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Computational mental simulation: A review

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Abstract
This paper is dedicated to the study of existing approaches that explicitly use mental simulation. Current implementations of the mental simulation paradigm, taken together, computationally address many aspects suggested by cognitive science research. Agents are able to find solutions to nontrivial scenarios in virtual or physical environments. Existing systems also learn new behavior by imitation of others similar to them and model the behavior of different others with the help of specialized models, culminating with the collaboration between agents and humans. Approaches that use self models are able to mentally simulate interaction and to learn about their own physical properties. Multiple mental simulations are used to find solutions to tasks, for truth maintenance, and contradiction detection. However, individual approaches do not cover all of the contexts of mental simulation and most rely on techniques which are only suitable for subsets of obtainable functionality. This review spans through four perspectives on the functionality of state-of-the-art artificial intelligence applications, while linking them to cognitive science research results. Finally, an overview identifies the main gaps in existing literature on computational mental simulation and provides our suggestions for future development.

KEYWORDS
agent controller, analogical representations, decision-making, inner virtual world, mental simulation, robot cognition

1 | INTRODUCTION

Interactive virtual environments pose a wide variety of challenges for intelligent agents, especially to make decisions in order to reach their goals. The difficulty of decision-making tasks rises quickly by introducing continuous space and real time into question.[1] It also becomes increasingly harder to build intelligent agents that can meaningfully interpret and act in unknown situations.

Classical approaches to decision-making, such as production systems,[2,3] semantic networks and other formal knowledge representation frameworks[4] require domain experts to provide descriptions of the agents' environments, the types of objects to be used, and entities to interact with.[5] Upon these approaches, learning algorithms have been used to learn new rules[6,7] and policies[8] that tell the agent how to behave in various situations.

However, their application is limited when dynamic environments are considered,[9] where agents must assess multiple interactions between entities and their environment, such as the effects of collision, object shape, action timing, and visual occlusion on behavior. Research efforts have been made to address the issues posed by dynamic environments and have yielded important results, such as in robotics,[10] but challenges still remain that span over several research fields. Concurrently, cognitive architectures have been proposed to integrate multiple techniques into autonomous agents that are better suited for dynamic environments, but some significant aspects such as anticipation and adaptation are still weakly integrated[11] in existing approaches. A recent review[12] also describes the relevance of embodied simulation for social interaction in robots, where the authors conclude that, while this approach would benefit social robots, existing models remain scattered. Other authors[13] also point to the potential advantages of a more complete computational model for human–robot interaction. In this work, we focus on deriving the outline of a functional computational approach, and hence, we broaden our study to encompass more general traits of the simulation paradigm.

For intelligent agents to interact with their environment and other agents, they must have an understanding of how the world around them functions, what effects their actions will have, and what decisions are optimal in given scenarios. With the aim to inform the implementation of such an agent, this paper focuses on mental simulation-based anticipation. This paradigm has received moderate attention by other researchers, but insufficiencies exist and a generic approach that can function in both simple and complex scenarios has not yet been proposed.

The mental simulation paradigm enjoys significant interest from the cognitive science community.[14–18] It is used to explain how humans make certain predictions for making decisions, imagining "what if" scenarios (multiple worlds) and revisiting past events in novel ways.[19] Moreover, there exists evidence that mental simulation is not strictly a human capability, but that some animals may also be able to perform it for goal-oriented decision-making.[20] The principle of mental simulation consists in constructing an imaginary world that can function on its own, based on which various future states of the environment can be inferred and decided upon, resulting in an individual's behavior.

With respect to this principle and considering its multidisciplinary nature, we present the motivation for this work by drawing connections between mental simulation in humans and computer simulations, and discuss how these fields can be merged into various applications through virtual reality (Section 2).

Afterward, this survey aims to identify and classify existing approaches in literature that rely on the mental simulation paradigm or that make use of it to enhance the functionality of an agent. The technique of using computational mental simulation in decision-making can be applied in various contexts depending on the type of environment, whether simulation targets are objects or intelligently behaving entities and the level of realism the simulations reflect.

Consequently, our study is structured based on four questions about the application of mental simulation in an agent:

- Where is the mental simulation based system used? (Section 3)
- What is mental simulation used for within these systems? (Section 4)
- Why is mental simulation useful in a given case? (Section 5)
- How do these systems implement computational mental simulation? (Section 6)

To answer these questions, we analyze the properties of existing approaches from each point of view. Hence, to answer where these systems are used, we compare approaches that are applied to virtual reality and those which have a robotic implementation. Thereafter, we investigate what these systems are able to anticipate by making use of their mental simulation capabilities, by surveying their ability to predict physical phenomena and behavioral traits of other agents. From the point of view of cognitive science, we are also interested in why they require mental simulation—that is, which of the cognitive functions, namely, prospection, navigation, theory of mind (ToM), and counterfactual reasoning, are accomplished through this mechanism. Finally, we look into how these systems are built, where we classify approaches based on three major schools of thought in artificial intelligence: symbolic, sub-symbolic, and analogical representation systems.

This structure allows a clearer analysis of existing approaches that use the simulation paradigm and shows how various implementations fit into a generic view of using mental simulation for decision-making. Moreover, to the best of our knowledge, there exists no comprehensive survey on computational approaches to mental simulation that discusses all facets of the paradigm in an integrative manner. The remainder of this paper is structured into these four aspects of the computational use of mental simulation and their more specific sub-cases.

Finally, our study concludes with an overview (Section 7) of existing approaches and how they cover the multiple contexts of using simulation in decision-making.

2 | APPLICATIONS OF MENTAL SIMULATION TO COMPUTER ANIMATION AND VIRTUAL REALITY

Before diving into the discussion about the overall properties of existing approaches to computational mental simulation, it is important to present the insight that motivated our work.

The very term of mental simulation implies a way to reproduce external processes in one's mind, much like simulation has been used since the advent of computers to model physical phenomena, animal behavior, social interaction, and many other topics at varying levels of abstraction (e.g., from molecular dynamics to planetary systems). This technique is especially useful when the modeled process cannot be analytically predicted, being the result of a great number of complex interactions over time.

Like with computer simulations, mental simulations may include various levels of detail and scale. While it is true that arguably all such mental scenarios are constructed from sensory input (hence, the focus of related work on sensory prediction[21]), humans can easily imagine more than just what they can directly sense, by using analogies to abstract over unknown details (e.g., thinking of atoms as tiny spheres or radio waves as ripples on a water surface). Most importantly, mental representations tend to be structurally and functionally equivalent to their real counterparts.[22] While they work differently from how the brain obtains these representations, simulation systems like physics engines show a remarkable resemblance: real objects are approximated by platonic shapes or more complex mesh structures, and their dynamics are simulated over a large number of small steps, which makes it possible to express virtually continuous interactions between them (e.g., collisions and attractive forces).

Similar to how human behavior is shaped by the fact that physical reality and imagination share some common mechanisms,[23] computational mental simulation may help to achieve more credible agent behavior (Section 2.1), create better virtual environments for training, and build intelligent agents that use inner worlds as reasoning mechanisms (Section 2.2), to name a few.

2.1 | Computer animation

Realistic animation of virtual characters is a challenging task, and a large body of research has focused on finding techniques to produce believable behavior. Embodied approaches have resulted in agents that take the physics of their environment into account.[24] Moreover, anticipation has been deemed the hallmark of skilled motions,[25] as motions and gestures that we consider believable are often shaped by a preparation for what is to happen.

Mental simulation is applicable to virtual characters, to obtain believable behavior through continuous anticipation.[26] Reacting to other agents and one's own actions as perceived by others has also been approached with the use of mental simulation coupled with existing cognitive architectures[27,28] to obtain adaptive behavior.

The difficulty of obtaining believable characters mainly comes from the subjectiveness of the topic. However, using cognitive mechanisms similar to those found in humans could bring them a step closer to behavior perceived as human-like, and therefore, more "believable."

2.2 | Virtual reality

We can identify two levels at which mental simulation and virtual reality can be brought together.

First, in the context of virtual environments for training in domains where situated anticipation is a critical human skill, such as firefighting, computational mental simulation could be used in association with intelligent tutoring systems[29] to teach trainees to make better use of this technique themselves in practice.[30]

Second, we consider virtual reality as the basis for the inner world of an intelligent agent. With recent advances in simulation techniques,[31] deep learning,[32] and generative models,[33] the possibility of perceiving the world as an analogous virtual environment is becoming a real option. More precisely, computational mental simulation could benefit from advances in virtual reality, computer animation, and machine learning, making it reasonable to discuss using a virtual environment as the "mind" of an agent, which could be itself populated by other agents (representations of real objects/individuals) that interact in complex ways within this inner world.

3 | ENVIRONMENT TYPE

Artificial intelligence applications, since their advent in the second half of the 20th century, have diversified to tackle many areas of human intelligence. Research in this field has led to optimal algorithms on a number of problems and superhuman performance on others such as in the 90s, when the Deep Blue computer[34] won against a chess world champion. However, humans still excel in many quotidian tasks such as vision, physical interaction, spoken language, environmental and behavioral anticipation, or adapting ourselves in the constantly changing conditions of the natural world in which we live. To this end, hard problems have often been idealized in computer simulations (virtual reality) where research could focus on the essentials of the artificial agents' intelligence without the need to solve low-level problems like noisy perception, motor fatigue, or failure to name a few. Once matured in virtual reality, such agents would be ready for embodiment into a robotic implementations where, only few prove to be feasible. From this point of view, we can categorize existing approaches through the prism of environment complexity, namely, those that have been implemented in virtual environments (Section 3.1), and those that have a robotic embodiment (Section 3.2).

3.1 | Virtual world

The challenge for an intelligent agent in a virtual world is to cope with potentially complex behavior, but in an accessible sandbox context. The virtual world is a controlled environment where observing events and object properties are simplified so that agent development can focus on behavior while neglecting problems that arise from interfacing with the world. An example of such simplicity is given by the trajectory of an object moving under the effects of gravity, whose exact coordinates can be directly sampled by the agent without requiring to capture, segment, and analyze an image. The main characteristic that describes this environment type is the focus on behavior, but this brings the drawback of possible poor scaling of developed methods towards the real environment due to noise, uncertainty, and interface issues.

Regarding computational approaches to mental simulation, most existing works have been evaluated in virtual environments of varying complexity. Discrete environments provide a simple but informative view of the behavior of an agent,[35] under controllable circumstances. As complexity rises, namely, the transition from discrete to continuous space, the challenge for intelligent agents to perform tasks increases significantly, but it also enables a wider range of behavior. Only now does the use of mental simulation begin to find its applications and advantages over traditional methods in agent decision-making. Literature provides mental simulation approaches to constrained two-dimensional continuous space,[27,36–38] which focus on developing models to cope with the increased complexity of the environment. Other works go even further, to continuous three-dimensional space where trajectories are more dynamic as human users intervene[26] and collisions[39] or occlusions[40] take place.

A recent trend that relates to the paradigm of mental simulation is the application of Monte Carlo tree search (MCTS) to real-time video games, as an enhancement to its history of success in turn-based games. Succinctly, if given the capability to simulate the outcomes of its actions, an agent can rely on MCTS planning algorithms such as Upper Confidence bounds applied to Trees (UCT)[41] to perform more efficiently in real-time strategy games[42,43] or similar scenarios. We note that MCTS consists in planning algorithms reliant on a simulator—that is, a way to obtain the effects of performed actions—while mental simulation encompasses the mechanisms for constructing such a simulator, which could eventually be used together with heuristic planning techniques.

3.2 | Real world

In the real world, agents require a physical embodiment (or interface) in order to interact with the environment. The challenge of performing mental simulation within a real setup is to anticipate the behavior of real entities, which are perceived through noisy and fault-prone sensory input. In addition to issues that exist in virtual worlds, reality poses further obstacles to object detection and recognition, and therefore can be viewed as a significantly more complex version of a continuous three-dimensional virtual world. Systems that aim to achieve functionality in the real world must also solve interface problems in order to exhibit their behavior. Interface issues include acquiring adequate information from sensors and effectors, and the possibility of externally caused damage to the system and environment noise.

Several systems using mental simulation have been developed as dually compatible with both virtual environments and robotic embodiments. This allowed the authors to evaluate the cognitive process of their approach[40,44] in virtual reality where the agent can perform more dexterous actions that its robotic counterpart. Computer simulations were also used by[27,36] to evaluate their approach to improving a robot's performance within a team.

Other researchers have directly approached reality with robots that use mental simulation to support their natural language skills,[45] reasoning,[28] and resilience.[46] We note that these are difficult problems in robotics, and it is interesting that mental simulation is able in these cases to decrease complexity of the original tasks and allow robots to perform better in the real world.

4 | MENTAL SIMULATION TARGETS

Depending on what the agent encounters in its environment, the use of mental simulation in existing research can be divided into two categories: inanimate objects and entities, which exhibit some form of behavior. In the following, we explore what existing approaches use mental simulation for, namely, the physical and social challenges of the world they inhabit (Sections 4.1 and 4.2).

4.1 | Environmental aspects

One aspect of mental simulation is represented by anticipating how insentient systems evolve based on a model of the laws that govern their behaviors. Such systems can be composed objects that move according to the laws of physics or deterministic mechanisms such as, for example, a light switch that can be used to turn a light bulb on and off. Such systems are "simple" in the sense that the underlying rules are deterministic and exhibit little or no change over time, for example applying a force to an object will always trigger a mass-dependent acceleration on that object; this does not exclude the potential complexity of such system.

Possessing a mental model of physical phenomena allows humans to anticipate the consequences of actions that are performed in the environment.[47] Having a representation of properties such as mass, gravity, elasticity, and friction are necessary in successful predictions of mechanical outcomes. Humans tend to construct a mental image of a given scenario, as it would visually appear in reality, in order to reason in certain contexts.[48] The ability of humans to analyze environmental information has been linked to their capability of focusing on relatively small sets of data, through the process of attention management,[49] due to not being able to process the entire depth of the observable world. Nevertheless, humans are proficient at high-precision tasks such as anticipating and counterbalancing weights using body movements.[50]

A wide range of approaches have been proposed to control an agent's behavior in complex physical environments, with arguably one of the most successful being those based on reinforcement learning.[8,51] While particularly well suited for noisy, real-world data, these approaches usually assume a direct function between the agent's sensors and effectors, which can ultimately lead to limited scalability of their adaptiveness[52] in novel scenarios. In this sense, our focus turns to adaptability using internal model-based approaches.[53]

From the perspective of anticipating environmental aspects, existing research on computational mental simulation makes use of this paradigm to predict object trajectories[26] and eventual collision between them.[54] Mental models can also serve to represent objects that exit the perception field[28,45] and enable an agent to maintain a consistent world view in the absence of direct input. Representing collisions between objects allows agents to evaluate their actions,[54] determine their own appearance,[46] or interact with objects of interest.[38]

4.2 | Behavioral aspects

The second use case of mental simulation is represented by anticipating behaviors of more complex and autonomous entities. This class of entities is comprised of systems (both artificial and natural) that exhibit some form of non-determinism, free will or high-behavior complexity. Characteristics of environmental mental simulation are inherited and extended in anticipating complex entities, and if the assumption is made that these entities are also able to make inferences on others, several levels of anticipation arise. For example, in the scenario where John knows that Mary falsely thinks that Joe has a toy car, John has a two-level mental image of his friends, which allows him to know that Joe does not own a toy car (Level 1) but Mary thinks he does (Level 2).

Three types of behavioral mental simulation can be distinguished based on which entity is considered for such reasoning, namely, entities that have a high degree of resemblance (Section 4.2.1), those that do not (Section 4.2.2), and one's own self (Section 4.2.3).

4.2.1 | Agents with similar structure

The context of anticipating and learning from the behavior of other entities, which are similar in structure, is considered a special case due to the possibility of using one's own internal structure to achieve such inference. In its simple form, one can consider for example two identical robots (with identical internal states) that when put in exactly the same conditions will behave in the same manner.

One of the requirements for understanding similar others is recognizing what they intend to do. The challenge in this context is to anticipate goals and actions based on the fact that the other entity is similar or identical in structure and reasoning mechanisms.

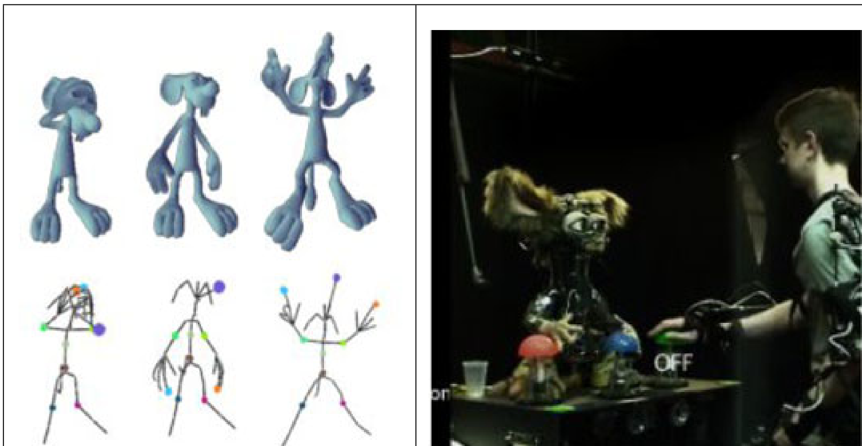
Humans are not only able to reproduce behavior[55] but can also understand the underlying goals of another's actions.[56] Experiments showed that intention recognition can be achieved from both successful and failed attempts to perform an action, given the performer was a human and not a mechanical device.[57,58]

To mentally simulate the actions of other entities that closely resemble themselves, agents in existing approaches use their own mechanisms to infer useful information about chosen targets (examples in Figure 1). Body mapping techniques are used, generally based on simplified skeleton structures,[59] to create the gestural information link between agents. Once mapped, motion patterns are matched against the agent's inventory of actions in order to infer intentions.[40,44]

Due to the fact that mental simulation targets have similar behavior mechanisms and embodiments, the need for additional specialized models for others' behavior is avoided. Unfortunately, when differences increase, this technique leads to the occurrence of the correspondence problem.[60,61] Moreover, current implementations are limited to a predefined inventory of actions, based on a specific model of self and others, restricting them from more flexible behavior.

Subsequent to identifying the intentions of a similar other, the challenge is to extend one's knowledge by learning from observed actions. Learning complexity in this context is still relatively reduced because, in this case, novelty is expressed as different utilizations of the same underlying mechanisms.

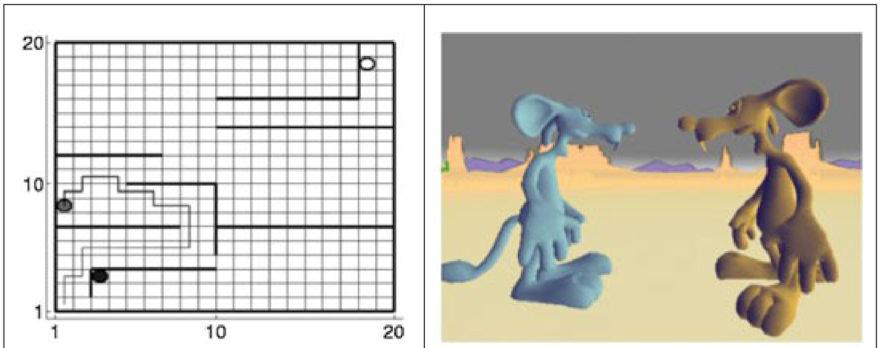
In a close relation with understanding intention, humans are able to learn novel methods of achieving the intended goal. The phenomenon of imitation in humans and animals is covered in a wide range of research, clustered into two main contexts by Rizzolatti[62]: the capacity to replicate an observed action and to learn new behavior through observation.



Max T Mouse described in [59], using a skeleton to map movements of other mouse on its own.

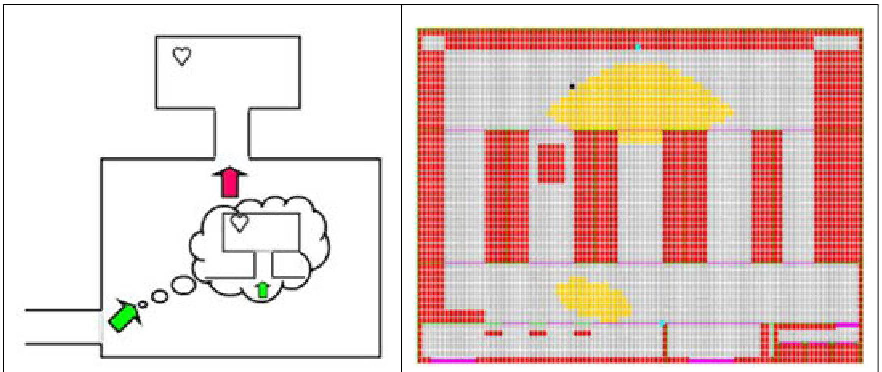
Leonardo from [40], using its own body model to infer human intentions.

FIGURE 1 Excerpts from works using mental simulation in understanding similar agents



Imitation in a maze environment from [56]. | Virtual agent in [59] can learn new behavior from its peer.

FIGURE 2 Excerpts from works performing imitation learning with the aid of mental simulation



Quakebot in [77] which can simulate what other players will do. | Mental simulation of intruder from [35], within a physical security scenario.

FIGURE 3 Excerpts from works performing mental simulation-based behavior prediction on agents with different structure

Depending on their implementation, current approaches have mechanisms to extend their knowledge base by observing other agents or human-experts performing actions (examples in Figure 2). An example of such mechanism are behavior trees, branches of which can be extended with new nodes.[59] Prototypic fuzzy cognitive maps have been employed to learn by imitation without modifying the structure of the prototypes themselves.[38,63] Software images[64] have been proposed as a framework for enabling agents to identify similar others and to learn by imitation.

The use of one's own mechanisms to reason about others provides a fast and convenient way to learn new behavior. However, the occurrence of the correspondence problem still imposes limitations on agents. Knowledge extension is not performed when the internal structure does not correspond between agents.

4.2.2 | Agents with different structure

The general case of understanding other entities, involving anticipation and learning, requires the capability to formulate theories about how structurally different others behave. Using one's own mechanisms for this purpose is fundamentally limited, and therefore, the challenge is to obtain a generic method of representing others.

The general challenge in the interaction with a heterogeneous agent environment is to anticipate complex entities, which may be dissimilar to oneself and to predict what they believe and how they will act. In this case, prediction of environmental changes should also be taken into account, as behavior generally depends on changes in the agent's surroundings.

Whether implicit or explicit, a certain level of anticipation is required by any autonomous entity for it to function in its environment. The phenomenon of anticipation has been studied in a variety of domains such as biology, neuroscience, cognitive science, and artificial intelligence.[65]

The predominant approach in existing implementations is represented by the use of custom theories or models of other entities (examples in Figure 3). Agents place themselves "in the shoes of others" and mentally simulate what their intentions and beliefs are[35], based on the information they have available.

Existing approaches use simplified models to predict essential aspects of the behavior of other entities. Some agents use feedback to improve their models, in order to more accurately anticipate behavior. The drawback of current methods is that a general-purpose approach for anticipation has not been proposed. Models are tailored by domain experts for specific scenarios, which fail when faced with novel contexts.

Understanding other entities leads to the challenge of being able to collaborate and form teams. Anticipating team members becomes important towards the achievement of common goals. As with other forms of complex anticipation, this context includes both environmental and behavioral simulation.

Human interaction within a collaborative context relies on several aspects of social cognition such as role-taking and empathy. Being able to understand others, thereby developing a ToM, enriches the cognitive ability of individuals to perform social interaction.[66]

By adding models of humans in a collaborative context, existing approaches (examples in Figure 4) make simulations to determine the intentions of other members to improve team performance,[27] by adopting others' point of view.[45] Research using simulation techniques in this context is focused on collaboration within human teams,[36] while the agents have the role of helpful companions. There exist, however, implementations that allow agent-to-agent collaboration.[67]

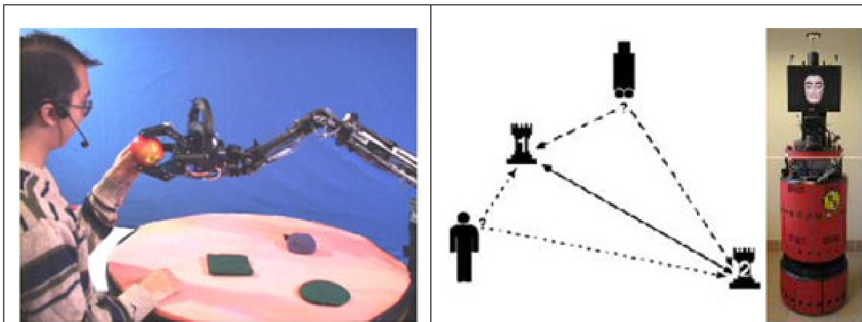
Team-oriented approaches can make decisions based on simulations of others' behavior. They are capable of taking the perspective of other team members in order to understand requests and act accordingly, but this is currently done using expert-tailored cognitive models of the teammates (either human or artificial). These implementations function in relatively simplified scenarios and require further configuration in case of scenario changes. Moreover, the agent's emotional system, seen as responses to an examination of self, others, and environment, is not approached.

4.2.3 | The self

Once capable of simulating the evolution of the environment and other entities, the challenge is to achieve introspection and include the self into these simulations. This context requires a functional model of self and information about possible interactions with the surroundings.

Recent studies suggest that common mechanisms are responsible for the accounts of ToM and awareness of self mental states or "theory of own mind".[68–70]

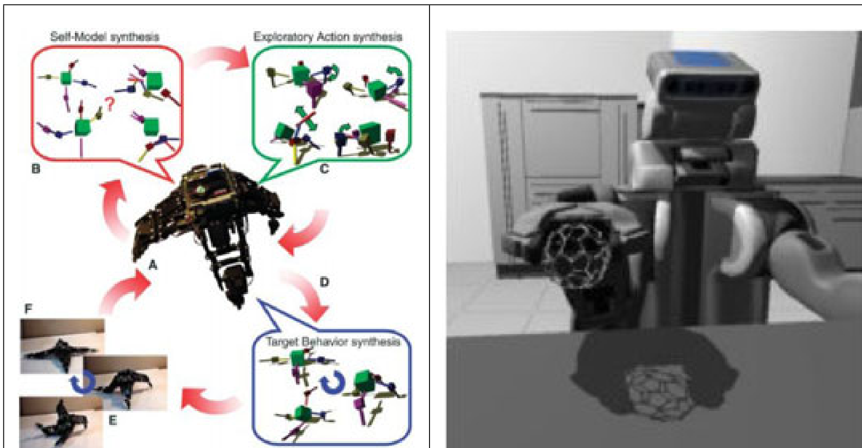
Existing implementations approach this case using either preassigned physical selves or by creating their own models based on interactions with the environment (examples in Figure 5). Physical engine-based approaches enable agents



Robot in [45] takes human's perspective to communicate.

Team robot from [36] uses cognitive model to anticipate human decisions.

FIGURE 4 Excerpts from works using mental simulation for collaboration with humans or other robots



Robot described in [46] that uses continuous self-modeling to recover from damage.

Approach from [54] using a self model to simulate actions.

FIGURE 5 Excerpts from works performing mental simulation of the agent's own self to emulate themselves carrying out an action[54] and leverage mental simulation results to make decisions in reality. Such mental simulations allow agents to evaluate strategies in advance and choose the optimal course of action.[38] This can be done without a predefined model of the agent, by using primitives to automatically construct simplistic models of themselves, using sensory data.[46]

Virtual physics models help agents to interact with the environment. Updating the self model during interaction makes such systems more robust to changes such as unexpected damage. By automatically creating the models, expert intervention is minimized. Even though virtual selves may conflict with reality, errors can be used to improve the current model. However, a trade-off occurs between model simplicity and accuracy as faster simple models may lack details while slower complex ones lead to erroneous mental simulation. Currently, self models do not have adaptable levels of detail, and approaches are generally limited to the physical self. Moreover, few approaches consider the need for a detailed representation of the self.

5 | COGNITIVE FUNCTION

From the point of view of cognitive science, we investigate why existing approaches use mental simulation. Research[71] suggests that mental simulation can be regarded as a common mechanism—that is, overlapping areas of brain activity—in the brain for remembering events, performing prospection, navigation and accounting for a ToM. More recent studies[72] also connect counterfactual reasoning—thinking about "what could have been"—to related brain regions used by the previously mentioned cognitive functions. Each of the four cognitive functions discussed in this section is illustrated in Figure 6.

5.1 | Prospection

Prospection is a form of self-projection into the future, through which one anticipates future events to find actions which are most favorable towards achieving a certain goal. Great emphasis is placed on the role of mental simulation on this ability in cognitive science research,[73] while computational approaches have recently begun to make use of the paradigm in artificial intelligence systems.[26,39]

Planning has been one of the first research directions since the advent of artificial intelligence (for an in-depth review, see Wilkins[74]). With the development of novel MCTS variants (for survey, see Browne et al.[75]), efficient algorithms have been proposed for more complex environment conditions such as real-time strategy games.[43] Existing approaches using MCTS show promise in providing an efficient way to make decisions in complex scenarios, but all such approaches rely on the assumption that a simulator is provided which can compute future states of the environment on demand. For simpler scenarios like games, this simulator can be developed as the game mechanics are known and accessible, but generally this is not the case for agents that interact with the real world, where such a simulator does not exist.

In this sense, mental simulation is a candidate mechanism for enabling the prospection ability required by general purpose planners. Existing approaches make use of the mental simulation paradigm to make predictions of the behavior of other entities[38] in order to reach their goals, to evaluate their own actions,[54] and also as a medium for estimating which actions can provide more information about an unknown state of the agent's embodiment in the world.[46]

5.2 | Navigation

The ability of humans to recall places for navigation purposes differs from map-like artificial systems in that it also

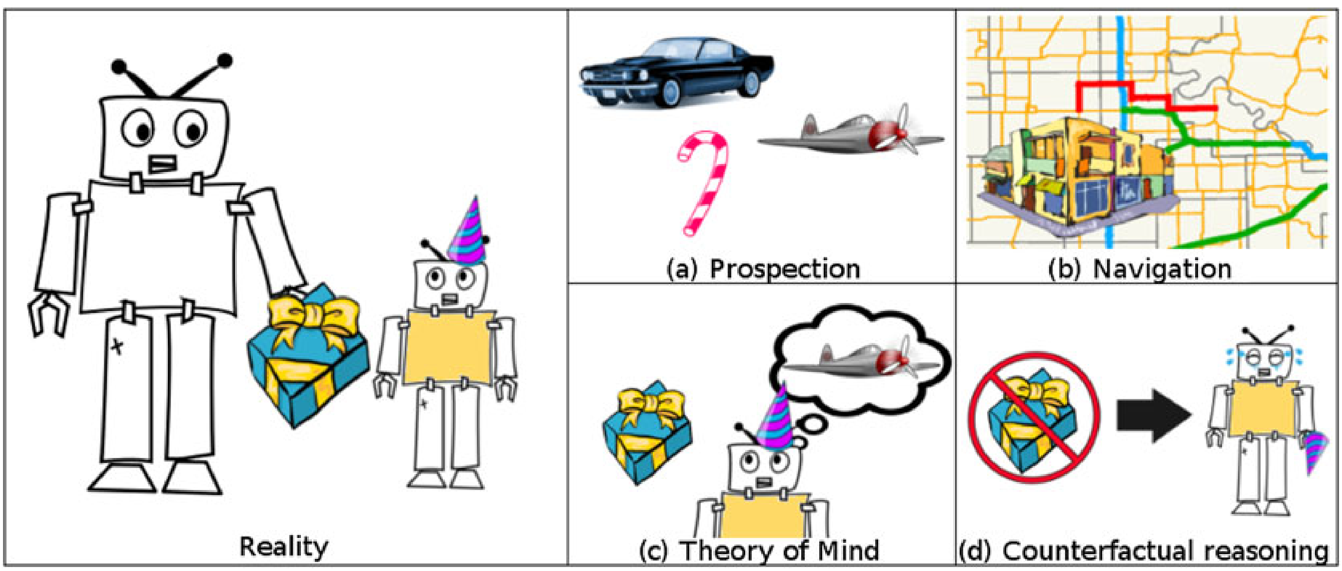


FIGURE 6 Birthday present example: in order to arrive in the position to hand the gift, the agent was required to (a) reason on which type of gift would be most suitable, (b) find which way through town would be best to go to the store, (c) have an understanding of what the other wishes for a gift, and (d) imagine that not bringing a present would have had undesirable results

elicits contextual information based on previous visits of the location in question. Intuitively, it is not difficult to imagine why prospection would be beneficial to our ability as humans to navigate efficiently: when performing navigation, memories, [76] and emotional information associated to certain places that we visited in the past can make us prefer or avoid them. If our memory had not provided us with a location-related context, we would not be able to perform goal-oriented navigation.

Navigation itself does not refer only to large-scale movement. Within the meaning of navigation, we identify multiple nuances that depend primarily on scale and the individual who is performing it. Using mental simulation, an agent can move its arm towards an object using different perspectives than its own.[45] Similarly, one can take the perspective of another to infer a navigation plan.[27,35,36,77] Larger scale self navigation—that is, where the agent itself moves from one location to another—can also be evaluated[38] and anticipated[37] through mental simulation-based prospection.

5.3 | Theory of mind

The capability of an individual to assign mental states to oneself and others is known in the literature as ToM.[78] Functionally, possessing a model of others' decision process, which takes observations as input, enables the individual to determine goals, anticipate actions, and infer the causes of certain observed behaviors. The two predominant approaches to how the decision process is represented are the theory-theory,[79] which relies on a "folk psychology" that is used to reason about others in a detached way, and the simulation theory,[80] which claims that the individual's own decision mechanism is used for inference (simulation), using pretend input based on observations.

Simulation theory has received enthusiasm from artificial intelligence researchers, arguably because it provides an interesting and computationally feasible mechanism for reasoning about other individuals. The "like me" approach[81] has been adopted in various social agents that interact with others in virtual[59] and real[40,44] environments. It has also been used in team scenarios to enable a robot to take the predicted behavior of its team mates into account to improve its own plan.[27,36] Theory-theory-based approaches are less common, but show that "objectively" reasoning on the behavior of others can lead to comparable results.[35,77]

5.4 | Counterfactual reasoning

Whether expressing the regret that things could have been better if only actions were taken, feeling relieved that the worst scenario did not happen or simply imagining what would have happened if past events were different, humans often think in a counterfactual manner.[82] Counterfactual reasoning has been thoroughly documented in psychology[83] throughout the development of children and adults. This type of inference has been studied within the more general problem of causation.[84]

Interestingly, works that implement forms of counterfactual reasoning into autonomous agents are scarce. Examples include making use of this mechanism for minimizing regret in games with incomplete information[85]. Mental simulation has also been discussed as a mechanism for counterfactual reasoning.[86] However, computational approaches to inference about what could have been, via mental simulation, are limited, focusing on relatively simple cases of object continuity[28] under the form of integrating new knowledge into past events.

6 | COMPUTATIONAL IMPLEMENTATION

Based on how computational mental simulation has been approached in literature, we identify three main perspectives on modeling the paradigm.

The first type of approach is given by traditional symbolic systems, which model the process of mental simulation through sets of rules and logical inference. This category is characterized by a coarse level of granularity in prediction, as the rules they use are abstracted away from low-level information such as the detailed geometry of the environment, collisions, or location of obstacles. The majority of existing computational approaches to mental simulation are, at least to some extent, symbolic systems. Some of the most relevant examples of such agents[27,28,36,77] are constructed on top of well known cognitive architectures such as Adaptive Control of Thought - Rational (ACT-R)[87] and Soar.[88] Focus is placed on goal recognition through mentally simulating others' actions using the agent's own reasoning model[40,44,59] and on evaluating the outcomes of actions.[39] Using a symbolic approach, an agent would be able to perform mental simulation on high-level information like beliefs and annotated actions, but would require other, low-level tasks to be modeled separately and abstracted so that it can be used as a black box.

The second category consists in using sub-symbolic techniques to make predictions in the form of mental simulations. Granularity of the mental simulations is, in this case, finer as trajectories are continuously taken into account.[38] Likewise, sensory information can also be predicted,[37] which leads to a plausible approach to implicit anticipation. However, using only low-level controllers narrows the use of mental simulation to specific targets.

Finally, the category of systems based on analogical representations[89,90] consists in approaches, which model their environment as an internal virtual world.[26] This allows agents to change perspective,[45] anticipate behavior,[35] and generate scenarios that help them obtain useful information about the world and themselves.[46] Using analogical representations[91] provides a natural approach on mental simulation, similar to mental imagery in humans.[16] Nonetheless, existing computational approaches use specific models to perform this type of mental simulation.

7 | DISCUSSION

Within this review, we examined computational approaches that use mental simulation for decision-making by anticipating events in the environment and behaviors of entities that populate it. The study was divided into four main sections, each reviewing the state of the art through the prism of where, for what, why, and how mental simulation was used. Hence, relevant systems from literature have been discussed and analyzed, to identify their strong and feeble characteristics, within the context of the type of environment they aim for, which phenomena they are able to predict, which cognitive functions they achieve, and finally, the techniques used for their implementation.

7.1 | Analysis

The approaches that explicitly use mental simulation are compiled in Table 1 for a complete view of the level to which they address the aspects of this paradigm as suggested by the cognitive science community. Additionally, we investigate the way in which they achieved their functionality and also whether or not their authors provided testable proofs-of-concept or open source code.

Taken together, existing approaches cover all areas of interest in using mental simulation as an anticipation and decision-making technique; however, there exists no implementation that addresses all of them on its own. Neither does any approach propose a generic way that makes it extensible over all examined features simultaneously.

The majority of implementations have begun in virtual reality, but fewer have taken the leap to robotic embodiments due to dependencies on specific information about their environment. Those that do however pass into the real world are either limited in the actions they can perform or rely heavily on repositories of actions that are abstracted for the use within a higher level framework.

Focus is placed on solving only a subset of the cognitive functions associated with mental simulation, and this is done using specific models of the task at hand. Hence, not many elements are taken into account into mental simulation, for example, anticipating trajectories but not collisions, or focusing on only one of the environmental and behavioral aspects of the environment, although they are generally interdependent. One of the cognitive abilities linked with the paradigm of mental simulation—counterfactual reasoning—has been scarcely approached and only in a relatively simplistic fashion.

We have also discussed three trends in implementing computational mental simulation, namely, those using symbolic, sub-symbolic, and analogical representations. These approaches vary in mental simulation granularity, that is, the space and time scale to which an agent can perform a mental simulation of its environment. In essence, coarse granularity leads to faster computation of abstract knowledge, while fine granularity can cope with highly detailed models of reality. The advantages and drawbacks of these approaches are illustrated in Table 2.

Furthermore, as Table 2 also shows, the two major ways of addressing anticipating the actions of other presumably intentional entities in the environment—"like-me" and different/unknown structure—stem from the two dominant theories of how ToM is performed by humans: simulation theory and theory-theory, respectively. In effect, this led to implementations that are constructed to resemble humans (or other entities they may interact with) and use these models in mental simulation, while the others attempt to create abstract models of others' behavior for prediction.

Overall, specific implementations are often preferred due to convenience. However, this leads to limited functionality when the environment and the behavior of simulated agents change significantly. One example of technique, which is only used in few implementations, is automatic model creation. This enables the agent to infer its own body structure, but it is not currently used for other physical entities. Another example is represented by production rule systems, which have relatively high expressive power, but are not used in complex scenarios due to the difficulty of problem formalization. Connectionist approaches also exhibit high performance in creating efficient controllers, but learning rate drastically decreases with the size of the network and are therefore only used for specific tasks.

Finally, we investigated the availability of functional software support for the computational approaches to mental simulation. Few researchers have published runnable demonstrations of their work (including videos, test cases, and open-source code). For some works, only the cognitive architecture used is provided, but not the actual extension of the architecture to the mental simulation paradigm.

This study has led us to identify several shortcomings of existing works that use the simulation paradigm for anticipation and decision-making:

- Current approaches are constrained to function in relatively specific setups, with few exceptions, which do not provide access to the details of their implementation. Such exceptions that do aim to be more generic rely heavily on models created by experts which tend to be difficult to obtain for contexts with higher degree of complexity.
- Existing implementations are generally used in controlled scenarios and are not designed to be fully autonomous.
- Although approaches exist that function in real time, online learning is used only for specific tasks. The mechanism of the simulation paradigm, such as continuous imagination-reality comparison in complex environments and imaginative behavior, are not yet fully exploited.
- Due to either context simplicity or specific functionality, believability is only achieved to a relatively low level.

TABLE 1 Overview of areas of interest covered by relevant existing approaches

	Computational use of mental simulation															
	Where?		(for)What?						Why?				How?			Open?
			Environmental			Behavioral										
	Virtual world D/C, 2D/3D[a]	Real world	Trajectories	Collisions	Occlusions	Similar	Different	Self	Prospection	Navigation	Theory of mind	Counterfactuals	Symbolic	Sub-symbolic	Analogical	Source code or demo available[b]
77	C_{3D}						✓	✓		✓	✓		✓			~
45		✓	✓	✓	✓					✓					✓	
28		✓	✓		✓					✓		✓	✓			
59	C_{3D}					✓		✓			✓		✓			
40	C_{3D}	✓	✓		✓	✓		✓			✓		✓			
46		✓		✓				✓	✓						✓	~
35	D_{3D}		✓				✓			✓	✓				✓	
27	C_{2D}	✓	✓				✓	✓		✓	✓		✓			~
44	C_{3D}	✓	✓		✓	✓		✓			✓		✓			
36	C_{2D}	✓	✓				✓	✓		✓	✓		✓			~
37	C_{2D}		✓							✓				✓		
38	C_{2D}		✓			✓		✓	✓	✓				✓		✓
54	C_{3D}		✓	✓					✓				✓			✓
26	C_{3D}		✓	✓					✓					✓		✓
43	C_{2D}		✓						✓						✓	✓

[a] Virtual world categories: discrete/continuous and two-dimensional/three-dimensional.

[b] Partial source code, such as providing only the main architecture sources but not the full implementation of the approach, is marked with ~.

TABLE 2 Pros and Cons of approaches to computational mental simulation

Approach	Pros	Cons
"Like-me"	◇ Mechanism for goal inference	◆ Correspondence problem
		◆ Specific
Different (unknown)	◇ Independent of other's structure	◆ More difficult to learn
	◇ No assumptions	
Symbolic	◇ High-level inference	◆ Actions abstracted away
	◇ Direct rules	◆ Can miss details
Sub-symbolic	◇ Low-level control	◆ Specific controllers
	◇ Precise movement	◆ Difficult to model interactions
Analogical	◇ Intrinsic ability to generate scenarios	◆ Construction difficulty
	◇ Multi-scale interaction	

7.2 | Insights into computational mental simulation

In attempt to overcome these shortcomings, we have developed a generic agent architecture, which has mental simulation as its core mechanism for decision-making, using analogical representations.[92] The genericity of the open-source architecture was shown by instantiating it into agents within environments with varying complexity such as continuous space, real time, two and three spatial dimensions, and varying embodiments.[93,94] The cognitive process implemented in our work is described in Figure 7, which constitutes the conceptual framework to enable the capabilities studied in this paper.

While the results have been encouraging, the main difficulty consisted in automatically adapting the agent's mental models of its environment. As we have seen in related works, conveniently implementing specific models leads to a narrow range of applications for the resulting agent. In response to this challenge, we suggested a heterogeneous model approach, which can also accommodate machine learning techniques, with the long-term goal of obtaining a self-sufficient, adaptive, and autonomous agent that can make decisions in a complex environment.

With regard to the pitfalls associated to existing implementations and challenges encountered in our own work on the subject, we propose a number of insights, which we hope will further guide the development of agents with mental simulation capabilities:

- Mental simulation should be used as an integration paradigm or a central architectural layer rather than a separate module to an existing agent. A separation would most likely lead to duplicated or translated information to and from the module with possible loss of functionality, while integrating the mechanism as a central part of the agent would theoretically enable the agent's entire knowledge to be processed in a more coherent way.
- Whether with sensory information or arbitrary data structures, mental simulations should use a common representation. For the time being, pure sensor data may not be suitable for an artificial agent to use as internal structure even if it seems biologically plausible. Instead, intermediary analogical representations, such as geometric shapes or complex meshes, could suffice until more powerful structures are developed. Regardless the choice, these representations should be expressive enough to model physical interaction.
- Temporal synchronization is necessary for the applicability of mental simulations. The agent must keep track of real and virtual time in order to correctly apply

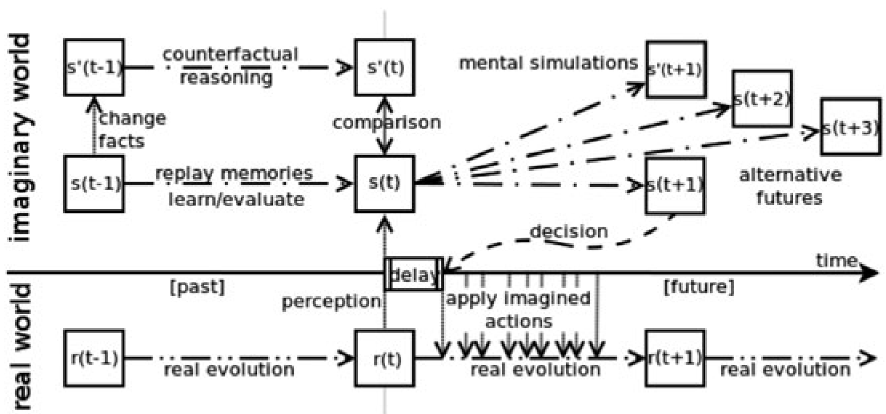


FIGURE 7 Cognitive process of a mental simulation based agent at an arbitrary time t: the state of the real environment $r(t)$ is transformed into a mental image $s(t+1)$ through perception, from which alternative futures $(s(t+n), s'(t+n))$ can be obtained, past events $s(t-m)$ can be reenacted or changed to produce "what if" scenarios (s'). Decisions can be based on evaluating alternative futures

simulated actions in the real environment. This also applies in the case where mental simulations and environment perception run at different time scales.

- In addition to synchronization, due to the concurrency of simulation and reality, a number of simulated actions will be inapplicable because by the time the mental simulation reaches a result, the world would have progressed enough to make early actions impossible and therefore invalidating the entire prediction. A prediction can only be considered valid if all the simulated actions are applied to the environment; therefore, the agent must estimate the duration of a simulation and block novel actions within that virtual time interval.
- In a dynamic environment, mental simulations should take the agent's current action plan into account. This not only avoids invalid predictions (such as failing to account for actions in the near future, which may completely change the outcome) but it also allows the agent to, in a way, regain the time lost by blocking novel actions at the beginning of a simulation.
- Multi-agent systems seem like an attractive candidate for constructing the inner world. Each entity could have it's own controller which can be learned separately by observing and trying to replicate the behavior of its real counterpart.
- Mental simulation by itself is not enough; it must be integrated with perception, learning, and planning. Perception should translate sensor information into the internal representation of choice, machine learning should be used to internally replicate and predict the representations of external targets, and finally, the agent should be able to include planning techniques within its predictions.
- The models used to evolve the inner world of the agent should be stable in relation to observed reality. In other words, the output of a model, when given unseen data, should not stray far from perceived reality, as this will propagate errors through the mental simulation rendering it invalid. Small errors are unavoidable, but they should be limited by using statistical or memory-like learning algorithms rather than pure regression.
- Goals should be expressed as an environment configuration, using the agent's internal representation. First, this would be coherent with the unique internal knowledge representation and, second, favorable configurations could be learned by the agent, possibly leading to a generalized goal system approach.

To conclude, there are still efforts needed to obtain a self-sufficient set of mechanisms that enable an agent to be fully autonomous and adaptive in arbitrary environments. Meanwhile, extensive research has been done in planning, machine learning, computer vision, and robotics, which led to robust algorithms that provide satisfactory solutions to say the least, to many individual problems. In this review, we presented our study of a relatively recent approach to artificial cognition – computational mental simulation – and determined that it is indeed applicable to a wide range of scenarios. Our own work on the subject also showed that a generic mental simulation agent architecture is feasible and can integrate a series of currently existing algorithms in a novel way that may lead to more adaptive virtual and robotic agents.

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