Important AI Applications: A Short Survey

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***Abstract*—A wide range of agent applications, including training, education, virtual companies, and collective robots, require multi-agent collaboration. Human-assisted tools for analyzing, evaluating, and comprehending team actions are also becoming more essential. This paper provides a brief survey of various agent-based models and technologies, including autonomous agent design principles, multi-agent collaboration, strategy acquisition, real-time reasoning, and many more. The goal of this detailed survey paper is to illustrate important applications of Artificial Intelligence such as distributed AI systems, Intelligent tutoring systems, and so on, its significance, and limitations. In addition to this, this paper also focuses on agents that aid humans in evaluating, comprehending, and enhancing multi-agent team behaviors by finding essential components of team behaviors that are critical in team success or failure; (i) identifying team behaviors, particularly those that are troublesome; (ii) recommending alternate courses of action and (iii) presenting relevant information to the user in a comprehensible manner. One of the best applications of AI is the Robot World Cup Initiative (RoboCup) aims to promote AI and intelligent robotics research by presenting a standard issue that can be used to integrate and test a wide range of technologies in order to implement for a robot squad to actually play a soccer game.**

Keywords—multi-agent systems, sensory networks, distributed planning, agent based models, expert systems, AI applications.

I. Introduction

In recent years, teamwork has become a significant field of agent research and development, as seen by a wide range of multi-agent applications, such as autonomous multi-robotic space missions, virtual environments for training and education, and Internet software agents. With the rising significance of cooperation, tools to assist people assess, evaluate, and comprehend team behaviors are in high demand.

Agent interactions are frequently complicated and dynamic in multi-agent domains with tens or even hundreds of agents in teams, making it challenging for human engineers to evaluate agent-team behaviors [6]. The difficulty is compounded in situations where agents are created by a variety of developers, and even the planned interactions are unexpected. Unfortunately, the challenge of studying team behaviour to help human engineers understand and improve team performance has largely gone unsolved. Previous research on agent teamwork has mostly focused on directing autonomous agents through their teamwork, rather than analyzing it for humans. Individual agents can explain their behaviors based on internal state using agent explanation systems like Debrief, but team analysis is not possible [6]. Recent work on multi-agent visualization systems, was driven by multi-agent understandability issues, but it still relies on humans to analyse agent actions and interactions.

One of the applications of Artificial Intelligence is sensory networks, such as air traffic control, urban traffic control, and robotic systems, have been the focus of most distributed artificial intelligence (DAI) research [1]. The fundamental reason for this is that these applications require distributed interpretation and distributed planning via intelligent sensors [1]. Planning entails not only the activities to be carried out, but also the utilization of material and cognitive resources to complete tasks such as interpretation and planning. The activities of sensory data interpretation and action planning are time and spatial interdependent. To avoid collisions, a plan for guiding an aircraft under air traffic control, for example, must be synchronized with the plans of other surrounding aircraft.

Another important AI application named RoboCup is a long-term research project aimed at creating a squad of completely autonomous humanoids capable of defeating human world cup champions by 2050. A wide range of agent applications, including training, education, virtual companies, and collective robots, require multi-agent collaboration. Human-assisted tools for analyzing, evaluating, and comprehending team actions are also becoming more essential.

II. Related Works

The multi-agent system is being developed as part of the project ARCHON (Europe's largest Distributed AI project), which aims to build a cooperative environment. The system, which was constructed using an ARCHON prototype system named Generic Rules and Agent Model Testbed Environment to run a high-energy particle accelerator, controls a high-energy particle accelerator (GRATE). GRATE is a general-purpose integrated Distributed AI system that contains generic collaboration and situation assessment knowledge.

Another ARCHON industrial application, Cooperating Intelligent Systems for Distribution System Management (CIDIM), is being developed as a tool for control engineers (CEs) who are responsible for ensuring the supply of electricity-to-electricity users. CIDIM was created to assist CEs by automatically offering services like as fault diagnosis, user-driven restoration planning, and security analysis, as well as collecting much of the information CEs manually collect by referring to standalone systems.

Intelligent tutoring systems (ITSs) provide a lot of freedom in content presentation and a lot of flexibility in responding to unique student requirements. These systems gain "intelligence" by reflecting pedagogical judgments about how to educate as well as learner information. This gives the system more flexibility by changing how it interacts with the student. Intelligent tutoring technologies have been demonstrated to improve student performance and motivation significantly.

Despite the widespread usage for categorization tasks, decision trees are rarely employed for agent control. Based on the confidence factors supplied by the decision tree method, this study provides a unique technique for agent control in a complicated multi-agent domain. Robotic Soccer as an example of a domain in which it combines a previously trained decision tree into a comprehensive multi-agent behaviour capable of directing agents during an entire game.

In the layered learning model, this multi-agent behaviour serves as a link between low-level and high-level learning. In game settings, the newly developed behaviour is empirically evaluated. Multi-agent Systems is a branch of artificial intelligence that seeks to provide both concepts for building sophisticated systems containing numerous agents and techniques for coordinating the behaviors of autonomous agents. Layered learning is a method for integrating low-level learn behaviors into higher-level behaviors in complicated multi-agent environments.

III. Open Researches And Challenges

Some systems use a less strict approach to modelling the environment; the scenarios provided are close to real-world circumstances in which the knowledge may be used, but they are not precise simulations. Other Intelligent tutoring systems focus on teaching pupil's ideas and mental models. These systems face two major challenges. For starters, education necessitates a greater depth of domain expertise. Second, there is less cognitive theory to guide knowledge representation and the pedagogical module since learning ideas and frameworks are less well known than learning procedures. As a result, these Intelligent tutoring systems are frequently referred to as knowledge-based instructors since they demand a greater domain knowledge base.

The primary driving factor for AI research has been standard AI issues. Computer chess research, which is the most common example of a standard problem, led to the development of a number of strong search algorithms. Moreover, experts can solve a lot of challenging challenges in order to construct a humanoid robot, including basic materials, walking and running behaviors, sensors, batteries, and high-level cognition.

Robot learning approaches appear promise since scripting robot behaviors for all scenarios, taking into account the uncertainties in sensory input processing and action execution, is impossible. A many-to-many competition is considered at the final stage. Collective behaviors should be learned in this scenario. It appears impossible to define all of the collective actions as a team, especially in circumstances where one of several behaviors must be done. A scenario can be seen as a pattern rather than the actual placements of all players and a ball. The RoboCup's challenges, like as task representation and environment modelling, are also difficult to solve.

IV. Conclusions And Future Work

To deal with the complexity of industrial applications, a Distributed AI method can be implemented. Other industrial products, such as distributed databases, computer-supported cooperative work, and air traffic management, will develop in the near future as a result of Distributed AI methods being applied to other areas [1]. The flexibility to integrate current stand-alone knowledge-based systems is a significant advantage of a Distributed AI strategy.

Intelligent tutoring systems have been demonstrated to improve student motivation and learning outcomes [2]. It's helpful to look at these systems when designing them as being made up of five parts: the student model, the pedagogical module, the expert model, the domain knowledge module, and the communications module [2]. Aside from ongoing work on these components, decreasing the time and cost of developing such systems is a significant research topic. The development of writing tools and the creation of modular systems are two current techniques for doing this [2].

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