Multi-Agent Distributed Artificial Intelligence

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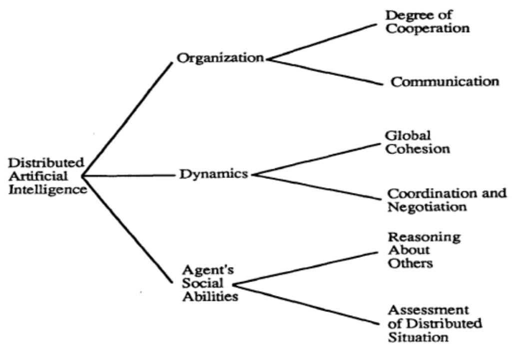
Abstract—**Distributed artificial intelligence (DAI), a relatively new but growing body of research in AI, is based on a different model than traditional artificial intelligence. DAI is a subfield of artificial intelligence that attempts to construct intelligent agents that make decisions allowing them to achieve their goals. It deals with interactions of intelligent agents in a world populated by other intelligent agents with their own goals. A DAI Taxonomy, based on the social abilities of an individual agent, the organization of agents, and the dynamics of this organization through time is also presented. It also involves improving the performance or increasing the knowledge of a single agent by implementing concept of Multi agent into it.**

Index Terms- **Distributed artificial intelligence, learning, multi-agent, reasoning about others, single-agent.**

I. INTRODUCTION

An intelligent system simulates a certain form of human reasoning, knowledge, and expertise for a given task, whereas distributed artificial intelligence systems were conceived as a group of intelligent entities, called agents, that interacted by cooperation, by coexistence or by competition. Agents with distinct interests or knowledge can benefit by engaging in negotiation whenever their activities potentially affect each other. Through negotiation, agents make joint decisions, involving allocation of resources, adoption of policies, or any issue of mutual concern. Multiple related issues are typically negotiated at once, with each negotiation issue involving multiple agents.



[Figure:1- Distributed Artificial Intelligence Taxonomy]

Research shows that single agent environments where an agent evolves in a static environment and its main activities are: Gathering information, planning and, executing plans; to achieve its goals, which is insufficient due to the inevitable presence of a number of agents in the real world.

Figure1. Above shows the taxonomy of DAI, based on the social abilities of an individual agent, the organization of agents, and the dynamics of this organization through time. Social abilities are characterized by the reasoning about other agents and the assessment of a distributed situation. Organization depends on the degree of cooperation and on the paradigm of communication. Finally, the dynamics of organization is characterized by the global coherence of the group and the coordination between agents.

II. OBJECTIVE

We must plan the agent's activities while keeping in mind the other agents' activities that can either help or hinder him. There are many reasons for wanting to distribute intelligence or cope with multi-agent systems. DAI research includes the following:

A. Parallel Problem

Mainly deals with how classic artificial intelligence concepts can be modified, so that multiprocessor systems and clusters of computers can be used to speed up calculation.

B. Distributed Problem solving (DPS)

The concept of agent, autonomous entities that can communicate with each other, was developed to serve as an abstraction for developing DPS systems. See below for further details.

C. *Distributed* Multi-Agent Based Simulation (MABS)

A branch of DAI that builds the foundation for simulations that needs to analyze not only phenomena at macro level but also at micro level, as it is in many social simulation scenarios.

The key concept used in DPS and MABS is the abstraction called software agents. An agent is a virtual (or physical) autonomous entity that has an understanding of its environment and acts upon it. An agent is usually able to communicate with other agents in the same system to achieve a common goal, that one agent alone could not achieve. This communicate system uses a language. A first classification that is useful is to divide agents into:

A. Reactive agent

A reactive agent is not much more than an automaton that receives input processes it and produces an output.

B. Deliberative agent

A deliberative agent in contrast should have an internal view of its environment and is able to follow its own plans.

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C. Hybrid agent

A hybrid agent is a mixture of reactive and deliberative that follows its own plans, but also sometimes directly reacts to external events without deliberation.

Well-recognized agent architectures that describe how an agent is internally structured are: Soar (a rule-based approach)

A. *BDI* (Believe Desire Intention, a general architecture that describes how plans are made)

B. *InterRAP* (A three-layer architecture, with a reactive, a deliberative and a social layer)

C. *PECS* (Physics, Emotion, Cognition, Social, describes how those four parts influences the agents behavior).

Basic diff b/w Artificial Intelligence and Distributed Artificial Intelligence- An intelligent system simulates a certain form of human reasoning, knowledge, and expertise for a given task, whereas distributed artificial intelligence systems were conceived as a group of intelligent entities, called agents, that interacted by cooperation, by coexistence or by competition.

III. WHY DAI

The interest and high regard that researchers have for DAI are shown in many ways:

A. *First way*: Necessity to treat distributed knowledge in applications that are geographically dispersed such as sensor networks, air-traffic control, or cooperation between robots.
B. *Second* way**:** Attempts to extend the man-machine cooperation with an approach based on the distributed resolution between man and machine(s). To accomplish this, we need to build intelligent machines capable to reason about human intentions.
C. *Third way***:** DAI brings perspective in knowledge representation and problem solving, by providing richer scientific formulations and more realistic representation in practice.
D. *Finally***:** DAI sheds light on the cognitive sciences and artificial intelligence.

Certain researchers believe that DAI could be crucial to our understanding of artificial intelligence. There are many arguments to support this belief. First, a system may be so complicated and contain so much knowledge that it is better to break it down into different cooperative entities in order to obtain more efficiency viz. modularity, flexibility, and a quicker response time, that facilitates simultaneous interactions between several people and several machine-agents collaborating on the same task. A second argument is that work done with DAI could allow the modeling of our intuitions about the reasoning based on knowledge, actions, and planning. Currently, methods exist that represent beliefs, plans, and actions for the purpose of reasoning about interactions between intelligent systems. Hence, knowing how an artificial system can reason about others should help us to better understand how this same system can reason about itself. A third argument is that methods used by an intelligent system to reason about the actions of other systems can also be used to reason with other environmentally non-intelligent dynamic processes. Without these methods it is probable that artificial intelligence would remain confined to the study of static areas. Lastly, research in DAI contributes to our understanding of the communication process using natural language. Indeed, communicative acts between intelligent systems generally are an abstraction of certain aspects of the production and comprehension of natural language, and the study of this abstraction can help to clarify certain problems studied in natural language.

IV. LEARING

Learning each agent's task solving abilities and capabilities allows better matching between tasks and agents and also allow lower communication costs. In every organization, agents must communicate with other agents. Without any information about other agents, an agent must broadcast its queries. Once information about other agents' knowledge, data and task solving ability is learned, selective or on-demand communication can be used, that help lower communication costs. In fact, if enough information is known about other agents like task assignments and non-local information needed, agents can anticipate other agents' needs and send them unsolicited information to further lower communication costs. Learning the optimal amount of cooperation between agents is best done at the group level since it may be difficult for an agent to measure or estimate its affect on other agents. Change in cooperation from some agent while measuring the group performance allows the effect of agents upon other agents to be determined. Also, the ability of the agents to adapt and learn to work with the other agents allows the system to maintain optimal performance even when new agents join or old agents leave the group.

A. Single Agent Learning

It involves improving the performance or increasing the knowledge of a single agent [1]. An improvement in performance or an increase in knowledge allows the agent to solve past problems with better quality or efficiency. An increase in knowledge may also allow the agent to solve new problems. An increase in performance is not necessarily due to an increase in knowledge.

It may be brought about simply by rearranging the existing knowledge or utilizing it in a different manner. In addition, new knowledge may not be employed immediately but may be accumulated for future use may be classified according to their underlying learning strategies. These strategies are ordered according to the amount of inference or the degree of knowledge transformation required by the learning system. This order also reflects the increasing amount of effort required by the learning system and the decreasing effort required by the teacher.

These strategies are separated into the following six categories:

1) *Rote Learning* - This strategy does not require the learning system to transform or infer knowledge. It includes learning by imitation, simple memorization and learning by being programmed. In this context, a system may simply memorize previous solutions and recall them when confronted with the same problem.

2) *Learning from Instruction* - This strategy, also called learning by being told, requires the learning system to select and transform knowledge into a usable form and then integrate it into the existing knowledge of the system. It includes learning from teachers and learning by using books, publications and other types of instruction.
3) *Learning by Deduction* - Using this strategy, the learning system derives new facts from existing information or knowledge by employing deductive inference. These truth-preserving inferences include transforming knowledge into more effective forms and determining important new facts or consequences. Explanation-based Learning is an example of deductive learning.
4) *Learning by Analogy* - This form requires the learning system to transform and supplement its existing knowledge from one domain or problem area into new domain or problem areas. This strategy requires more inference by the learning system than previous strategies. Relevant knowledge must be found in the system's existing knowledge by using induction strategies. This knowledge must then be transformed or mapped to the new problem using deductive inference strategies.
5) *Learning from Examples* - This strategy, also called concept acquisition, requires the learning system to induce general class or concept descriptions from examples and counter-examples of a concept. Since the learning system does not have prior or analogous knowledge of the concept area, the amount of inference is greater than both learning by deduction and analogy.
6) *Learning from Observation and Discovery* - Using this strategy, the learning system must either induce class descriptions from observing the environment or manipulate the environment to acquire class descriptions or concepts. This unsupervised form of learning requires the greatest amount of inference among all of the different forms of learning.

B. Multiple Agent Learning

It solves problems using multiple cooperative agents where control and information are often distributed among them. This reduces the complexity of each agent and allows agents to work in parallel and increases problem solving speed. It can continue to operate even if some of its agents cease to operate which allows the system to degrade gracefully. It involves improved performance or increasing the domain knowledge of the group. It also includes increasing communication knowledge. In the context of improving the performance of a group of agents, allowing individual agents to improve their performance may not be enough to improve the performance of the group.

To apply learning to the overall group performance, the agents need to adapt and learn to work with the each other. Indeed, the agents may not need to learn more about the domain, as in the traditional sense of machine learning, to improve group performance. In fact, to improve the performance of the group, the agents may only need to learn to work together and not necessarily improve their individual performance. In addition, not all of the agents must be able to learn or adapt to allow the group to improve.

These learning strategies can be separated into four proposed categories:
1) *Control Learning* - Learning and adapting to work with other agents involves adjusting the control of each agent's problem solving plan or agenda. Different tasks may have to be solved in a specific sequence. If the tasks are assigned to separate agents, the agents must work together to solve the tasks. Learning which agents are typically assigned different types of tasks will allow each agent to select other agents to work with on different tasks. Teams can be formed based on the type of task to be solved. Some of the issues involved are the type, immediacy and importance of task, as well as each agent's task solving ability, capability, and reliability and past task assignments. Each team member's plan would be adjusted according to the other agent's plans.
2) *Organization Learning* - Learning what type of information and knowledge each agent possesses allows for an increase in performance by specifying the long term responsibilities of each agent. By assigning different agents different responsibilities, the group of agents improves group performance by providing a global strategy [3].
3) *Communication Learning* - Learning what type of information, knowledge, reliability and capability each agent possesses allows for an increase in performance by allowing improved communication. Directly addressing the best agent for needed information or knowledge allows for more efficient communication among the agents.
4) *Group Observation and Discovery Learning* - Individual agents incorporate different information and knowledge. Combining this differing information and knowledge may assist in the process of learning new class descriptions or concepts that could not have been learned by the agents separately [4].

Examples of learning:
1. Multiple Intelligent Node Document Servers System
2. The Learning Contract Net
3. Shaw and Whinstone
4. The Knows Environment

V.MULTI-AGENT AS A PROBLEM SOLVING PERSPECTIVE

The multi-agent problem solving system is an information system which consists of a network of intelligent nodes capable of performing problem solving, referred to as *agents.* An example of such a system is a network of rule-based expert systems, each incorporating an area of expertise as represented by the content of its rules. When such a multi-agent system is presented with a problem to be solved by the group of agents, the system needs to figure out a strategy so that the problem can be solved in the most efficient way by the group collectively. The considerations here in many ways are similar to those involved in assigning a group of people, with varying areas of specialties, to solve a set of problems. There are three different types of multi-agent problem-solving systems that have been developed:

A. Problem-solving through distributed systems

In these systems, the overall problem to be solved is decomposed into sub-problems assigned to the agents, each agent, asynchronously, would plan its own actions and turn in its solutions to be synthesized with the solutions of other agents. The agents in these systems use either task sharing to cooperate with other agents.

B. Reasoning through collaborative systems

The agents in this second type of systems would be solving the same problem collaboratively. The main issue here is not the decomposition into sub-problems assigned to the agents, but the solicitation of contributions from the participating agents so that the problem can be solved jointly by the group, simultaneously.

C. Connectionist Systems

The third type of multi-agent systems use agents as the basic computational elements. These agents individually are just simple computing units and they not intelligent; but together they can solve complicated problems quickly. Unlike the previous two types of systems, where the agents are intelligent problem solvers, the agents in the connectionist model are only simple computation units. As a result, they are restricted to perform simple tasks. The agents learn to solve problems more effectively by adjusting their connections with each other.

VI. CONCLUSION

Learning every single agent's knowledge and task solving ability, a team of agents can be brought together based on the individual agent's knowledge, data and task solving capability. Different team performances can also be compared to determine the best team for a specific type of problem. The performance could be measured based on solution time, solution quality or communication overhead.The most promising area of research in distributed artificial intelligence systems is improving task allocation and communication. Also, the ability of the agents to adapt and learn to work with the other agents allows the system to maintain optimal performance even when new agents join or old agents leave the group. This paper has also investigated trends in DAI and the examination of the process of-human interaction and social organization. It allows a single agent to have a sophisticated local control in order to reason about its own problem solving and how this fits in with problem solving by other agents in Multi agent problem solving. It allows DAI designers to conceive a dynamically adaptive organization of agents. The paper also reviews some recent work done in DAI and also reflects upon how DAI research brings to the forefront issues in areas such as introspection, planning, language, and reasoning about belief. As a result, we must plan the agent's activities while keeping in mind the other agents' activities that can either help or hinder him.

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Achievements:

1. Paper Published in International Conference on Advanced computing, communication and Networks-2011(ICACCN'11) that is going to be held on 2-3 June.
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