MULTIAGENT SYSTEMS FOR ENVIRONMENTAL PERCEPTION

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1. INTRODUCTION

Multiagent systems are distributed systems in which a number of individual autonomous heterogeneous agents interact and operate in an environment. Agents can be physical (computers or robots) or logical (software) entities. One of the early classical applications of the multiagent systems was in distributed sensing and monitoring, as appears from the work by Victor Lesser and colleagues (1981) on the Distributed Vehicle Monitoring Testbed (DVMT). Starting from this pioneering work, a number of techniques for multiagent-based environmental perception have been developed.

In this paper, we discuss the state of the art and the main techniques used in multiagent systems in relation to their possible application to environmental perception. Moreover, we set off some issues that must be addressed for developing multiagent perceptive systems.

This paper aims to pose problems and to present general ideas rather than giving definite answers and assessed results. In this sense, we do not intend to provide a survey of the current state of the art in the field of distributed environmental perception and, as a consequence, the works cited here are those that (to the best of our knowledge) we deem most suitable to support our argumentation. Moreover, since the field of distributed environmental perception is definitely multifaceted and since we have not competences in all the involved disciplines, we concentrate on the architectural software characteristics of the multiagent perceptive systems. The need for such system wide architectures is expressed in a very clear way by Estrin *et al.* (2002). Finally, we remark that the work presented here differs from that reported by Amigoni *et al.* (2002) because the latter provides a general and unitary framework in which an historical overview of the advent of multiagent systems in measurement science can be settled, whereas this paper is more oriented on some specific problems that arise when multiagent systems for environmental perception are implemented.

This paper is organized as follows. In the next section, we shortly present the field distributed artificial intelligence and the DVMT application. Section 3 surveys the concepts and the methods of multiagent systems. In Section 4, the application of multiagent systems to environmental perception is illustrated. In Section 5, we made this discussion more practical by describing a case study of application of multiagent systems to environmental perception. Finally, Section 6 concludes the paper.

2. DVMT: AN HISTORICAL APPLICATION IN DISTRIBUTED ARTIFICIAL INTELLIGENCE

Distributed Artificial Intelligence (or *DAI* for short (Bond and Gasser, 1988)) is a discipline in which several artificial intelligence systems are put together to form a single ensemble that addresses given applications. There is a distribution of “intelligence” among different decentralized components that have specific abilities. Usually, a DAI system is implemented as a network of problem solvers (i.e. systems of artificial intelligence) that work together.

A lot of work has been done in the field of DAI; several important results have been stimulated and experimentally tested within the Distributed Vehicle Monitoring Testbed (DVMT) by Lesser and colleagues (1981). In this very important application, the task is the generation of a “dynamic area-wide map of vehicles moving through a monitored area”. The DVMT simulates a number of processor nodes equipped with acoustic sensors that are geographically distributed over the area to be monitored. The nodes can communicate among them and operate to minimize the perception errors due to the noise. These errors usually lead to false positive and false negative identifications that need to be eliminated. This is achieved by cooperation among the

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distributed nodes. The DVMT has been used to develop and evaluate several forms of cooperation and cooperative work, including the *functionally accurate cooperative* approach presented by Lesser and Corkill (1981) that involves the exchanging and the refinement of tentative partial results among nodes. A number of other important paradigms in the field of distributed artificial intelligence have been devised starting from the DVMT; among them it is worth noting the classical *contract-net protocol* by Smith (1980) to dynamically assigning tasks to the processing nodes on the basis of a market-based mechanism.

3. A SHORT INTRODUCTION TO MULTIAGENT SYSTEMS

From the previous example it emerges that, whereas the focus of artificial intelligence is on the development of systems that emulate the intellectual and interactive abilities of a single human being, the focus of distributed artificial intelligence is on the development of systems that emulate the intellectual and interactive abilities of a *society* of human beings. In the last years, the concept of DAI system has evolved to the concept of multiagent system. In this perspective, a typical artificial intelligence system, which exhibits performances such as making diagnoses, proving theorems, allocating resources, scheduling activities, and planning and performing complex sequences of actions, is called *intelligent agent*. In general, an agent has the following characterizing properties: autonomy (it determines its course of actions), social ability (it interacts with other agents), reactivity (it perceives its environment and responds to the changes in it), and proactiveness (it not only passively responds to the environment but it can also take the initiative).

A *multiagent system* is composed of a number of intelligent agents that interact (Weiss, 1999; Wooldridge, 2002), where, as said, an intelligent agent is a (traditional) system of artificial intelligence, maybe performing inferential activities, that can be implemented as a software program, as a dedicated computer, or as a dedicated robot (Russell and Norvig, 1995). The performances of a typical multiagent system are for example negotiating prices of goods, sharing knowledge about a subject, competing for resources, and cooperating toward a global goal (e.g., the construction of a model of a given environment or the movement of a set of objects in a factory). More specifically, the intelligent agents (in the following simply called agents) of a multiagent system interact together to *organize their structure*, *assign tasks*, and *exchange knowledge*. The structural organization of a multiagent system can be statically decided by the designer or can be dynamically determined by the agents themselves during the activity of the system accordingly to the current conditions. To cite an abused example, in a fleet of box gathering robots the role of manager can be played by the robot that first finds the boxes room, while the other robots play the role of executors of the actions commanded by the manager. It is also possible to conceive the dynamic modification of the composition of a multiagent system whose agents enter and leave the system during its activity. Also the decomposition of tasks and their assignment to the agents of a multiagent system can be done statically at design-time or dynamically at run-time. In the previous example of box gathering robots, the dynamic allocation of tasks to the robots is dynamically performed by the manager that determines which robots gather the boxes found in the room and which robots continue to look for other boxes. A possibility for the manager is to assign to the closer robots the gathering tasks and to the other robots the searching tasks. The knowledge exchanging is continuously performed by the agents during their activities. In our example, the exchanged knowledge includes the positions in the environment of the boxes and of the robots. Generally speaking, the interaction among agents can assume two forms: competition and cooperation, which are usually viewed as two extremes of a range of possible forms of interaction.

4. APPLICATIONS OF MULTIAGENT SYSTEMS TO ENVIRONMENTAL PERCEPTION

In this section we will focus on the possible applications of multiagent systems in environmental perception. It is worth noting that multiagent systems can be also employed in other distributed perception settings like industrial buildings and smart rooms. However, the environmental perception we will concentrate on covers a number of significant applications including meteorology, traffic, and security.

The multiagent approach to environmental perception naturally emerges from the evolution of a number of interrelated “classical” fields including:

- data fusion: in which a number of distributed methods have been developed to collect data from different sensors and integrate these data in a global environmental model (Joshi and Sanderson, 1999);
- cooperative perception in robotics: in which a number of methods are employed to track multiple objects with multiple robotic observers (Gutmann, 2002);
- sensor networks: in which the increasing "intelligence" of the sensors is triggered by the technological ability to pack more transistors in smaller places, to reduce the energy consumption, and to cut the production costs (Zhao, 2002).

In addition to the classical advantages connected with distribution (reliability, parallelism, low cost) the multiagent approach to environmental perception shows some characterizing properties.

- The agents may have inconsistent and incomplete views of the phenomena to be perceived. The agents can exploit different and complementary sensors to cooperatively reconstruct the representation of a complex phenomenon. For example, a multiagent system composed of agents able to detect the CO and CO_2 concentrations in the air and of agents able to detect the acoustic noise level can collectively (through cooperation) reconstruct the information about the status of the traffic in a given area. These partial views contribute to have “multiparadigmatic” multiagent systems in which the agents have independent but partially overlapping areas of interest (e.g., their ranges of validity are partially overlapping portions of the parameter space) as explained by Amigoni *et al.* (2001)
- A multiagent system builds a distributed interpretation of environmental phenomena at different levels of abstractions. An interpretation of a phenomenon starts from low-level signals returned by the sensors and provides a higher-level description of the phenomenon. Distributed interpretation is required in many fields including traffic control, inventory control, power network grids (Lesser and Erman, 1980). The interpretation provided by multiagent systems for environmental perception is distributed in two ways. Firstly, the agents are geographically located in different places. Secondly, the agents are conceptually differentiated by the particular interpretative models they embed.
- The design and deployment of a multiagent system oriented to a given environmental perception task will be done in future by recruiting agents already installed in the environment as a consequence of the spreading of the ubiquitous computing in everyday life (Weiser, 1993).

Some prototypal applications of multiagent systems for environmental monitoring have appeared in literature by Jamont *et al.* (2002) and Petriu *et al.* (2002). However, a lot of work is still required before applications envisaged by Estrin *et al.* (2002) and Zhao (2002) will be developed. A prominent open issue is about the coexistence of several dozens of robots, since the experiments conducted so far have been limited to few (often less than 5) coexisting robotic agents. In another paper (Amigoni *et al.*, 2002) we provide a general and coherent theoretical framework based on the concept of *perceptive agency* to conceive the application of multiagent systems to distributed perception.

5. A CASE STUDY: MAPPING

In this section, we consider a particular case of environmental perception devoted to determine the geometrical form of the environment, this problem is known in robotics as the *mapping problem*.

Building a map of an unknown environment using several robots is a research problem that has received a lot of attention in the research community in the last few years. The global goal of multirobot exploration is to build a map of an unknown environment by exploiting several mobile robots equipped with sensors. The obvious underlying assumption is that the explored area is larger than the sensing range of each robot. All the numerous methods proposed in literature are based on some sort of *incremental integration*: a newly acquired partial map is integrated with the old maps.

To integrate the partial maps provided by the single robots in order to construct a global map of the environment *localization* of the robots is fundamental. To perform localization, the estimations of both robot pose and obstacles positions are needed. These estimations are referred to as smoothing (update position of obstacles according to data from sensors) and filtering (estimation of robot pose according to the data collected so far and to the movement of the robot).

The mapping and localization problems can be given an elegant mathematical description as reported for example by Dissanayake *et al.* (2001). In this description, the current estimates of the "state" (namely of the locations) of the robots and of the environmental features form a vector **x** and the uncertainty of the estimates form a covariance matrix **P**. (The dimensions of **x** and **P** may change according to features added to, and deleted from, the map.) The motion of a robots is modeled as a function that updates the state **x** and that adds a noise to the covariance **P** to account for the uncertainty in the motion estimates. The measurement of a feature is modeled as a function that updates the state **x** and that reduces the covariance **P** to account for the new information obtained from the measurement. The main drawback of this approach is the large dimensions of **x** and **P** when the map is large and, consequently, the high computational cost required to manage them.

One of the most successful approaches to bidimensional environmental mapping has been devised by Thrun and his research group (1998). Considering a single robot, they adopt probabilistic descriptions of the robot motion (actions) and of the robot perception (observations), then they find the map of an environment by maximizing the likelihood of the map under the data, where the data are a sequence of actions interleaved with observations. The maximum likelihood estimation is performed in two steps: E-step (expectation step) and M-step (maximization step). In the E-step, the robot location is probabilistically determined based on the currently available map. In the M-step, the maximum likelihood map is estimated based on the locations computed in E-step. The iterative application of these two steps leads to the refinement of both the location estimate and the map. In this way, grid-based maps can be obtained. The probabilistic method has been also extended to multirobot and 3D mapping (Thrun *et al.*, 2000).

In general, the exploration and mapping activity can be characterized along several dimensions.

- Type of constraints: the robots may map the environment in minimum time, with minimum guaranteed error, and so on.
- Type of map: the robots may produce a geometrical map composed of grids (Thrun, 2001), points (Lu and Milios, 1997), or segments (Austin and McCarragher, 2001). The points and segments maps have two main advantages over grid-based approaches: firstly, they are a much more compact representation of the environment and, secondly, they are easier to use. The disadvantage of the points and segments maps is that they are harder to construct, requiring interpretation of the sensor data and extraction of geometric features.
- Type of sensors: the sensors used to perceive the environment may be cameras, laser telemeters, sonars; the robots may employ uniform sensors, namely sensors of the same type, or not (in the last case fusion of sensed data is required).
- Type of environment: the environment to be mapped may be either static or dynamic.
- Type of partial map integration: the global map is incrementally built by integrating partial maps on the basis of the (probabilistic) estimated positions of the robots or on the basis of the geometrical features of the partial maps, or on both these criteria.
- Type of localization: since it is usually the case when the partial maps are integrated according to the robots position, the robots have to localize themselves by detecting landmarks in known positions or by matching sensor data with existing model of the environment.
- Type of validation: once a map has been built, there are different ways for validating it: ground-truth (comparison of the obtained map with the "real" one), consistency, and clarity.

Moreover, to make the mapping of an environment efficient, a number of methods about where to move in a partially explored environment in order to maximize the information that could be acquired have been studied (Burgard *et al.*, 2000; Reckleitis *et al.*, 2001).

Starting from the mapping example, and considering it as a guideline, we set out a number of issues that have to be addressed in the development of a multiagent system for environmental perception.

- How to describe the phenomena that the system is built to perceive. Put differently, which is the best format of the "map" representing the perceived phenomena over the space-temporal range of interest.

- Given that usually the extension of the perceived phenomena is larger than the extension of the sensors onboard of agents, how to incrementally build a global environmental representation starting from local incomplete and partial representations.
- Since the incremental construction of a global representation of the phenomena is based on the successive integration of the partial representations, a reliable and efficient method for the localization (in the space-temporal region of interest) of the agents is required.
- Similarly, a way to exchange high-level knowledge among the agents is also needed.
- How to determine the best actions of the agents in order to minimize some constraints (time, energy) or to maximize the new information gathered. When the agents are mobile robots this problem is reduced to the determination of their best moves or displacement in the environment; in such case the problem can be tackled by geometrical considerations.
- How to distribute the perception and interpretation activities both geographically and conceptually (recall the above discussion) among the agents.
- Finally, how to provide and effective interface with the user. Constraints are that the user must be presented the high-level results of the perception activity, that the user can set and manage some functioning parameters of the system, and that the system is not centralized but distributed.

All these challenges are hard research problems that call for solution in order to develop multiagent systems for environmental perception and to exploit their advantages.

6. CONCLUSIONS

In this paper we have presented some issues related to the application of multiagent systems to environmental perception. As stated in the introduction, this paper does not aim at generality and completeness; its goal is to set off some main ideas and some problems that must be addressed in order to employ distributed systems of agents in environmental perception applications.

Given the theoretical nature of the discussions presented in this paper, it is obvious that in future a lot of efforts will be devoted to the development of real systems for distributed perception. In particular, we are addressing applications related to air pollution, electromagnetic pollution, and meteorological monitoring. These systems will be built with the aim of finding answers to the general problems posed in this paper and, more in general, with the aim of assessing the appropriateness, the effectiveness, the efficiency, the pros and the cons of the adoption of multiagent systems for environmental perception.

REFERENCES

Amigoni, F., Brandolini, A., D'Antona, G., Ottoboni, R., and Somalvico, M., 2002: Artificial Intelligence in Science of Measurements: From Measurement Instruments to Perceptive Agencies. *IEEE Transactions on Instrumentation and Measurement*, accepted for publication.

Amigoni, F., Schiaffonati, V., and Somalvico, M., 2001: Dynamic Agency: Models for Creative Production and Technology Applications. In Riva, G. and Davide, F. (editors): *Communications Through Virtual Technology: Identity, Community, and Technology in Internet Age*. IOS Press, 167-192.

Austin, D. and McCarragher, B., 2001: Geometric Constraint Identification and Mapping for Mobile Robots. *Robotics and Autonomous System*, **35**, 59-76.

Bond, A. H. and Gasser, L., 1988: *Readings in Distributed Artificial Intelligence*. Morgan Kaufmann, San Mateo, CA.

Burgard, W., Fox, D., Moors, M., Simmons, R., and Thrun, S., 2000: Collaborative Multi-Robot Exploration. *Proceedings of 2000 IEEE International Conference on Robotics and Automation*.

Dissanayake, G., Newman, P., Clark, S., Durrant-Whyte, H., and Csorba, M., 2001: A Solution to the Simultaneous Localization and Map Building (SLAM) Problem. *IEEE Transactions on Robotics and Automation*, **17(3)**, 229-241.

Estrin, D., Culler, D., Pister, K., and Sukhatme, G., 2002: Instrumenting the Physical World with Pervasive Networks. *IEEE Pervasive Computing*, **1(1)**, 59-69.

Gutmann, S., 2002: Cooperative Perception. *European Summer School on Cooperative Robotics*, http://www.informatik.uni-freiburg.de/~gutmann/talks/cooperative-perception.pdf.

Jamont, J. P., Occello, M., and Lagreze, A., 2002: A Multiagent Architecture for the Instrumentation of an Underground Hydrographic System. *Proceedings of the 2002 IEEE International Symposium on Virtual and Intelligent Measurement Systems*, 20-25.

Joshi, R. and Sanderson, A. C., 1999: *Multisensor Fusion: A Minimal Representation Framework*. World Scientific.

Lesser, V. R. and Corkill D. D., 1981: Functionally Accurate, Cooperative Distributed Systems. *IEEE Transactions on Systems, Man, and Cybernetics*, **11(1)**, 81-96.

Lesser, V. R. and Erman, L. D., 1980: Distributed Interpretation: A Model and Experiment. *IEEE Transactions on Computers*, **29(12)**, 1144-1163.

Lu, F. and Milios, E., 1997: Robot Pose Estimation in Unknown Environments by Matching 2D Range Scans. *Journal of Intelligent and Robotic Systems*, **18**, 249-275.

Petriu, E. M., Patry, G. G., Whalen, T. E., Al-Dhaher, A., and Groza, V. Z., 2002: Intelligent Robotic Sensor Agent for Environmental Monitoring. *Proceedings of the 2002 IEEE International Symposium on Virtual and Intelligent Measurement Systems*, 14-19.

Rekleitis, I., Dudek, G., and Milios, E., 2001: Multi-Robot Collaboration for Robust Exploration. *Annals of Mathematics and Artificial Intelligence*, **31(1-4)**, 7-40.

Russell, S. and Norvig, P., 1995: *Artificial Intelligence: A Modern Approach*. Prentice Hall.

Smith, R. G., 1980: The Contract Net Protocol: High-Level Communication and Control in a Distributed Problem Solver. *IEEE Transactions on Computers*, **29(12)**, 1104- 1113.

Thrun, S., Burgard, W., and Fox, D., 1998: A Probabilistic Approach to Concurrent Mapping and Localization for Mobile Robots. *Machine Learning and Autonomous Robots (joint issue)*, **31(5)**, 1-25.

Thrun, S., Burgard, W., and Fox, D., 2000: A Real-Time Algorithm for Mobile Robot Mapping with Applications to Multi-Robot and 3D Mapping. *Proceedings of 2000 IEEE International Conference on Robotics and Automation*.

Thrun, S., 2001: A Probabilistic Online Mapping Algorithm for Teams of Mobile Robots. *International Journal of Robotics Research*.

Weiser, M., 1993: Some Computer Science Issues in Ubiquitous Computing. *Communications of the ACM*, **36(7)**, 74-84.

Weiss, G., 1999: *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*. MIT Press.

Wooldridge, M., 2002: *An Introduction to Multiagent Systems*. John Wiley & Sons.

Zhao, F., 2002: Information Processing in Microsensors Network: An Introduction. *Teaching material for CS428 “Information Processing for Sensor Networks”*, Computer Science Department, Stanford University, Stanford, USA.