A Comparative Study of Artificial Intelligence Models and Human Hippocampus

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ABSTRACT

In the daily life of human beings, the frequency of use of robots is increasing year by year, which puts higher requirements on the capabilities of robots. How to accurately achieve navigation for predetermined goals is the biggest challenge at present. This paper focuses on several popular calculation models, by comparing the model with the physiological research related to spatial positioning and navigation in the hippocampus, we can judge whether the model design conforms to the physiological basis and is consistent with the behavior produced by human psychology to some extent. It can be concluded that if robots want to obtain higher intelligence and make more complex decisions, intelligent robots need to learn independently and cognitive memory of the current environment, which requires the study of physiological cognitive model and the comprehensive study of human brain cognitive model and hippocampus to form a set of comprehensive cognitive mechanism and computational model.

Keywords: Bayesian assumptions, neural networks, cognitive maps, spatial cells

1. INTRODUCTION

With the development of artificial intelligence, more and more intelligent robots are needed in more and more fields, such as modeling the environment, identifying and planning the path. This intelligent robot requires strong cognitive function. Traditional computational cognitive models are usually based on Bayesian probability, such as using nonlinear optimization to analyze the information in the environment. The huge database constructed in this way often needs huge computing power. For many characteristic problems, there are often unpredictable uncertainties, which cannot make the robot close to the real direction of artificial intelligence. Therefore, the ability to recognize the environment has become one of the hotspots in the field of robotics. This paper analyzes and compares the current mainstream computational cognitive models by combining several fields such as cognitive neuroscience, biological psychology and behavioral psychology, and predicts the development trend of computational cognitive models.

At present, computational models based on biological cognitive model can be divided into the following three categories: symbolic computational cognitive model, which is mainly based on the display rules of symbolic system and local representation logic; In the computational cognitive model based on neural network, a series of corresponding processing units are set and expressed in a distributed form. The cognitive process of mammals is simulated by connecting and influencing each other through weighted parameters, and the data is trained through learning; Computational cognitive model based on system cognitive structure is a hybrid model using symbols and neural networks

2. SYMBOL-BASED COMPUTATIONAL COGNITIVE MODEL

Cognitive map models are usually applied in the field of artificial intelligence, and traditional modeling methods in the field of artificial intelligence usually use physical symbols to represent [1], that is, to define physical symbols and operate on these symbols. Some rules and algorithms are proposed to operate, create, modify or delete these symbols [2]. The symbols of cognitive map models are usually defined as functional cells such as location cells, grid cells and spatial knowledge that constitute the cognitive map. Such models usually assume a discrete state between symbols, which can be modeled as symbols representing local places. However, the traditional artificial intelligence based on traditional physical symbols has been criticized due to the problem of symbol foundation [3]. Barsalou proposed a perceptual symbol system to replace the

traditional physical symbol system. The storage and reactivation of perceptual symbols operate at the level of perceptual components—not at the level of overall perceptual experience [4].

At present, some symbol-based cognitive map models have been implemented and have been applied in the field of artificial intelligence. Jefferies and Yeap [5] will use a cognitive mapping computing environment and express it as a cognitive map. Symbol-based cognitive map models usually use SLAM (Simultaneous Location and Mapping) to build a measurement table of the local environment. The realization of SLAM usually combines self-motion information with landmark observations, and relies on the estimated probability state to calculate the optimal method in the statistical sense.

The core idea of SLAM is related to the probability of symbols, and the "Bayesian brain" hypothesis proposed by Knill and Pouget holds that the brain probabilistically represents sensory information in the form of the probability distribution, so the two have similarities. [6] The Bayesian hypothesis has been proven to be successful in constructing the computational theory of perception and sensorimotor control, but the Bayesian hypothesis has fewer neurophysiological data. There are also some studies showing that through Bayesian clue integration, it is possible to predict the firing of location cells in the hippocampus at the neuron level. Studies have shown that spatial cues at the level of human and animal behavior have a high probability of being integrated through statistical methods. [7-9].

Figure1. Cognitive map comparison based on symbols

3. COMPUTATIONAL COGNITIVE MODEL BASED ON NEURAL NETWORK

Different from symbol system and discreteness and locality, cognitive map models based on neural networks usually choose non-local and distributed representations. A neural network is a simplified model of the brain that is composed of multiple units represented by neuron homotypes connected by weights. Learning is achieved by setting and modifying the activation value of the unit and the connection strength between each unit. Its model can also be called the Connectionist Models of Cognition. Its core is that knowledge is stored in the strength of the connection between the units, and the recognition is imitated by the activation mode of the simple processing unit connected to the complex network. Know [10].

Psychologists such as Freud, James and others have initially proposed early neural network theories. However, as Dang Rushley's research showed that the performance of the brain only depends on the number of injuries, neurons cannot be The specific participation in

the cognitive process no longer has scientific support for this theory. But since the 1930s and 1940s, people began to use computer technology to describe the behavior of neural cell networks.

There are many different construction forms and implementations of neural networks. First, the input can be multiplied by its weight and threshold to obtain a binary input, the simplest perceptron. This is followed by a two-layer feedforward network, a three-layer feedforward network, a competitive or self-organizing network, an interactive network, and so on. In addition, there are recurrent neural networks that facilitate feedback connections and loops, biological neural networks BNNS that can be reasonably assumed to conform to biological foundations, and pulse neural networks SNN that are most in line with actual physiological foundations and phenomena.

Many researchers have proposed artificial neural networks based on the hippocampus and another cognitive neuroanatomy. Burgess et al. proposed a

bioartificial neural network model, whose core thinking is that Gaussian response to drive input will cause positional cells to discharge and adjust to a characteristic distance position field. This model explains the location specificity of hippocampal cells [11]. Then O'KEEFE et al. extended the model to boundary vector position cells [12-13], emphasizing the importance of expanding clues in specific heterocentric directions, especially on environmental boundaries, and successfully recorded the rat's Nerve and human behavior data are not actually used in the field of artificial intelligence.

Strösslin et al. [14] proposed another bioartificial neural network model based on rodent representation (area) navigation based on previous modeling results. Compared with simple boundary distance measurement, this model adds complete visual processing. The system is composed of multiple interconnected neuron sub-networks and neuron groups. This model can accurately

record many behavioral and neurophysiological data of rodents. Through computer testing, the computer simulation behavior of the modified model can be more similar to the behavior of animals in the actual environment.

Similar to Strösslin et al. through Hebbian synapse driving to simulate the firing of head direction cells and position cells, Barrera et al. [15] proposed another biological neural network model of brain neurophysiology, which combines kinesthetic and visual The hippocampus and striatum, and use reinforcement learning in the form of an Actor-Critic architecture to give appropriate rewards to the spatial position learning, so that the applied robot can learn the best route from a fixed position specified in the maze to the target. Their model accepts four sensory inputs: motivation, self-motion information, visual landmark information, and providing possible actions.
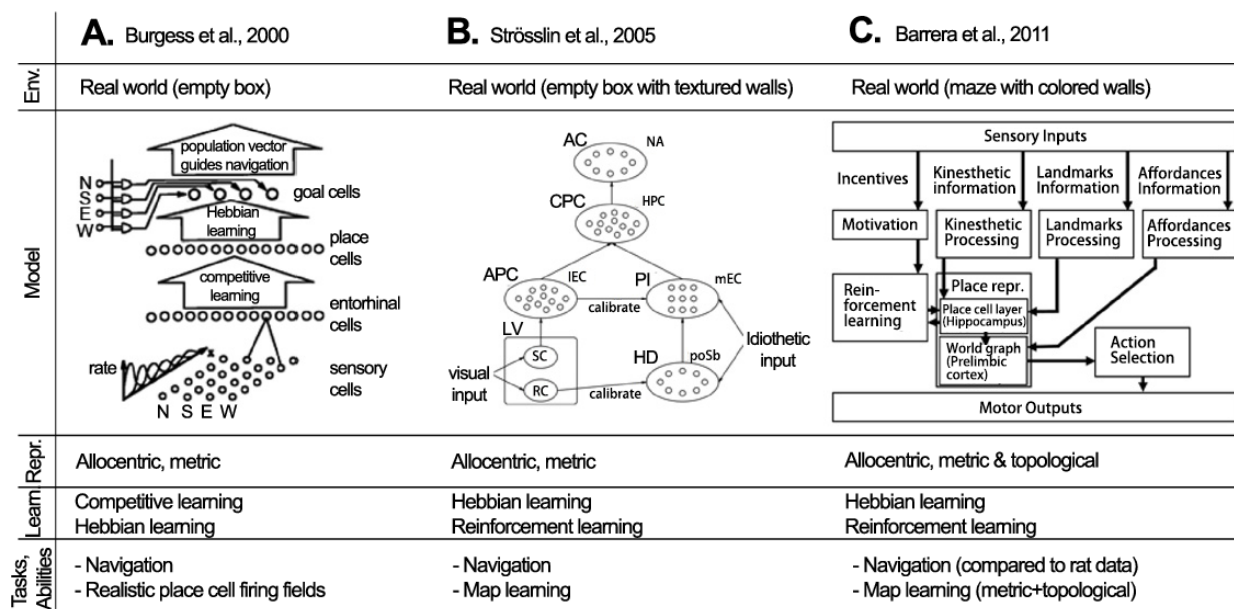

Figure 2. Cognitive map comparison based on Neural Network

4. COMPUTATIONAL COGNITIVE MODEL BASED ON SYSTEM COGNITIVE STRUCTURE

The core idea of the system-level cognitive architecture is to model a wide range of multi-level, multi-domain interconnected cognitive phenomena. Compared with the computational cognitive model that focuses on revealing one or a few local phenomena or processes, the system-level cognitive model attempts to study the overall behavior and explain the structural attributes of thinking [16].

Harrison et al. [17] proposed such an extended system called ACT-R/S. Two additional systems have been added to ACT-R: a "manipulable system" (an easy-to-operate object representing the spatial characteristics of

an object) and a "structural system" (representing the relative approximate structure of an object in space). The latter consists of a "path integrator" and a buffer containing multiple space blocks called "configurations". Each block stores a self-centered vector and its identification (ACT-R/S only contains Self-centered representation). The object is responsible for entering this structure buffer, which contains two or three nearest objects-when this capacity is exceeded, the nearest block will be discarded from this buffer (but will still exist in "declarative memory" For later retrieval).

Casimir [18] proposed by Schultheis and Barkowsky is a clearly designed cognitive architecture as a framework for computational modeling of human spatial knowledge processing. Its main part is composed of three parts, namely long-term memory (LTM), working memory (WM) and chart interaction components

(concreting working memory representation on a chart, or visually checking the chart to construct a working memory representation).

Another hybrid cognitive architecture is LIDA proposed by Franklin, Madl, D'Mello, and Snaider, which is an improvement of the method proposed by Madl et al. in 2013. Although there is no simulated neuron, LIDA is indeed inspired by biology. Each part of the function of the model is mapped to the brain area, mainly based on the global working space theory of functional awareness (by Baars and Franklin in 2009 and Baars in 2013 , Franklin and Ramsoa et al.), as well as many psychological and neuropsychological theories, including basic cognition, working memory, and the omans H-Cogaff cognitive framework. This is a recent architecture, only partially realized, but some psychological experiments have been reproduced [19-21].

The cognitive cycle of LIDA, which corresponds to the action perception cycle in neuroscience Foster research [22], consists of three stages. The "understanding" stage includes perception of the environment, detection of features, recognition of objects and categories, and construction of internal Express. The "attending" phase is responsible for deciding which part of the representative should be paid attention to and broadcast to other parts of the system, making it the content of the current consciousness. This section allows the agent to choose the appropriate action to perform during the "action" phase. In the comprehension stage, perception is recognized based on LIDA's perception knowledge base, Perceptual Associative Memory, which is a connected structure that contains nodes activated through links. The recognized objects, categories, etc. are stored in LIDA's preconscious "working memory" and are represented by the structure of PAM nodes and the links between them.

5. CONCLUSION

This paper studies the cognitive map comparison based on symbols, neural network and system cognitive structure. It can be concluded that although there are already generated navigation systems based on symbolic algorithms, due to the limitation of computational power, the similarity of the simulated brain is low, and more complex tasks require non-symbol algorithms. The connectionist model can be understood as an approximation of general brain mechanisms, which solves a long-standing philosophical problem about their role. In addition, understanding general scientific models from the perspective of general mechanisms can not only unify the types of inferences made in modeling and experiments. It also solves some internal problems in the mechanism literature about the relevance of models and interpretations. In addition, the system-level cognitive

architecture starts from the whole, focusing on the relationship and interaction between parts.

Intelligent robots need to organically combine various organs and link these organs with the main body. This is a distributed and autonomous organic combination, which is the same as the working principle of brain cognitive nerve and Haimo cognitive cortex, so as to form an advanced intelligent system, rather than a simple linear connection. This system can independently develop a set of expression of the environment through the cognition of the environment, and store it in the intelligent system in an abstract way, so as to complete the intelligent decision-making such as deduction and prediction. The construction of robot bionic cognitive model will also be a research hotspot in the future.

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