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Interactive Situated Autonomic Multi-Agents System-Comprehensive Survey

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ABSTRACT

Multi-Agent Systems (MAS) are made up of autonomous entities called agents. Agents collaborate to complete tasks, but their intrinsic capacity to learn and make independent judgments allows them to be more flexible. Agents learn new contexts and behaviors through their interactions with other agents as well as the environment. Agents then exploit their knowledge to determine and carry out an action on the environment in order to accomplish their assigned objective. Because of its versatility, MAS is well suited to solving issues in a wide range of areas, including computer science, civil engineering, electrical engineering, etc. Developing cooperative MAS necessitates tackling a variety of issues, especially coordination among agents. Consequently, this paper discusses several interaction ways among agents in many disciplines. Index Terms—multi-agent system(MAS), Robotic Process Automation, situated agents, interaction.

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1. Introduction

The term" *intelligent agent*" comes from the field of artificial intelligence; in fact, one widely recognized definition associates artificial intelligence with the study and creation of autonomous entities capable of intelligent action. According to this viewpoint, "an intelligent agent must be able to perceive its environment, reason about how to attain its goals, act on those goals using some rationality principle, and communicate with other intelligent agents, whether simulated or human agents."[1]. Simply put, a decision-making structure is a process in which an agent must choose a certain action from a set of options. In everyday life, such a procedure occurs regularly. Humans, for example, must frequently make decisions about what to dress, what to eat, and so on. Similarly, an agent is described as an entity that is placed in a certain environment and in order to pick a certain action, it observes, interprets, and comprehends the circumstances of that environment. Figure-1 illustrate how are agents interact its environment through its sensors and actuators. As a result, to make decisions, agents must acquire information that enables them to understand what actions they can and cannot execute. The agents who must collaborate must be able to interact with one another in order to share knowledge about the activities that each may do. As a result, in many situations, Massive software programs and incredibly complicated algorithms that leverage advanced design technologies are used to produce cooperative multi-agent decisions. Some research developments, in particular, have led to the use of agents to solve difficult and cooperative issues. In a dynamic, unpredictable, and often cooperative environment, a situated agent is defined as a physical and movable entity capable of flexible and autonomous activities [2]. Using agent technology, various findings for solving coordinated activities have been developed.

1.1. Agent idea

The existing literature has various agent definitions, making it difficult to introduce the notion of the agent in a precise and technical manner. The idea of an agent is a concept that has been around for a long time. a broad abstraction suitable for a wide range of applications. However, there are several exceptions. Most frequently used definitions are highlighted in this regard. "*Agents can be defined as computer systems capable of flexible and autonomous actions in dynamic, unpredictable and typically multi-agent domains*" [2]. More particularly, "*agents can be defined as autonomous and problem-solving computational entities capable of effective operation and flexible autonomous actions in dynamic, unpredictable, and open environments. Agents are often deployed in environments in which they interact and maybe cooperate, with other agents that have possibly conflicting aims. Such environments are known as multi-agent systems*" [3]. Furthermore, "*an agent denotes a software-based computer system that has several properties as autonomy, introspection, social ability, reactivity, pro-activeness, mobility, rationality, etc., which is capable of independent action to achieve some goals or desires*" [4].

In summary, as mentioned in [5] "agents are:

- Clearly identifiable problem-solving entities with well-defined boundaries and interfaces.
- Situated (embedded) in a particular environment over which they have partial control and observability.
- They are designed to fulfill a specific role and have particular objectives to achieve.
- Autonomous, they have control over both their internal state and their behavior.
- Capable of exhibiting flexible problem-solving behavior in pursuit of their design objectives, being both reactive (able to respond in a timely fashion to changes that occur in their environment) and proactive (able to opportunistically adopt goals and take the initiative).

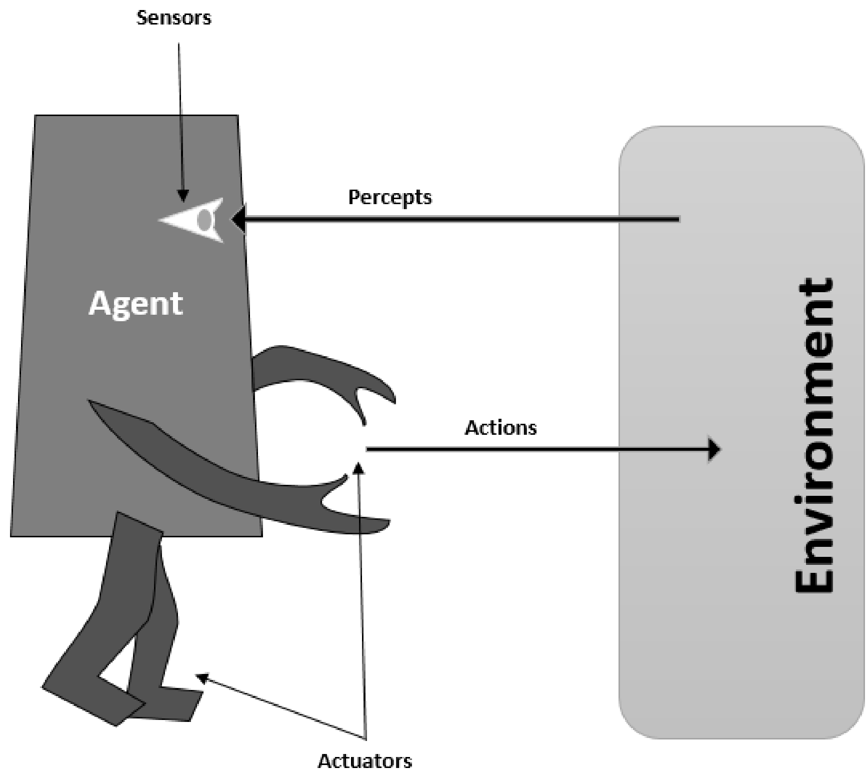

Fig. 1 - An agent interacts with its environment using sensors and actuators.

Thus, "*an agent is a computer program capable of independent action on behalf of its owner in order to achieve a set of goals*"[6]. It doesn't need to be instructed what to do; it figures it out on its own. Sensors give input to each agent, after which the agent performs logic of planning based on goals and percepts, which then leads to action, and effectors alter the environment at the output. To be deemed intelligent, it must possess the characteristics listed in Table 1.

Table 1 - Properties Of an Agent. [7].

PROPERTY	DEFINITION
"Autonomy/Flexibility	Ability to operate independently without intervention of any, but with basic control on its actions and decisions"
"Reactivity	The capability of accesses in the environmental changes and react timely"
"Pro-activeness	Initiation for goal-oriented execution without being dependent on reaction to inputs"
"Social ability	Communicate with humans and other agents on the basis of agent communication language"
"Collection of data	The agent should have sufficient data through its knowledge about the environment. It would assist them in taking decisions towards its goals"
"Protocols	List of well-defined protocols which suggest a proper mode of communication with either other agents or humans which belong to the system"
"Continuous learning capacity	Continuous learning capacity, i.e., by updating its data collection as per the performance of its commutating component, variation in the environment and position of college agents"
"Computational component	An agent should possess at least one computational component which would assist in the calculation of required results"
"Helping agent	An agent should possess an agent, who provide help, sharing of his location and has capabilities with other agents"

1.2. Situated Multi-Agent Systems (MASs)

Most studies in the field of MAS use situatedness as a feature of agents. Wooldridge and Jennings' definition of an agent in [8] is a well-known example *"an agent is a computer system located in some environment and capable of autonomous action in this environment to meet its design objectives*" The idea of situatedness is used in this definition to highlight the fact that an agent is not an isolated entity but rather existing in an environment, while the concept of context is maintained abstract. The definition does not define what it means for an agent to be placed in an environment; for example, nothing in the definition expressly states that an agent's presence in an environment implies the presence of a social component. Agents are notably social entities in located MASs. In a multi-agent world, the environment and the agents are complimentary. The local interactions between agents and objects in the environment are expressed by situatedness. In particular, these connections are what give the system its purpose and propel the MAS forward. An agent is located in a setting where he may observe and interact with other agents because of its situatedness. Intelligence is derived from these interactions rather than individual agent skills in a situational MAS.

2. Robotic Process Automation (RPA)

” *What tasks should really be automated and which can be left to humans?*” For many BISE (Business and Information Systems Engineering) authors and students, this is a fundamental question. This is not a new question. Data science, machine learning, and artificial intelligence advancements, on the other hand, push us to examine this subject regularly. One of these advancements is "*robotic process automation*" (RPA). RPA is a catch-all term for technologies that mimic human interaction with other computer systems' user interfaces. By automating procedures from the outside in, RPA aims to replace people. This differs from the typical "inside-out" approach to improving information systems. Unlike traditional workflow technology, the information system stays intact. The use of RPA raises a slew of intriguing research topics. Some of them aren’t new, but they’ve gotten more pressing in recent years. Here are some examples of questions to consider [9]–[13]: *What features characterize procedures that are suited for RPA support? ,How can RPA agents be taught? , What is the best way to train RPA agents? ,How can RPA agents be managed to avoid security, compliance, and financial risks? ,Who is responsible when an RPA agent “misbehaves”? ,How can RPA agents and people collaborate smoothly?* The questions raised above are important to the BISE community. As a result, the use of RPA creates exciting research prospects. The BISE community may, and should, be a driving force for RPA research.

3. Reaching interaction

High degrees of interaction are required because solving a more complicated problem is more likely to be successful if several autonomous and intelligent entities can collaborate with the same overall goal in mind. To get to the point of interaction, you must first perceive the circumstance. By assessing their operative rates from all available choices, such knowledge helps agents to determine what action they can take. A situated agent (SAj) is a physical representation of an intelligent entity that enables the system to affect the surrounding environment. By analyzing the knowledge included in these situated agents' capacity to conduct an action through its knowledge base, Inside its knowledge base(KB), the knowledge inherent in their ability to do an activity is embodied. Assume that a (SAj) is a member of a set of situated agents who work together (GSA). A group of situated agents must normally include more than one situated agent to complete a job.

"$SA_i, SA_j \in GSA \,\|\, SA_i \neq SA_j$ where $G_{SA} = \{SA_1, SA_2, SA_3, \ldots, SA_m\}$" (1)

According to this, an agent uses information provided by three (3) parameters [14], known as axes, where each axis provides situated agents with knowledge related to their capabilities to perform any determined action with a specific type of information in a specific time (t) within a specific spatial region, called scene (S). Axis 1: environmental condition (EC) is made up of data on the status of the environment that is directly engaged in the execution of a certain action. The definition, structure, and other important elements linked to the agent’s physical skills and traits are represented by Axis 2: physical knowledge (PK). Third axis: trust value (TV) is relevant to the capacity of an agent to connect, engage, and entrust other agents with essential facts.

4. Believes, Desires and Intentions (BDI)

For the last 30 years, much of the research on autonomous agent architectures has been centered on the BDI agent model, which is based on mental attitudes such as beliefs, desires, and intentions. The theory and practice of BDI agents have progressed in lockstep, with innovations at the semantic level leading to new architectural and language features, and new architectural features leading to new and extended semantics, beginning with Bratman’s philosophical work in [15] and implementations like the Procedural Reasoning System (PRS) [16].

Many agent architectures, languages, interpreters, platforms, and theoretical formalizations have been created throughout this time span, including a wide spectrum of agent programming capabilities and semantics. The resultant set of ideas and implementations is vast, and an overview of the BDI ecosystem's current condition seems appropriate.

Hussain and Obied [17] presented an overview of a popular agent (Beliefs Desires and Intentions (BDI) and its variants, such as Extensible Beliefs Desires and Intentions (EBDI), Beliefs-Desires-Obligations-Intentions (BOID)). In this review, they provide many decision-making frameworks for agents and talk about why and how well each one works in computer simulations. The amount to which the various architectures encompass these many aspects of decision-making is quite variable, as was made obvious via comparison.

The design of systems, or agents, in a dynamic environment is important from both a practical and theoretical standpoint. Obied [18] provides studies investigating the usefulness of dynamic sensing policies when the temporal cost of processing sensor input is substantial.

Artificial systems capable of intelligent, effective behavior in dynamic and uncertain environments are referred to as situated agents. Their construction poses crucial theoretical and practical concerns concerning the best way to control reasoning with limited computational resources. Obied and colleagues previously published a study in [19] that described theoretical and empirical research of self-regulation for located entities.

Hussain. and Obied [20, 21] set out with the intention of developing a multi-agent and agent-based system for the hospital. This article demonstrates how EBDI-based software agents and the Jade framework may be used to improve patient care while also automating business processes.

5. Interaction approaches

Several researchers have looked at the issues of physical agents' control, coordination, and cooperation when performing coordinated activities. From a control standpoint, these methods take into consideration the physical characteristics of the bodies of physical agent. A generic formalization based on control-grounded capabilities, on the other hand, has not been completed. For instance, a technique for passing a ball between two robots is demonstrated in reference [22]. The goal of this example is to show how multi-agent negotiations might be effective for decision-making structures that have explicit representations of dynamics. When it comes to static knowledge, this method also helps the initial decision of when as well as how to pass.

Reference [23] gives a sample of capabilities and demonstrates how it is a good way to describe information about a body of physical agent. As a result, this author emphasis on "introspective reasoning" on these skills to demonstrate how the multi-agent system's performance might be enhanced. The physical agents may govern their bodies using this technique, which takes into consideration the capabilities connected with their automated controllers.

Obied and Majeed's research [24] comprises a system for empirical evaluation of competing for theoretical and architectural approaches; more specifically, they constructed a Gridworld testbed that replicates a real-world dynamic environment and contains an embedded rational agent. The information provided to the interested party serves to review key concepts in the design and implementation of test environments, highlighting the importance of the testbed and the knowledge bases required by these designs, and presenting the definition of the intelligent agent and its features that have been disclosed within the testbed.

Reference [25] formulate two inter-agent teaching frameworks: one in which the teacher is responsible for observing the student behavior and initiating the instruction when it is most needed (i.e., Teacher-Driven), and one in which the learner is proactive to ask for instructions when desired (i.e., Learner-Driven). They suggest two frameworks that together cover all the bases when it comes to the difficulties of inter-agent education. They call attention to current best practices, outstanding issues, and promising future uses, and they suggest theoretical frameworks within which further study might be conducted.

The general case for knowledge reuse in MAS is illustrated in Figure 2 in [26]. When given a problem to solve, learning agents may draw on their own prior experience (K source) as well as information from other agents (K agents), who may be learning as well. Those knowledge sources may be coupled with information gleaned through researching the new task (K target), and the agent's knowledge base could be updated for reuse when the work is completed.

Kareem and Obied [27] reviewed essential points in the design and implementation of test environments, emphasizing the importance of the testbed as well as the knowledge bases that these designs necessitate, and presenting the definition of the intelligent agent and its features to be disclosed within the testbed. They provide a system for the empirical assessment of conflicting theoretical and architectural solutions; specifically, they created a Gridworld testbed that mimics a genuine dynamic environment and contains an embedded rational agent.

Reference [33] argues that "*introspective reasoning on control-grounded capabilities in physically grounded agents is required to enhance the agents decision-making performance in both individual and cooperative decisions, as well as to bridge the gap between agents and automatic control architectures with low abstraction levels*". Introspection on control grounded capabilities tolerates agents in cooperative systems to make definite and trustworthy commitments, hence enhancing agent performance in organized tasks and task allocations challenges.

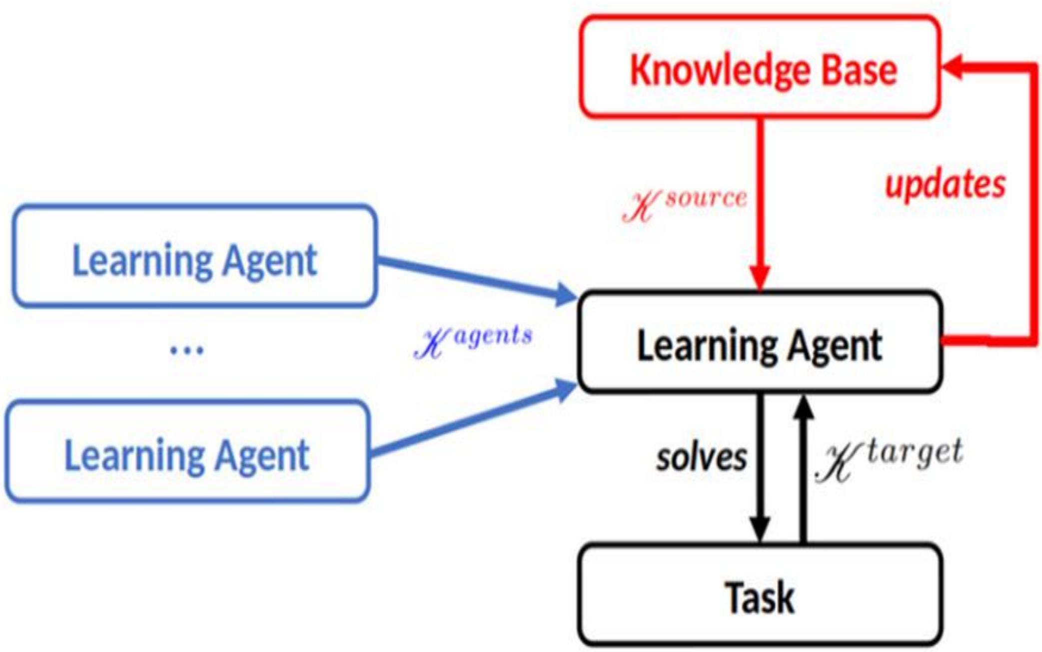

Fig 2:

Illustration of the general knowledge reuse problem for MAS. A learning agent might receive knowledge from communications with other agents (K agents) and/or reuse its previous knowledge (K source) for combining it with exploration in the target task (K target).

The simulation of smart grids is explored in [34], with an emphasis on the evaluation of various forms of demand-response schemes. Such system is interconnected with real-world resources., allowing users in order to test the effects of simulations on real-world equipment.

Table 2 - USING A MULTI-AGENT SYSTEM(MAS), STUDY DEMAND-RESPONSE'S WORK.

Publication	Functionality	Limitations
[12]	This article presents a reorganized version of the MASCEM simulator, which comprises the transfer of the agent-platform to JADE, the establishment of ontologies to simplify agent interaction, and the capability to integrate with other systems like smart grid simulators.	Only a few European market models are available, and only the wholesale market is available.
[13]	The goal of this study is to define a new dynamical demand-response system. The presented models are tested utilizing a multi-agent system that allows these programs to interact with various entities, energy management models, and physical resources.	The interaction is not exist with the wholesale market, and the number of supported situations is restricted.
[14]	To reduce home energy consumption, utilize the "Time-of-Use (ToC) demand-response system"	The proposed energy management system does not work in the real-time process. The Control Unit is not considered in the energy scheduler agent of the smart home.
[15]	Illustration using the "Time of Use (ToC) demand-response system" and the moving windows algorithm, enhance residential energy usage.	The suggested energy management system is not real-time compatible. The Control Unit is not taken into account by the smart home's energy scheduler agent.
[16]	Optimize household energy by using "Time of Use (ToC) demand-response system" and the adaptability of the storage unit of energy.	The proposed energy management system is not adaptive.

Generally, the use of situated MASs as an approach has a rich history and is on a wide domain in different fields. The most current efforts in demand-response (DR) employing MAS are shown in Tables 2 and 3. The demand-response work, which emphasizes modeling and simulating user behavior in advance of specific actions by energy suppliers, may be seen through an examination of these tables.

Table 3- USING A MULTI-AGENT SYSTEM(MAS), STUDY DEMAND-RESPONSE'S WORK.

Publication	Functionality	Limitations
[35]	Provides a method to implement a MAS on standard industrial components for DR aggregators that provide DR mechanisms. The demonstrator use case refers to the communication connection between VPP and TUs of industrial companies in Germany..	A MAS that combines and automates the scheduling, activation and accoud5nting process, might not be realized in the proposed way. It could require workarounds or a re-assessment of the regulatory requirements with regards to agent technology.
[36]	Investing on that notion, a novel, distributed, multiagent system (MAS) that aggregates consumers and prosumers and handles automatically OpenADR-compliant DR requests is introduced, following virtual power plant (VPP) principles	The accuracy of the forecasting engine used in the experiments, as well as, the stochastic behaviour of end-customers, have not been thoroughly examined. These challenges warrant further investigation that are part of ongoing research activities.
[37]	The 2011 version of the MASCEM simulator is presented in this study, which features sophisticated decision assistance for participants' discussions using machine learning. New sorts of participants, aggregators, as well as models that simplify the formation and management of these aggregations, are also available.	OAA has restricted scalability, only has real-time access to actual data, and is restricted to a few European market models.
[38]	A smart grid simulator containing agents that generally represent tiny stakeholders like customers, generators, electric vehicles, energy storage devices, and so on. This technology works with a variety of demand-response and energy resource management systems.	Without market interaction, a restricted number of supported situations, and a minimal usage of actual data

6. Conclusion

Knowledge based on capabilities provides physical agents with reliable information about their physical features. As a result, physical agents can determine with a high degree of accuracy if their physical bodies are capable of doing the desired duties. It is conceivable to claim in this work that situated agents that employ knowledge about their rates of actions are capable of making better judgments out of all the options available to them. In this view, when situated agents are able to estimate their position (i.e., their knowledge base) connected to the execution of any suggested activities, their decision performance (successful decisions) is better than when they do not. The number of successful tasks done by the located agent is connected to the number of successful decisions made in the experiments.

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