforcement learning [Weiss, 2000] , [Sutton, Barto, 1998], [Kaelbling, Littman, Moore, 1996].

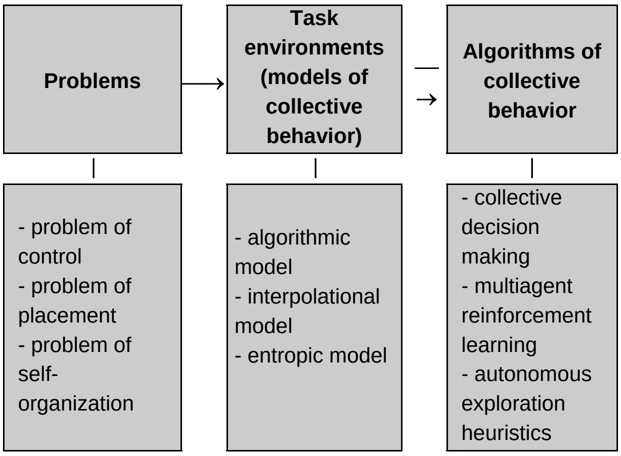

Figure 3. Research & development flow

Algorithmic model. Algorithmic model is used to find the appropriate methods of decentralized control (i.e. solutions to the problem of control) corresponding to the collective exploration specific. In the framework of this model procedures of decentralized collective measurements are developed. In algorithmic model, the problem of control of distributed autonomous explorations is interpreted in terms of load balancing problem [Botchkaryov, 2002] by analogy with algorithmic theory of measurements [Stahov, 1979]. Here each agent is thought as independent balance weight. The agent can change his individual weight in some range. The collective of agents must find the common weight equivalent to the unknown load (i.e. measured value). The agents do it step-by-step manner being reinforced by current difference between their common weight and weight of unknown load. Here the first question is solvability and the second question is quality of solution (minimization of number of steps). The key problem in this case is uncertainty about the actions of other agents. An agent cannot decide explicitly about appropriateness of his previous action because overall system reacts to the collective action. The analog problem from multiagent RL is credit assignment problem [Weiss, 2000]. Different techniques can be used to eliminate the uncertainty about other agents' actions. Even the most difficult case with lack of inter-agent communication is solvable. We develop the number of collective behavior algorithms based on learning automata [Tsetlin, 1973] and reinforcement learning techniques [Sutton, Barto, 1998], [Kaelbling, Littman, Moore, 1996]. We plan and conduct the number of numerical experiments with the algorithmic model [Botchkaryov, 2002]. The main results are the following: 1) speed of balancing increases with communication limitations decrease; 2) speed of balancing decreases with number of agent increase; 3) collective behavior algorithms based on reinforcement learning techniques shows the best results.

Interpolational model. Interpolational model is used to find the appropriate methods of autonomous explorations (i.e. solutions to the problem of placement). In the framework of this model procedures of autonomous explorations are developed. Here the discrete environment with function f(X) of some parameter realized over points is considered. Each explorer agent can locate in one environment point, sense the function value in this point and report this value to the center (parameter value and point coordinates). The agents can move through the environment in any direction. The center builds the image F(X) of environment function using some interpolation method. Here explorer agents play the role of mobile interpolation nodes. Deviation between f(X) and F(X) can be estimated and taken as value of Global Utility Function of explorer agents' team. The key problem in this case is uncertainty about the environment function and other agents' actions. Thus agents must find the best placement in environment (to minimize deviation between f(X) and F(X)) or organize convergence of their movements to the best placements. At first, we develop relatively simple "relaxation" algorithms with low inter-agent communication rate [Wooldridge, 2002]. The more sophisticated approach to develop corresponding collective behavior algorithms is based on S-transform (Vallee-Poussin algorithm) and R-transform (R-algorithm) of placements (case of Chebyshev's interpolation) and reinforcement learning techniques [Botchkaryov, 2005] [Botchkaryov, Golembo, 2005] . Another approach is based on computer geometry methods, extremum search heuristics, and reinforcement learning techniques [Botchkaryov, Golembo, 2005]. We plan and conduct the number of numerical experiments with the interpolational model [Botchkaryov, Golembo, 2003], [Botchkaryov, 2005], [Botchkaryov, Golembo, 2005]. The main results are the following: 1) quality of explorations increases with communication limitations decrease; 2) collective behavior algorithms based on heuristics shows the best results.

Entropic model. Entropic model is used to find the correlation between process of self-organization in explorer agent's team and amount of information gathered in environment. Self-organization techniques are main subject of interest here. According to the model environment is a network of stationary event sources (nodes) with different Shannon entropy values (number of different events is limited and equal to all sources). Each agent can move through the network, observe events in the node where he is currently located and report this information (node id and event id) to the center. Center builds the statistical image of environment based on information gathered by agents. Initially center supposes all event sources have the maximum entropy. Thus if an event source has maximum entropy then an agent located in corresponding node gives no new information to the center. The key problem in this case is uncertainty about the real entropy values of nodes and other agents' actions. Under these conditions, agents must collectively decide about next placement over environment nodes. Here some heuristics based on the statistical methods can be used. In this framework, we developed collective behavior algorithms based on idea of probabilistic automata and reinforcement learning techniques [Botchkaryov, Golembo, 2005]. We plan and conduct the number of numerical experiments with the interpolational model [Botchkaryov, Golembo, 2005]. The main result is the following: dependence between self-organization quantitative parameter and amount of gathered information shows increase of self-organization quantitative parameter with increase of amount of gathered information.

Results and Future research

The main results of our work are 1) proposition to use self-organizing multiagent exploration system; 2) task environments (models of explorer agents' collective behavior); 3) Global Utility functions in the context of corresponding task environments (models of explorer agents' collective behavior); 4) algorithms of explorer agents' collective behavior; 5) research and development software.

Complementary outcomes of our work are 1) algorithms of collective formation (inter-agent detection); 2) self-synchronization methods for explorer agents' team; 3) self-organization of explorer agents' team in space; 4) algorithms of keeping the communication connectivity while moving in space; 5) modifications and new variants of reinforcement learning techniques.

Extra outcomes of our work are 1) model of explorer agents' collective behavior based on poly-probe exploration method; 2) game models of collective behavior with emphasis on exploration techniques; 3) intelligent agent architectures adapted to the collective exploration domain.

Our future research will cover the following topics: 1) considering the multipurpose exploration case (for example exploration of several functions in interpolational model); 2) integrating information obtained by multiagent exploration system with data of satellite monitoring (including case where explorer agents play role of control points for correcting data of satellite monitoring); 3) combination of different methods of explorations (point, tail, bearing, center-probe, poly-probe); 4) emergent languages of inter-agent communication (problem of finding most appropriate language for communication and explored object description during the process of exploration); 5) most common case: collective perception (including the task of collective visual exploration of unknown object using the image processing techniques).

Conclusion

Development of the systems of distributed autonomous explorations is an actual problem for many applications. Multiagent approach can be successfully used for this purpose. The problem of effective environment exploration is important in multiagent systems design too. Main problems related to the distributed autonomous explorations were analyzed. Two of them are critical: problem of placement (how agent' team can find autonomously the best way of exploration?) and problem of control (how one can organize team of explorer agents without centralized control?). The way to use self-organization principle is proposed. Three models of collective behavior (algorithmic, interpolational, and entropic) were developed. The algorithms of collective behavior of explorer agents in the framework of these models were developed.

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