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Cognitive architecture for cognitive cyber-physical systems

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Abstract:

The desire to enhance cyber-physical systems (CPS) with cognitive capabilities represents a significant step forward in the evolution of robotics and intelligent automation. This paper focuses on the application of cognitive architectures to create cognitive CPS with the ability to perceive, reason and learn autonomously and also capable of interacting with the environment and human users in a meaningful and adaptive way. The analysis compares various cognitive architectures, highlighting their strengths and limitations for integrating cognitive functions into CPS. It examines how each framework supports cognitive processes such as sensory integration, attention management, action selection, memory recall, learning mechanisms and reasoning abilities.

Keywords: Cognitive architecture, Cognition, Cyber-physical systems, LIDA.

1. INTRODUCTION

In the rapidly evolving field of Cyber-Physical Systems (CPS), we are facing a technological revolution driven by advances in sensing, computing, communication and actuation. These systems, which include innovations such as self-driving cars and driverless vehicles, aren't just about automation; they're redefining the way we interact with the world [Bogdan and Pedram \(2018\)](#). However, the real challenge for CPS is not just to operate autonomously, but also to operate intelligently in the complex and uncertain world we live in. Thus, the concept of human-like intelligent machines is based on the idea that these machines can offer considerable benefits through their ability to interact and cooperate closely with humans. This derives from the idea that a machine endowed with human-like intelligence, or cognitive machine, will be better able to communicate with humans, not only through language, but also through various forms of interaction, both explicit and implicit [Sun \(2020\)](#). One of the main reasons for developing human-like intelligent machines is their ability to act as effective partners to humans. A machine with human-like characteristics is easier to understand and use. Another critical aspect is the establishment of trust between humans and machines. True social trust, the kind we feel between our fellow human beings, is based on shared motivations and experiences. For machines to gain this level of trust, they need to demonstrate intrinsically human behaviors and motivations. This includes understanding and responding to human emotions and motivations [Sun \(2006\)](#).

Cobots (collaborative robots) as a CPS have become increasingly popular in recent years. Although cobots are designed to work safely with humans, there are still concerns about their ability to make decisions autonomously. To

realize these potentials, we need a deeper computational understanding of the human mind. The human mind and its higher cognitive functions (e.g. learning, memory, language and complex problem solving) provide the basis for the creativity and ingenuity needed to flexibly meet new challenges [Bocklisch et al. \(2022\)](#). Consequently, social and technical developments should be harmonized - if possible at an early conceptual stage - on the basis of thorough technology assessments and a holistic understanding of systems. Such developments could lead to augmented cognitive systems and symbiotic cognitive-cyber systems, where human attributes of machines significantly enhance their usefulness in various domains [Sun \(2020\)](#). To this end, transdisciplinary cooperation between the humanities/social sciences and science and technology is required [Madni \(2018\)](#).

At present, most CPS are designed for specific tasks and lack the ability to reflect on their actions or adapt to new situations. The future of CPS depends on their ability not only to perform tasks, but also to discover and learn new ones, to understand and adapt to their environment, and to make informed decisions in scenarios for which they have not been explicitly programmed [Bogdan and Pedram \(2018\)](#). This reality requires a level of cognition - the ability to understand complex situations, make proactive decisions and learn from new experiences. It's not enough for these systems to follow pre-established instructions; they must have the ability to think, adapt and evolve. A crucial dimension of this evolution concerns the development of cognitive architectures that promote interoperability between human-centered systems and cognitive CPS [Gaffinet et al. \(2023\)](#), emphasizing the importance of designing systems that are not only technically advanced but also deeply integrated into the social and human fab-

ric. These architectures play a pivotal role in the advent of Cyber-Physical Social Systems (CPSS) [Yilma et al. \(2021\)](#) and Cyber-Physical Human Systems (CPHS) [Netto and Spurgeon \(2017\)](#), where the human and social dimension is at the heart of technological design [Annaswamy et al. \(2023\)](#).

In this article, we will examine in detail the importance of cognitive architectures and the benefits they bring to the implementation of cognitive capabilities within CPS. We will analyze various cognitive architectures, evaluating and comparing their functionalities for each cognitive function. The aim is to identify the key differences between these architectures in order to select the one that corresponds most effectively to our specific criteria for making CPS cognitive. This comparison process will help us understand which architecture can most effectively integrate cognitive capabilities into CPS, thus ensuring enhanced performance and autonomy for these systems, and better collaboration between these systems and with humans too. The discussion will be developed in the following sections, where we will examine cognitive aspects from a psychological and technological perspective (section 2), explore the role of cognitive architectures in the development of cognitive systems (section 3), compare various architectures and their abilities to support cognitive CPS (section 4), and present our final selection (section 5). We conclude with the main results of our research, and look ahead to future developments (section 6).

2. COGNITIVE SYSTEMS

In the industrial field, cognition, when applied to technological systems, is at the heart of the interaction between these entities for the execution of tasks and the understanding of information, from basic knowledge to complex concepts [Angulo et al. \(2023\)](#). Existing cognitive systems are designed to observe, adapt and constantly improve through experience. The interest in developing cognitive CPS lies in the objective of taking this capacity for adaptation and automatic learning even further, in order to meet specific and complex needs. Based on our systematic literature review [Ali et al. \(2024\)](#), which examines definitions of cognition, explores cognitive functions and the technologies used to integrate these functions in industrial systems, CPS and digital twins, we define a cognitive system as a *system that integrates cognitive functions inspired by the functioning of the human brain, capable of learning, reasoning and decision-making. They can interact naturally with humans and continuously improve through their ability to adapt.* Cognitive functions are mental processes involved in knowledge acquisition, information manipulation and reasoning [Kiely \(2014\)](#). These functions include perception, memory, learning, attention, reasoning, decision-making, problem-solving and linguistic abilities [Vernon et al. \(2007\)](#). They can be implemented in CPS that enable them to process and understand complex information, making it easier to solve a variety of problems and perform complex tasks. In our review [Ali et al. \(2024\)](#), it has been found that to build cognitive systems, we can refer to cognitive architectures as one of the enabling technologies, which are essential for the design of entities capable of emulating the complexity of the human mind for computational implementation [Naudet et al. \(2023\)](#).

The following section presents cognitive architectures that support the implementation of machine cognition into technological industrial systems, here reduced to CPS, in a way that is close to human cognition.

3. OVERVIEW OF COGNITIVE ARCHITECTURES

Cognitive architecture is a theory of the fixed mechanism and structures that underlie human cognition [Lehman et al. \(1998\)](#). In automation, the term *cognitive* is used at a higher level than in cognitive science [Bunte et al. \(2019\)](#). A cognitive architecture in the automation field autonomously adapts the process to new situations, for example by creating an adjusted production plan in the event of a module failure. Secondly, these cognitive architectures are essential to the creation of cognitive machines because of their fundamental role in the design of more intuitive, adaptive and efficient AI systems, capable of problem-solving, decision-making and learning. They are essential because they enable complex and prolonged interaction with the environment, going beyond simple instantaneous reactions to include complex reasoning and continuous learning. Inspired by biological cognition, they facilitate a more natural imitation of information processing and intelligent behavior. By focusing design efforts on content, such as the selection of relevant knowledge and problem-solving strategies, they enable automatic management of the learning and application of this knowledge [Kurup and Lebiere \(2012\)](#). This is advantageous for several reasons:

- (1) **Adaptability:** Cognitive architectures enable systems not only to learn from experience, but also to reason, understand and make decisions autonomously, reflecting the complexity and flexibility of the human brain.
- (2) **Efficient processing:** They are oriented towards fast cognitive processes, minimizing the need for intensive calculations or large amounts of memory.
- (3) **Multi-functionality:** Capable of handling general-purpose tasks in multiple domains, these architectures support the collaboration of heterogeneous software systems to solve a variety of problems.
- (4) **Artificial agent control:** Designed to direct agents, whether operating in virtual worlds or as physical robots in the real world, they provide a solid foundation for artificial intelligence [Thórisson and Helgasson \(2012\)](#).

Architectures also target a diverse set of cognitive functions, although learning, reasoning, planning and memory seem to be more common than others.

In our research work, we explore the integration of cognitive architectures within CPS to develop cognitive interoperability [Naudet et al. \(2023\)](#). We aim to equip the CPS with cognitive capabilities, enabling them to perceive their environment, understand the intentions of their collaboration partners (whether humans or machines such as robots) and make intelligent decisions that promote effective collaboration. Cognitive architectures are investigated as the computing component to bring such human-like cognitive functions. To do this, several criteria need to be taken into account. Listed below are the key requirements:

- Ability to perceive and understand the environment: The architecture must enable cobots to analyze sensory data to understand their environment in real time.
- Interpretation of intentions: It must provide the tools to interpret the intentions and actions of collaboration partners, whether human or CPS, to enable fluid interaction.
- Intelligent decision-making: It should facilitate autonomous decision-making based on perceived and interpreted data, enabling cobots to choose the most appropriate actions to achieve the common goal.
- Computational efficiency: It must offer sufficient computational efficiency to enable rapid information processing, essential for real-time interactions in a dynamic environments.
- Flexibility: It should be flexible enough to adapt to different scenarios.

To identify the architecture that satisfies these requirements, the following section (4) proposes a detailed comparison between different cognitive architectures.

4. COMPARISON BETWEEN COGNITIVE ARCHITECTURES

Here we review architectures that have been developed with the aim of integrating cognitive functions into CPS. According to [Schaat et al. \(2015\)](#), cognitive architectures can be classified into three categories. *Symbolic architectures*, like SOAR, ICARUS and NARS, use high-level symbols representing objects or concepts to deduce courses of action, focusing on structured reasoning and decision-making processes. *Emergent architectures*, like IPCA and NOMAD, work by propagating low-level activation signals in networks, focusing on self-organization and adaptability, with a variety of neural network models. *Hybrid architectures*, like ACT-R, CLARION, LIDA and DUAL, combine the characteristics of symbolic and emergent architectures.

Based on this article [Kotseruba and Tsotsos \(2020\)](#), which compares several cognitive architectures through their cognitive skills such as perception, attention mechanisms, action selection, memory, learning, reasoning and metareasoning, we have selected four cognitive architectures: SOAR, ACT-R, LIDA, and CLARION. This selection is not only based on their reputation, but on concrete evidence of their adaptability to constantly changing environments, their ability to handle complex information, their versatility in a multitude of functions, and their proven experience in enhancing interactions between humans and CPS. In what follows, we present a detailed comparison of these four architectures, focusing on their performance in each cognitive function.

4.1 Perception

Regardless of its design and purpose, an intelligent system cannot exist in isolation and needs input to produce behavior. Although historically all major cognitive architectures have focused on high-level reasoning, it is becoming clear that perception and action also play an important role in human cognition [Anderson et al. \(2004\)](#). Perception

is a process that transforms raw data into an internal representation of the system, enabling cognitive tasks to be performed. In the following, we compare the selected cognitive architectures according to two main sensory modalities: vision and multimodal perception.

Vision Table 1 represents a systematic comparison of the visual processing capabilities of key cognitive architectures, providing an overview of their performance in different sensory modalities. *Real Vision* refers to the architecture’s ability to process visual data from physical sensors. *Simulated Vision* refers to how the architecture handles visual data in a simulated environment. *Stages of Visual Processing* represents the number of visual processing steps the architecture can perform: 1. Feature detection. 2. Grouping into objects. 3. Object labeling. 4. Building spatial relationships. 5. Contextualization. 6. deep scene interpretation.

Table 1. Comparison of Visual Processing Capabilities in Different Architectures

Architecture	Real Vision	Simulated Vision	Stages of visual processing
SOAR	Partial	Basic	1-2
ACT-R	Partial	Advanced	1-4
LIDA	Advanced	Advanced	1-6
CLARION	Partial	Basic	1-3

For ACT-R, advanced visual processing covers from initial detection of visual features to contextual interpretation, spanning four process steps. This indicates a thorough integration of visual perception, from the recognition of edges and colors to the contextualization of objects in their spatial environment. SOAR and CLARION, while also processing visual information, are limited to initial stages, focusing more on identifying and grouping features into objects without reaching the complexity of spatial relationships or contextual interpretation. LIDA stands out for its ability to perform complete visual processing, including additional steps such as the construction of spatial relationships and advanced contextualization, enabling a rich and nuanced understanding of the visual scene.

Multi-modal perception Table 2 highlights the multi-modal perceptual processing capabilities of different cognitive architectures. *Integration of sensory modalities* measures the architecture’s ability to combine information from different sensory modalities, such as sight and hearing, to create a unified perception. *Cross-modal interaction* evaluates whether the architecture can handle interactions between different sensory modalities.

Table 2. Comparison of multi-modal perception capabilities in different architectures

Architecture	Integration of sensory modalities	Cross-modal interaction
SOAR	Basic	Limited
ACT-R	Advanced	Limited
LIDA	Advanced	Yes
CLARION	Partial	Limited

Table 2 shows that ACT-R and LIDA are advanced in the integration of sensory modalities, with LIDA also distinguished by its ability to enable cross-modal interactions. SOAR and CLARION offer basic sensory integration with limited cross-modal interactions.

4.2 Attention

Perceptual attention enables the selection of relevant information and the filtering of irrelevant information from incoming sensory data. ACT-R and LIDA stand out for their advanced suppression, selection and restriction mechanisms, indicating a superior ability to handle information overload and focus on relevant elements in complex visual scenes. These systems can implement these attention mechanisms in both real and simulated vision contexts. Conversely, SOAR and CLARION have basic capabilities in these same areas.

4.3 Action selection

Action selection determines at any point in time “what to do next”. ACT-R takes a moderate approach to decision flexibility through rule-based assessment. SOAR, on the other hand, shows great flexibility thanks to its hierarchical learning. LIDA and CLARION stand out for their very high flexibility and the integration of emotions in decision-making, with CLARION adding mixed symbolic-connectionist learning.

4.4 Memory

Memory is an essential component of any cognitive model, whether that model is used to study the human mind or to solve engineering problems [Kotseruba and Tsotsos \(2020\)](#). Thus, cognitive architectures have memory systems that store intermediate results of computations, enabling learning and adaptation to the changing environment. Memory is described in terms of duration (short and long term) and type (procedural, declarative, semantic, etc.). Long-term storage is subdivided into semantic, procedural and episodic types, which respectively store factual knowledge, information about actions to be taken under certain conditions, and episodes of the system’s personal experience. Short-term storage is divided into sensory and working memory. Sensory or perceptual memory is a very short-term buffer that stores many recent percepts. Working memory is a temporary storage of percepts that also contains other elements related to the current task, and is often associated with the current focus of attention. ACT-R and SOAR share a similar approach, relying on active working memory and long-term memory that combines declarative and procedural elements. LIDA stands out with perceptual sensory memory and episodic working memory, indicating an ability to maintain recent sensory information for more complex processing. CLARION, however, presents no sensory memory but focuses on a working memory model integrating both bottom-up and top-down processes, and a long-term memory that clearly distinguishes between implicit and explicit components.

4.5 Learning

Learning is the ability of a system to improve its performance over time [Kotseruba and Tsotsos \(2020\)](#). Learn-

ing is divided into two categories: declarative and non-declarative knowledge acquisition, which includes perceptual, procedural, associative and non-associative types of learning [Squire \(1992\)](#). ACT-R stands out for its multifunctionality, with capabilities in declarative learning via chunking and in procedural learning through the use of Explanation-Based Learning (EBL) [Minton et al. \(1989\)](#), as well as in associative learning for action adjustment. SOAR, on the other hand, focuses primarily on procedural learning by creating and managing rules via EBL, with no specific indications for perceptual, declarative, associative or priming learning. LIDA is unique in asserting a perceptual learning capability and using an activation model for priming, suggesting a facility for preparing the system for efficient information processing. CLARION appears to focus on declarative and procedural learning, with the ability to extract and induce rules and knowledge, while recognizing the importance of priming in the form of positive and negative priming.

4.6 Reasoning

ACT-R relies on probabilistic and inductive reasoning, using rule-based inference to simulate long-term declarative memory that mirrors human behavior [Kotseruba and Tsotsos \(2020\)](#). This approach enables ACT-R to produce reasoning behaviors that closely match the results observed in human experimental studies [Nyamsuren and Taatgen \(2014\)](#). In contrast, CLARION encompasses a broader spectrum of reasoning processes by integrating symbolic and sub-symbolic mechanisms that enable it to model deductive, inductive, analogical and heuristic reasoning. This gives it the ability to capture a diversity of psychological phenomena beyond traditional reasoning frameworks [Hélie and Sun \(2014\)](#).

4.7 Metacognition

Metacognition [Flavell \(1979\)](#), defined as *thinking about thinking*, is a set of skills that enable us to monitor internal processes and reason about them. Certain architectures thus demonstrate a form of introspection and adaptation, key aspects of metacognitive thinking. ACT-R applies a theory of mind model to a mobile robot, enabling it to recognize and adapt its behavior to changes in human activities. SOAR focuses on improving learning by building on previous experience and eliminating ineffective strategies. CLARION, on the other hand, implements metacognition by assessing confidence in task-related knowledge.

5. DISCUSSION

Unlike traditional automated systems that operate on the basis of predefined responses, cognitive architectures are distinguished by their ability to interact dynamically, without relying on predefined scenarios or responses. They provide a platform for integrating a variety of advanced cognitive functions, including metacognition, enabling self-assessment and self-improvement. These capabilities are crucial for systems that must not only act, but also reflect on their actions and decisions. Traditional automation tools, such as fixed control algorithms or rule-based systems, lack this essential capacity for reflection and adaptation.

Subsequently, we can deduce the strengths and weaknesses of each cognitive architecture. SOAR offers a generalist capability for modeling a variety of cognitive behaviors, with a remarkable aptitude for reasoning. Nevertheless, SOAR is less able to support continuous learning and perceptual skills, although it is advantageous for solving complex, structured problems. ACT-R stands out for its strong symbolic component, and is highly effective in modeling human cognitive tasks and rule-based decision-making. However, it is less effective in changing environments and in real-time perception, although it has significant potential for structured and symbolic tasks. LIDA is particularly effective in modeling consciousness and perception, adapting effectively to dynamic environments, despite its notable implementation and calibration complexity, which makes it particularly suitable for dynamic interaction with the environment. Finally, CLARION strikes a balance between symbolic and sub-symbolic elements, covering both explicit and implicit learning, in addition to social cognition and motivation. This complexity, which is an integral part of its architecture, may pose challenges, but it is well suited to social interaction and continuous learning, crucial aspects for human-robot collaboration.

Taking into account the analysis presented in section 4, which evaluates various architectures with regard to their cognitive functions, the LIDA architecture proves to be the ideal choice for CPS requiring cognitive integration, it proves to be particularly suitable for a range of relevant reasons. This architecture is distinguished by its deep support for complex perceptual processes, enabling efficient analysis and synthesis of sensory information from multiple sources. LIDA's ability to simulate consciousness and process information sequentially and in parallel aligns with human cognitive processes, facilitating adaptive decisions and reactions in dynamic environments. Its memory model is particularly advanced, supporting not only the storage and retrieval of information, but also the continuous learning that is essential for the autonomous evolution of CPS. LIDA's flexibility in reasoning, incorporating both inductive and deductive methods, enables it to solve a variety of problems and model realistic scenarios, a crucial feature for cognition in unpredictable contexts. Its ability to integrate metacognition reinforces its potential for self-improvement and self-supervision, key elements for advanced cognition. Furthermore, LIDA, our selected architecture, has been experimentally tested in this article [Lv et al. \(2023\)](#) to perform autonomous maintenance of machine tools via self-construction, self-assessment and self-optimization, showing good results. All these advantages meet our requirements set out in section 3: the ability to perceive and adapt to the environment, interpret intentions, make intelligent decisions, computer efficiency and flexibility. They also validate our decision to choose LIDA as the ideal cognitive architecture to equip CPS with cognitive capabilities.

6. CONCLUSION AND PERSPECTIVES

Choosing a cognitive architecture as the foundation for cognitive CPS is a necessity if we are to achieve a degree of intelligence and interaction that is truly in tune with human capabilities. In our analysis, LIDA appears to be the cognitive architecture best suited to our objectives,

notably because of its advanced capabilities in multimodal perception, memory and learning, flexibility in attention and action selection, and its integrated approach to consciousness and reasoning. These elements are fundamental to realizing CPS that can interact naturally and intuitively with humans, taking social interactions into account, and to establishing true cognitive interoperability between machines and human beings.

As part of our future projects, we plan to implement this cognitive architecture in a real-life scenario, by integrating it into a cobot (collaborative robot) as a CPS. This practical implementation will aim to validate the effectiveness of the LIDA architecture in an industrial context, by observing how the cobot adapts and interacts with its environment and with human operators. We expect that the application of this architecture in a real-life case will provide valuable insights into how cognitive CPS can improve human-machine collaboration, enhance operational efficiency and enrich workplace safety.

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