Learning Coordination in RoboCupRescue

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Abstract. In this abstract, we present a complex multiagent environment, the RoboCupRescue simulation, and show some of the learning opportunities for the coordination of agents in this environment.

1 Introduction

A fundamental difficulty in cooperative multiagent systems is to find how to efficiently coordinate agents' actions in order to enable them to interact and achieve their tasks proficiently. One solution for this problem is to give the agents the ability to learn how to coordinate their actions. This type of solution is well suited for complex environments as RoboCupRescue, because the designer does not have to come up with all the rules for all possible situations.

2 RoboCupRescue

The goal of the RoboCupRescue simulation project is to build a simulator of rescue teams acting in large urban disasters [3]. More precisely, this project takes the form of an annual competition in which participants are designing rescue agents that are trying to minimize damages, caused by a big earthquake, such as civilians buried, buildings on fire and blocked roads. The RoboCupRescue simulation is a complex multiagent environment that has some major issues like: agents' heterogeneity, long-term planning, emergent collaboration and information access [2].

In the simulation, participants have approximately 30 agents of six different kinds to manage and each of them has different capabilities, for instance, *AmbulanceTeam* agents can rescue civilians, *FireBrigade* agents can extinguish fires and *PoliceForce* agents can clear roads. As we can see, this multiagent system is composed of heterogenous agents, having complementary capabilities, that will have to cooperate and coordinate their actions to accomplish their goals.

3 Coordination Approaches and Learning Opportunities

Solutions to coordination problems can be divided in three general classes [1]: those based on communication, those based on convention and those based on

Y. Xiang and B. Chaib-draa (Eds.): AI 2003, LNAI 2671, pp. 627–628, 2003.

learning. In the RoboCupRescue environment, approaches based on communication are not appropriate, because the constraints on communication are too restrictive. We could use an approach based on convention and presently it is the most used approach, because it is the simplest. However, since the RoboCupRescue simulation is a complex environment in which many different situations could occur, it becomes very difficult to find all the right conventions for all the possible situations. In such an environment, learning becomes interesting because it removes from the designer the hard job of defining all coordination procedures required for all possible situations.

We think that the RoboCupRescue environment is a good testbed for the study of coordination learning techniques in a complex real-time environment and we will show some of those learning opportunities in the next paragraphs.

The first learning approach consist of learning how to use the communication channel efficiently by enabling agents to learn, over some simulations, which messages are really useful and which ones are not. With this information, agents will take more enlightened decisions concerning the messages they send and the ones they listen to. By doing so, their coordination can be improved because the communication is more efficient; thus, the most important messages for the coordination have less chance to be lost.

The second approach consist of learning the best way to manage a disaster depending on which sectors of the city are in trouble. This improves the coordination because agents have a plan telling each one of them the more important things to do if there is a problem in a specific sector of the city.

The last approach presented in this short paper consist of enabling agents to anticipate their actions and other agents' actions. For this purpose, agents have to learn how the disaster evolves in time and how the agents' actions interact with the environment. With a better anticipation of the other agents' actions, each individual agent will be able to construct more accurate long-term plans, which plans will help to improve the coordination of their actions because each agent will have an idea about what the other agents are doing.

4 Conclusion

In conclusion, the RoboCupRescue simulation is a good testbed for the study of learning approaches used to improve agents' coordination in a complex real-time environment. It's an ongoing research project at our laboratory to design and test some learning algorithms that will be well suited and useful for this type of complex real-time systems.

References

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