ON THE ROLE OF DISTRIBUTED AI
IN
LARGE SCALE NETWORK SIMULATION

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ABSTRACT

In this paper, we look at the possible role for a Distributed Artificial Intelligence (Distributed AI) concept to be applied in a large scale networked training environment. Here, a battle conditions environment, would consist of many intelligent simulators, each of which is equipped with different, but possibly overlapping expertise. The goal is to coordinate these battle forces in such a way as to carry out an offensive attack. The motivation for developing and applying a Distributed AI concept seems clear since the problem of a large scale network simulation is, itself, inherently distributed.

We will first introduce the critical role of Distributed AI in a large scale simulation environment in terms of knowledge, goals, skills, and coordination for the intelligent simulators. Some basic concepts in Distributed AI will be presented together with a number of ongoing research studies in distributed intelligence. We will then give a few domain examples in battlefield simulation, and describe how Distributed AI methodologies may be explored in such diverse environments. Finally, we will look at the advantages and disadvantages of Distributed AI as a viable technology for distributed training. A large conceptual framework will be used in the analysis of difficulties and possibilities of Distributed AI as applied in the distributed training system environment.

I. INTRODUCTION

Today's increasingly complex tactical environment demands innovative solutions to the associated problems of training and combat team readiness. Significant emphasis is being placed on developing technologies, which support large scale networks of interactive simulators to provide a viable training solution. This technology development provides the capability to interconnect a large number of simulators through an interactive network, which allows for manned platoon, company, and battalion-level units to fight force-on-force engagements in a combined arms battle simulation. To conserve human resources using these networked simulators, it is necessary to alleviate the need for the full complement of a battle force and the role playing opposing forces in the war-gaming environment. To this end, some research and development work has been initiated to build intelligent simulators that are capable of generating friendly as well as opposing forces in a wide range of complex operational settings using artificial intelligence techniques.

In this paper, we will focus on approaches to the problems of distributing and coordinating knowledge and actions in distributed problem-solving and multi-agent systems. The application of Distributed AI will be discussed in Section II. We will introduce the basic concepts in the field of Distributed AI in Section III. In Section IV, a number of basic problems that Distributed AI addresses in terms of knowledge, goals, skills, and coordination required for large scale network simulation will be presented. This is followed, in Section V, by a discussion of various advantages and disadvantages associated with Distributed AI. Some domain examples in battlefield simulation will be given in Section VI.

II. WHY USE DISTRIBUTED AI?

The nature of many military problems is very complex in terms of command, control, and organization in extremely diverse environments. To properly address and manage such difficult problems, very complex organizations are required. This theory is founded based on the principle of bounded rationality for human systems (Simon [1957]), which states that the human mind's can only assimilate a limited quantity of data. This points out that it may not be possible, from a manageability point of view, to realistically model complex military problems such as battlefield simulation using centralized AI approaches.

Consider the military problem of determining an enemy force's intention based on information about its combat troop maneuvers. An accurate assessment of this task would require the effective application of knowledge about many different domains such as the tactical situation, the environment, its force capabilities, and so forth. To cope with the complexity of such a battlefield environment, we believe that an incremental approach will be required to progressively address organizational, command, and control issues at higher levels in the chain of command. The point here is that no single person would be able to master all this knowledge, and therefore, would require a network of experts to interactively solve such complex problem domains by means of coordinating and cooperating within various organizations. Within the traditional military hierarchy, this is a multi-agent planning problem wherein, at any level of the command, a number of independent agents must work together to achieve a certain goal. In most cases, these agents are geographically distributed. That is, global war gaming requires a high degree of force distribution, and depending on the situation, each agent will be required to act with some degree of autonomy in choosing its instantaneous responses while at the same time cooperating with other agents within the group in order to achieve a common goal. This implies that close cooperations among forces must be achieved.

In addition, we are currently facing many changes in requirements for training our military forces. For instance, with the ongoing global change toward disarmament, training tactics and doctrine will be greatly impacted. Furthermore, we are witnessing a continuous change in political environment and technologies, which suggest the development of a more flexible framework for training in a dynamic environment.

The above illustrates the distributed nature of the military hierarchy. Therefore, to realistically model the organizational, command, and control issues in a dynamic environment such as the battlefield, we must approach it from a distributed AI perspective. From hereon, we shall refer to the term "agent" to mean a processing entity whether it be a module, processing unit or system.

III. WHAT IS DISTRIBUTED AI?

Distributed AI is concerned with problems in concurrency and distribution in AI. This is a result of recognizing the fact that human problem solving and activity involves a group of people. Unlike distributed processing, which addresses the problem of coordinating a network of computing agents to accomplish a set of disparate and mostly independent tasks, distributed AI is concerned with distributing control as well as data and can involve extensive cooperation between processing entities. This involves a high degree of interaction between processing agents as they move toward resolving a single task.

Based on the historical interests of researchers in the field of Distributed AI, we shall partition the world of Distributed AI into three areas (Bond and Gasser [1988]):

- *Parallel AI*
- Distributed problem solving
- Multi-agent systems.

Parallel AI (PAI) is concerned with the problem of developing parallel computer architectures as well as languages and algorithms for AI (Davis [1980]). While these studies are directed toward solving performance problems of AI systems, no focus is placed on conceptual advances of understanding the nature of intelligent behavior among multiple agents. On the other hand, distributed problem solving (DPS) and multi-agent (MA) systems are two areas of distributed AI that require some levels of cooperation among a number of modules and nodes. More specifically, distributed problem solving is concerned with partitioning problem solving among a number of modules or nodes that cooperate by means of dividing and sharing knowledge about a particular problem and developing a solution (Lesser [1987] and Decker [1987]). In multi-agent systems, emphasis is placed on the problem of coordinating intelligent behavior. That is, knowledge, goals, skills, and plans among a collection of (possibly pre-existing) autonomous intelligent agents, to take actions or to solve problems (Hewitt [1985]). Agents in MA systems may work toward a single global goal, or toward separate individual goals that interact. This is similar to DPS, but in addition to sharing knowledge about problems and solutions, agents must reason about the processes of coordination among agents. This results in a much more complex problem because globally consistent knowledge, shared goals, or success criteria may not exist. Table 1 illustrates various characteristics of the different AI systems.

TABLE 1

Systems	Problems Addressed	Characteristics
PAI	Architecture, languages, and algorithms	Adaptive to temporal uncertainty, but not to alternative solution paths due to loss of problem solving knowledge.
DPS	Task sharing; knowledge sharing and partitioning in cooperative frameworks	Adaptive to uncertainty in problem solving knowledge, but not to alternative problem contexts or to changing problem-solving roles for modules.
MA	Coordination of intelligent behavior among multiple agents	Capabilities to form and restructure coordination frameworks based on emerging contexts.

IV. DISTRIBUTED AI AREAS OF STUDY

As defined in Section III, Distributed AI is the study of how a group of individual intelligent agents can combine to solve a difficult global problem. In the following narrative, we will present a number of areas of study in Distributed AI that are concerned with knowledge sharing, resource allocation, communications, and interactions among intelligent agents to achieve certain military objectives. Here, it is important that we emphasize the military aspects because military applications are quite different from other domains. For example, the military operates on a hierarchical chain of command with an authority structure. This implies that while there may be some level of cooperation and coordination among agents, elements of negotiation and competition among agents (Davis et al. [1988], Smith [1988], and Conry et al. [1988]) do not exist.

Some research studies in Distributed AI now follow. A more detailed discussion can be found in Bond and Gasser [1988].

a) Cooperation

Cooperation among military forces constitutes an important part of battlefield management, in which organizations are required to work together within the military chain of command to achieve certain objectives. This is an extremely important area of study that forms an integral part of Distributed AI systems. A number of approaches have been proposed to study cooperative systems. Lesser and Corkill [1981] suggest the need for cooperative systems to deal with the control uncertainty that occurs when the distribution of control information differs from where the control decisions are actually made. Smith and Davis [1981] discuss cooperation as a method to use when each agent has different knowledge. In a battlefield environment, for example, we may be interested in the problem of how forces, such as tank battalion, attack helicopter, and air-to-ground fighter, can cooperate to carry out either an offensive or a defensive move. This requires a system of cooperating experts, where each expert has all the knowledge for its particular domain. Furthermore, cooperative frameworks may be employed to minimize communication, allow load balancing and distributed control, while at the same time maintain coherent behavior.

b) Coherence

Coherence is concerned with how well the system behaves as a unit. Therefore, to achieve coherent behavior, some level of cooperation among problem-solving agents is required.

Assuming that a level of cooperation is reached among agents in a system, coherence may be defined as the system's ability to achieve satisfactory solutions, the system's overall efficiency in accomplishing some tasks, and the quality of the solutions it produces. Some aspects of coherent behavior include the dynamic behavior of the system and expectation-driven communication. That is, communication is minimized when an agent has a model of the state of other agents and, therefore, only needs to communicate when that model incorrectly reflects an agent's perceived reality (Smith [1985]).

c) Interaction

Complex problems require complex organizations. Therefore, strong interactions among these complex organizations will be required to resolve a given task. This process of interaction, which makes it possible for several intelligent agents to combine their efforts, is of considerable importance as a basic concept in Distributed AI. While knowledge, perception, goals, actions, and so forth may or may not be distributed, interaction is inherently distributed and dependent upon the coordinated action of at least two agents. See, for example, the work of Rosenschein [1986].

d) Task and Resource Allocation

An important part of the military command and control is the problem of task and resource allocation between various elements of military forces. In a battlefield environment, for example, the problem of designating responsibility and assigning resources to available units is of key interest to achieve a given mission.

Generally, the task allocation in Distributed AI system is concerned with the problem of assigning responsibility for a particular activity. This is a metaproblem that may either be addressed statically or dynamically. Static allocation may be achieved by establishing a collection of specialized agents with predetermined roles (Bendifallah et al. [1987]). On the other hand, dynamic allocation may be accomplished by a collection of agents themselves, using techniques such as contracting (Malone [1983]) and organization self-design (Corkill and Lesser [1986]).

On the other hand, resource allocation is a subproblem of task allocation in Distributed AI system. Because tasks without resources cannot run, allocating resources to tasks may be viewed a way of prioritizing the tasks. Several important approaches in this area include resource allocation using specialist "sponsor" agents (Kornfeld et al. [1981]) and resource allocation based on the criticality of tasks (Lesser et al. [1988]).

e) Organization

An organization can provide a framework of constraints and expectations about the behavior of agents (that is, a set of roles) that focuses on the decision making and action for particular agents. Generally, low-level agents are data driven, and high-level agents are goal driven. An agent is not necessarily constrained to act immediately on the request of its superior. However, in a military environment, agents are required to respond to the requests of their superiors, and therefore, no negotiation is allowed (see for example, Kornfeld et al. [1981]).

f) Communication

The need to communicate an increasing amount of information becomes crucial with increased coordination and cooperation among problem solving agents. This probably places the nature of communications in Distributed AI as its most important aspect.

Communication in Distritubed AI systems can be achieved through either shared global memory, message passing, or some combination of the two. Much has been written about communication in distributed AI through shared global memory, but perhaps, the model most often used is the blackboard model (Hayes-Roth [1985]). In this model, the shared global memory is viewed as a blackboard onto which messages and partial results are posted. To represent different levels of abstraction of a given problem, a blackboard can be partitioned accordingly. Another model follows from the work by Hewitt [1976] through the concept of an actor. Here, an actor is characterized by its behavior. Because each actor responds to messages independently of other actors, systems of actors inherently have a high degree of parallelism. Actors are very much like objects in object-oriented languages but existing in parallel with one another.

g) Planning

With explicit divisions of labor, the process of synchronizing the activities of agents toward common goals forms the basis of planning in which, interactions among various agents within the plans must be controlled. Because many plan interactions may involve incompatible states, incompatible orders of steps, or incompatible use of resources, the task of synchronizing activities of agents can become quite complicated. This area of study is very rich and closely related to battlefield planning and management. Some works in this area include the development of smoothly interacting plans hierarchically (Corkill [1979]), control of plan interactions using multiagent planning (Georgeff [1983]), or using distributed planning (Hayes-Roth [1985]).

h) Modeling of Agents

The existence of a large number of agents in a Distributed AI system creates a critical need to accurately and effectively model agents within the system. To realistically model an agent, it is crucial to accurately represent the knowledge of an agent's capabilities so that allocation decisions, performance assessment, and feasibility analysis may be achieved. In addition, knowledge of agent resources and demands must be considered to realistically reflect behavior of agents. From an effectiveness point of view, we need to properly assign responsibilities to various agents to provide a way of reducing task-allocation overhead. Furthermore, to effectively coordinate activities among agents, some knowledge of the actions of other agents and the ability to reason about the effects of those actions are required. Further reference to knowledge of the plans, goals, and beliefs of agents that have led to actions, and the causal relations among these, as well as knowledge about how they will evolve are required in order to anticipate or explain the action of agents (see for example, Georgeff [1983]). Consider the problems in battlefield planning, for example. Here, a number of agents acting semi-autonomously and asynchronously populate the battlefield in coordinating an attack mission. While the role of agents is to carry out the orders specified by their superiors, these agents have unique and limited perspectives on the state of the environment. Thus, depending on an agent's local situation on the battefield, an agent will have to determine its own response. Hence, the ability to react, as well as to act in carrying out orders, are essential to agents taking part in a mission.

V. DOMAIN EXAMPLES

To show how Distributed AI may be of use in the solution of a number of military problems, let us consider the problem of battlefield simulation. Our eventual goal is to incorporate Distributed AI techniques in the simulation of combat operations for platoon-sized units in battalion-level engagements. We will identify the important roles of Distributed AI in large-scale, networked simulation. Within this scope, we must consider the various levels in a hierarchical chain of command. For example, lower levels would perform tasks that are more or less in an active or reactive mode. At higher levels, planning tasks and goal abstractions become more and more definitive. The overall goal is to model the military command hierarchy from regiments to platoons in a realistic battlefield environment (Lehnert et al. [1989]).

We now give an outline of a number of considerations that are required in the problem of battlefield simulation. Table 2 illustrates a mapping of various components between battlefield simulation and Distributed AI.

- Military force structures, that is, a unit (platoon of vehicles or men), company (team), battalion (task force), regiment, or brigade.

- Adjustment or realignment of units for more efficient utilization of available units' strengths and for regrouping of disrupted forces during combat.

- Allocation of weapons to targets to maximize target destruction.

- Coordination of forces in an attack mission or a defend mission.

- Adaptability of agents in a hostile environment: units are subjected to disruption and destruction by hostile forces.

- Imperfect information due to battle interference.

- Agent capabilities, that is, weapon systems, movement characteristics.

- Agent-World interaction: combat takes place over realistic terrain. Therefore, spatial calculations for movement, and line of sight must be taken into account. The complexities in terrain representation versus computational cost of terrain operations must be considered. Generally, more complex terrain impacts movement and combat, that is terrain obstruction impedes movement of forces and target detection.

- Agent-Agent interaction: How should agents interact with each other to achieve a certain goal? Each goal is associated with a risk factor, which determines the course of actions to be taken, that is, attack or avoid combat with enemy units in the course of achieving its goal. Actions may be path planning to reach an operational area and setting its combat readiness features to either move quickly or fire weapons.

TABLE 2

Battlefield Simulation	Distributed AI Research
1) Force Structures	Organization
2) Force allocation	Resource configuration, task allocation
3) Weapon allocation	Resource configuration
4) Attack mission	Cooperation, planning, coherence
5) Adaptability of agents in hostile environment	Interactions, communications
6) Imperfect information due to battle interference	Communications
7) Agent capabilities	Agent modeling
8) Agent-World interaction	Interaction, agent modeling
9) Agent-Agent interaction	Interaction, agent modeling

VI. Advantages and Disadvantages of Distributed AI in Large Scale Networked Simulation

As pointed out earlier, many important military problems require solutions to large and complex problems, and therefore, demand a very broad perspective that spans a variety of domains. Considering the types of decisions within a military chain of command, for example, the decisions within each functional command would range from very high level, that is, goals, to lower level for each type of activity, which includes strategic, tactical, and operational control. Knowledge or activity is, thus, inherently distributed. The distribution also arises from the fact that in the battlefield environment, military forces are geographically distributed. Typically, Distributed AI offers the following advantages to large scale networked simulation:

- Naturalness: Distributed AI will provide a realistic model of the dynamic battlefield environment because it can realistically represent the hierarchical structure of the military chain of command, the interactions between intelligent agents in terms of reasoning, and reactions about their environment.

• Adaptability: Distributed AI system can provide alternative perspectives on emerging situations in the battlefield environment, and potentially greater adaptive power due to its logical, semantic, temporal and spatial distribution make-up.

• Extensibility: Distributed AI provides a mechanism for interconnecting multiple expert systems that have different, but possibly overlapping expertise. This would support a more flexible architecture for training in a dynamic environment such as the battlefield. As requirements change, additional intelligent modules can be developed and integrated into the system. In addition, Distributed AI can potentially solve problems that are too large for a centralized system because of resource limitations.

• Cost: Distributed AI can provide a cost-effective way of interconnecting a large number of simple computer systems of low unit cost or pre-existing simulators.

• Performance: Concurrency may increase the speed of computation and reasoning. However, concurrency must be traded off against the overhead of problem-dependent coordination.

• Reliability: Distributed systems are well-known to be more reliable than centralized systems because they provide redundancy and cross-checking of results.

• Design and Development: Because Distributed AI allows expert systems to incrementally developed. This simplifies the design of each expert module, and thus, reduces the complexity of the overall system design process. Consequently, development and maintenance costs will be reduced.

• Reusability: Distributed AI provides a modular approach to design and development of expert systems. Therefore, any developed expert module can be reused as a part of many distributed expert systems.

• Knowledge acquisition: In a complex environment such as the battlefield, knowledge about many different domains is needed. Because it is easier to find experts in narrow domains, one should take advantage of problem domains that are already partitioned or hierarchical.

• Resource limitations: Large, complex military problems require computational resources that may be too large for a centralized system because individual computational agents have bounded rationality, limited resources for problem solving, and possibly bounded influence. This implies that some level of cooperation and coordination are necessary to solve large problems.

While Distributed AI systems may provide many advantages over existing AI methodologies, they present some difficult problems in systems analysis and development. This is due in part to many aspects that can be independently distributed. For instance, agents may have different levels of authority or responsibility with different focuses on different aspects of the world. In addition, actions or reactions of intelligent agents may take place at different physical locales or occur at different points in time. Moreover, due to the presence of a large number of intelligent agents operating in some coordinating fashion, the problems of intepretations and perception for any of these agents become extremely complex because events and objects may mean different things to different agents. Furthermore, what each agent perceives about events or objects may vary a great deal given the fact that each agent only has a partial view of the world. As a result, the knowledge that each agent holds may be different, with the possibility that no agent may hold a complete representation of some important collection of knowledge or situations. Regarding system reliability, it may be true that Distributed AI systems may be more reliable than centralized systems due to redundancy or cross-checking. However, considering the large number of subsystems that exists within a Distributed AI system, the overall system reliability will be contingent on some collection of these subsystems because different agents may be differentially reliable.

VII. SUMMARY

In this paper, we have emphasized that the work in a military environment is cooperative in nature. In such settings, tasks often require the coordinated effort of a group of people to accomplish a desired goal, and cannot be carried out by an individual. Particularly in battlefield environment, the size and complexity of military goals and the limited abilities, knowledge, skills and resources of individuals often make a cooperative approach the only way to achieve results. These factors have led us to Distributed AI approaches in order to realistically model battlefield simulation. We established the basic concepts of Distributed AI and show the importance of Distributed AI in battlefield environment. To illustrate the usefulness of Distributed AI techniques, we presented a number of research studies in Distributed AI conducted in the areas of cooperation, interaction among agents, communication between agents, and, organization and models of agents. These are then related to some domain examples given in a battlefield simulation context.

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