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Parallel cognition: hybrid intelligence for human-machine interaction and management*

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Abstract: As an interdisciplinary research approach, traditional cognitive science adopts mainly the experiment, induction, modeling, and validation paradigm. Such models are sometimes not applicable in cyber-physical-social-systems (CPSSs), where the large number of human users involves severe heterogeneity and dynamics. To reduce the decision-making conflicts between people and machines in human-centered systems, we propose a new research paradigm called parallel cognition that uses the system of intelligent techniques to investigate cognitive activities and functionals in three stages: descriptive cognition based on artificial cognitive systems (ACSs), predictive cognition with computational deliberation experiments, and prescriptive cognition via parallel behavioral prescription. To make iteration of these stages constantly on-line, a hybrid learning method based on both a psychological model and user behavioral data is further proposed to adaptively learn an individual's cognitive knowledge. Preliminary experiments on two representative scenarios, urban travel behavioral prescription and cognitive visual reasoning, indicate that our parallel cognition learning is effective and feasible for human behavioral prescription, and can thus facilitate human-machine cooperation in both complex engineering and social systems.

Key words: Cognitive learning; Artificial intelligence; Behavioral prescription
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1 Background of cyber-physical-social-systems

The networking and automation of traditional devices and equipment have fiercely expanded the complexity of cyber-physical-social-systems (CPSSs) (Wang, 1999, 2003, 2010), such as the manipulation of aerospace craft, nuclear power plant surveillance, and high-speed railway control. Such CPSSs require efficient collaboration between humans and machines to jointly complete final tasks (Wang, 2013; Zhang JJ et al., 2018; Wang and Wang, 2020). During their constant interaction, the fast exchange of information or control instructions among system components and operators may create human-machine conflicts, which then leads to many sorts of safety accidents (Bi et al., 2017; Palmer, 2020). Despite the variety of potential reasons, one fundamental issue is that traditional system design internalizes operators as part of the system and strictly regulates their operations according to pre-determined operational rules or instructions.

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This design principle characterizes mainly coarse human operator requirements and assumes that they can "perfectly" undertake their assigned subtasks. However, different operators have different physiological and psychological foundations such as cognitive load, distraction, and knowledge level. Distinct cognitive status may result in different decision-making styles, or even unsafe operations (Walters et al., 2005). To consider such differences in the human-centered design paradigm, monitoring is required to "learn" the operator's physiological and mental states (like the fatigue or risk preference) and further prescribe operator actions to reduce unconscious human errors.

Apart from the above interactive human-machine systems, the demand for prescribing human behaviors derives from another typical CPSS—the management of social group decisions (Wang, 2004, 2020; Wen et al., 2013). Because the collective strategy stems from a bottom-up aggregation of the group members' decisions, the macro emergent phenomenon is also grounded in one's micro cognitions and behaviors. However, because most members are self-interested and have access to only local information, their "myopic" decisions may not lead to the optimal choice overall. With the support of social media, which seriously accelerates people's social process, even a few myopic actions can result in inefficient operation of the whole system or radical public events (Gover et al., 2020). Therefore, scholars concentrate on modeling and analyzing social behavior by capturing individual cognitive features and the interaction between actual social and physical systems, and on a mechanism design that can prescribe behavior that maximizes the utility of the social system. Some research has already begun, but further achievements are still expected (Ye and Wang, 2018; Ye et al., 2020).

Virtual reality (VR), augmented reality (AR), artificial intelligence (AI), and other emerging technologies provide tools to achieve the goal of prescribing human behavior. By creating a virtual environment that is consistent with the real situation, we can present particular stimuli to an operator to lead him/her to react or respond in specific ways. This would supply personalized operational services and deal with individual cognitive heterogeneity. Based on the demands and technological support mentioned previously, we propose a new research paradigm—parallel cognition—to computationally interpret, learn, predict, and prescribe individual behaviors under certain circumstances in given tasks, as underlined initially in Wang (2018a, 2018b, 2018c, 2018d) and Wang et al. (2019). Parallel cognition starts by integrating existing psychological models into a virtual agent, and then exploits AI to build equivalent machine learning surrogates. Using a data-driven approach, the learning surrogates will adaptively extract new cognitive knowledge from an individual's environment-action data flow to adjust or enrich his/her customized cognitive model. This stage focuses on describing one's mental state, and is thus called "descriptive cognition." By recombining the fine-grained cognitive knowledge, the virtual agent will computationally search numerous deliberative paths to investigate one's probable decisions in different situations. The search process is called "computational deliberation experiments" and represents "predictive cognition." Finally, with the best response to the current environment, the intelligent agent will select the most appropriate environmental signals to direct the individual's action in the expected way, which is called "prescriptive cognition." The learning–search–prescription loop (like the human perception–reasoning–decision loop) is constantly executed during the whole interaction, so the human-machine system would be iteratively optimized through the entire life of the task. The contribution of this paper is three-fold: (1) a new research paradigm called parallel cognition is proposed to reduce the human-machine conflicts in decision-making in CPSSs and harmonize their cooperation in human-centered interaction; (2) a hybrid learning method based on both a model and data is proposed to adaptively learn an individual's cognitive knowledge; and (3) the proposed architecture and method are tested and validated in travel-related behavioral management and vision-reasoning tasks.

2 Research paradigms of cognitive science

Proposed by Prof. George Miller in the 1970s, cognitive science is an interdisciplinary research approach that includes six traditional fields as Fig. 1 shows (Miller, 2003). Miller initially saw psychology, linguistics, and computer science as central, and the three other fields as peripheral. However, the

six fields were fully connected later to form the famous hexagon in the figure. From the top down in a clock-wise direction, philosophy, linguistics, and anthropology represent mostly right brain functions. They are affective knowledge from social sciences. From the bottom up, by contrast, neuroscience, AI, and psychology stand for left brain functions, where the rational thinking from an engineering perspective is "encoded." As the breadth of cognitive science is so great, we will review mainly the research paradigms of cognitive psychology, AI, and cognitive neuroscience, which share some common links.

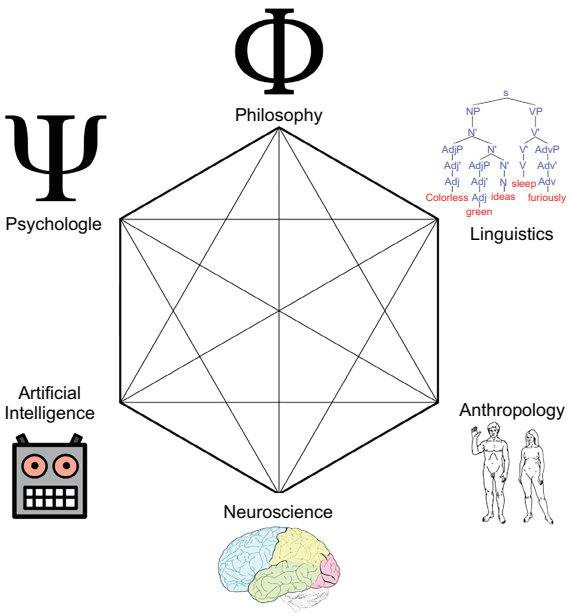

Fig. 1 Hexagon of cognitive science

Partly originated from cybernetics, which was defined as "the science of control and communication in the animal and the machine," cognitive science first attempts to uncover the mechanisms of cognitive behaviors using an approach referred to as cognitivism (Wiener, 1948). The birth of the cognitivist paradigm, and its sister discipline, AI, dates from a conference held at Dartmouth College in 1956. The basic thought of cognitivism is that cognition is achieved by computations performed on one's internal knowledge. By exploiting the newly invented computer at that time as a literal metaphor for cognitive function and operation, internal knowledge is encoded as a collection of explicit symbols—localized abstract encapsulations of information that denote the state of the world around the agent. In this way, symbolic information about things and actions is associable and the cognitive agent can then reason effectively about the knowledge to reach conclusions, make decisions, and execute actions they deem appropriate (Morse and Ziemke, 2008). This reasoning usually adopts a heuristic search in its implementation. Allen Newell and Herbert Simon, in their 1975 ACM Turing Award Lecture, summarized that a physical symbol system has the necessary and sufficient means for general intelligent actions and it exercises its intelligence in problem-solving by search (Newell and Simon, 1976).

Although the operation of knowledge in cognitivism is quite intuitive, it does not seem biologically plausible. Thus, the emergent paradigm of cognitive science seeks to maintain the autonomy in cognition (Brachman, 2002). Different from cognitivism, many emergent approaches adhere to the principle that the primary mode of cognitive learning is through distributed information processing rather than knowledge, as is the case in cognitivism (Christensen and Hooker, 2000). Emergent cognition takes the abstract structure of the biological brain and tries to "reproduce" the process of human cognition from the bottom up. By adopting a hierarchical structure, the bottom level simulates the human cortex and neurons using an artificial neural network in AI, while the top level simulates the active consciousness (Medler, 1998). The psychological knowledge of the world in this paradigm is implicitly encoded in the state of neural networks, and intelligent behavior is produced among the interactions of such relatively simple neural connections.

The connectionism in emergent cognition further relates to the study of cognitive neuroscience, whose objective is to examine the internal activities of the brain that lead to particular decisions. Generally, cognitive neuroscience techniques can be divided into two main categories. Measurement techniques, as the name implies, measure changes in the brain function while a research participant (human or animal) engages in some cognitive activity (Huang et al., 2005). A typical experiment using a measurement technique might require the participant to make a series of simple decisions while researchers record changes in neuronal firing or metabolic activity. Five main techniques are usually exploited to measure the neuronal axonal signaling and dendritic integration: single-unit recording (Matsumoto and Hikosaka,

2009), electroencephalography (EEG) (Gehring and Willoughby, 2002), magnetoencephalography (MEG) (Hunt et al., 2012), positron emission tomography (PET) (Huettel et al., 2009), and functional magnetic resonance imaging (fMRI) (Huettel et al., 2006). Manipulation techniques, in contrast, investigate how perturbations of the brain's function—by transiently changing neuronal firing rates or neurotransmitter levels or by permanently damaging tissue—change cognitive functions or behavior. They are sometimes called causal approaches. In brain stimulation, two popular techniques, transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS) technologies, are used to impose weak electric signals on brain regions, which alters the choices people make (e.g., in interactive games) (Walsh and Pascual-Leone, 2003; Knoch et al., 2006; Fecteau et al., 2007). In animal experiments, invasive microstimulation or lesion study is used to shape implicit brain-behavior relationships (Romo and Salinas, 2001; Tsai et al., 2009).

In summary, the research paradigms in cognitive psychology, AI, and cognitive neuroscience focus mostly on the deep understanding of how one's decision is achieved. Although there are some brain stimulation techniques to influence people's choices in cognitive neuroscience, they are based in only a few experiments on research participants. In real systems, brain stimulation cannot be applied to a group of people and the model can rarely grasp the heterogeneity of individuals limited by the small scale of experiments.

3 Parallel cognition: prescribing heterogeneous behaviors computationally

As indicated by Prof. Marvin Minsky, a father of AI, it is vast individual diversity that causes the emergence of intelligence (Minsky, 1986; Wang, 2016). Such diversity derives from different mental beliefs of the world. Individual cognitive differences can ultimately result in the emergence of systemic complex dynamics, sometimes chaotic, sometimes oscillating, and sometimes in a nice order. Description, analysis, and even prescription of such individual heterogeneity demand distinct cognitive models, or at least distinct parameter levels. The traditional modeling approach that relies on the "experiment–induction–modeling–validation" cycle, however, is probably not applicable for real systems such as complex CPSSs. On one hand, subjects in psychological or neural biological experiments usually account for quite a small part of the whole studied group. This often creates sampling bias, leading to inaccurate cognitive models that do not reflect behavioral differences among individuals. On the other hand, the final cognitive models from the traditional approach are "static." They can hardly model the dynamic cognitive process: human reasoning and decision-making patterns may evolve as their knowledge and skills gradually accumulate (such accumulation usually comes from learning, imitation, socialization, etc.). Therefore, to analyze and prescribe heterogeneous human behavior, we propose the research paradigm of parallel cognition.

The parallel cognition framework is composed of two peer systems—artificial and real human cognitive systems. These two cognitive systems form their own autonomous computational loops and keep running throughout the task in an independent way (Fig. 2). Either system operates on classic feedback, but performs interactions with the other in three stages: descriptive cognition, predictive cognition, and prescriptive cognition. Such interactions correspond to the modeling of artificial systems, computational deliberation experiments, and parallel behavioral prescription. Accordingly, we elaborate on these three stages in detail as follows.

3.1 Descriptive cognition: modeling of an artificial cognitive system

The first step of building an artificial cognitive system (ACS) is to synthesize an artificial population that characterizes the basic attributes and structures of studied groups. This step is essential for the analysis and prescription of social group behaviors that involve multiple members' decisions. For some human-machine interactions that are composed of only a few operators, the population synthesis is optional. The acquired artificial population acts as a start point of the subsequent computational deliberation experiments and parallel behavioral prescription. Thus, it needs to generate the "best possible" estimates of the actual population according to statistical metrics or other available micro individual data. Currently, the mainstream methodologies of population synthesis include joint distribution inference (Ye et al., 2017),

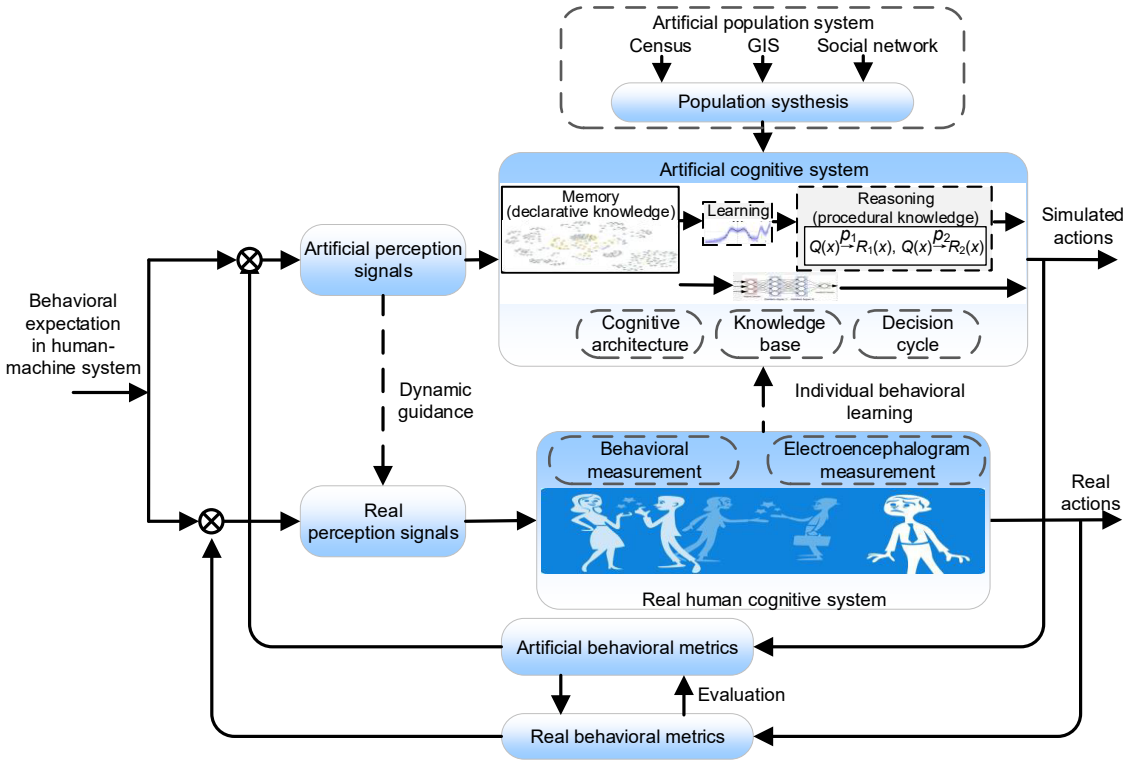

Fig. 2 Interactive loops of parallel cognition for human-machine systems (GIS: geographic information system)

copula-based estimation (Ye and Wang, 2018), and tensor-based optimization (Ye et al., 2021b).

The second step of building an ACS is to establish each individual's cognitive model. Because it is difficult to acquire human deliberation dynamically, the ultimate goal of an ACS is to open this cognition "black-box" by exploiting cognitive psychology and machine learning. Usually, an ACS adopts multi-agent techniques, where each agent can represent a particular individual or a group of people, depending on the model granularity. During computation, the agent performs a "perception–learning–reasoning–planning–action" cycle iteratively. The universal cognitive process is illustrated in Fig. 3, which is a two-layer structure and involves two parallel decision-making cycles (Ye et al., 2020). The bottom level contains deep neural networks (DNNs) to send and receive environment signals and social information from other agents. This layer simulates an individual's biological sensory and motor systems. The perception DNN (proactively or passively) receives low-level sensory signals from the surrounding environment and converts them into symbolic concepts or numerical values for the upper-level deliberative layer. Typically, convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversary networks (GANs), and their derivatives are used to simulate one's visual, auditory, and other perceptions, because these are the primary sensory patterns in humans. The actuation DNN controls the agent's actuators according to the input parameters provided by the deliberative results. The interaction network updates the messages from the agent's social network. Note that for convenience, the two neural networks for sending and receiving social messages are drawn together in the figure.

The upper layer of the cognitive model is an uncertain symbolic system that simulates human deliberative decision-making. As mentioned before, the decision-making may involve two parallel cycles (drawn in red lines in Fig. 3). One is the logical reasoning that simulates human rational deliberation. According to classic cognitive science, such rational deliberations are called system 2, where knowledge is stored in an explainable way and reasoning is conducted with explicit semantics (the cycle formed by the uppermost red lines in Fig. 3). A good example comes from proving mathematical theory. When

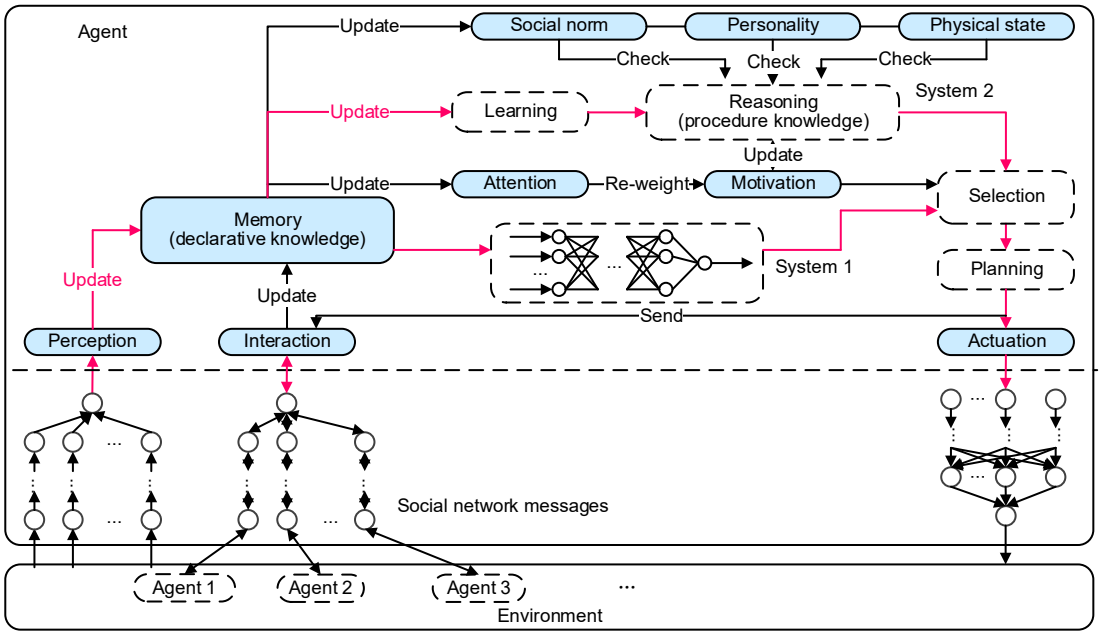

Fig. 3 A universal cognitive architecture (References to color refer to the online version of this figure)

doing that task, we need to understand every proof step in logical thinking from the assumptions to the final conclusions. This requires a common knowledge set among agents with each concept unambiguously referring to a specific kind of entity. The reasoning path can also be recognized by most people and can be taught to novices who have not completed that task before. The cycle of system 2 logic reasoning is composed of perception, memory, learning, reasoning, planning, and actuation. Perception/Interaction is based on the output of the DNN in the bottom layer that maps environment signals into uncertain facts with confidence levels. These uncertain facts are also called "mental beliefs" or "declarative knowledge" and are maintained in memory. They are typically stored as fuzzy logic rules like

$$\text{IF } x_1 = s_1 \text{ 'and' } \cdots \text{ 'and' } x_n = s_n \text{ THEN } D(\underline{s}) - f_s.$$

Here $\underline{\boldsymbol{x}} = (x_1, x_2, ..., x_n)$ is the input data from universe $\boldsymbol{U} \subset \mathbb{R}^n$, and $\underline{\boldsymbol{s}} = (s_1, s_2, \ldots, s_n) \in S_1 \times S_2 \times \cdots \times S_n$ represents the linguistic values defined on $\boldsymbol{U}$. f_s stands for the firing strength of the rule. In each computational iteration, the agent updates its beliefs by comparing the current environment state and historical knowledge. The inconsistency between the current state and the agent's expectations may result in learning, which updates the firing strengths of common reasoning rules that are stored in the reasoning module (Wang, 1992). These common reasoning rules are also called "procedural knowledge." Then a reasoning process is affected by social norms, personality, and the physical state, and multiple reasoning results are selected by motivations that are sorted in different priorities by attention to satisfying the most urgent needs. The motivation with the highest priority will be decomposed in planning and generate a series of actions. Such actions will be maintained until the corresponding motivation is fulfilled or canceled.

The second decision cycle corresponds to system 1 in cognitive science (formed by the lower red lines in Fig. 3). This cycle is somewhat direct as it models human-experienced decision-making. The "perception–learning–reasoning–action" cognitive loop is built on the artificial neural network (especially DNN), which implicitly encodes the agent's endogenous knowledge. Due to the adaptive learning ability of DNN, the cycle can dynamically imitate particular decision patterns from the environment and from others. Usually, reinforcement such as Q learning is added to this process so that the agent interactively improves its responsive strategies in specific situations. In general, reasoning of the second decision cycle involves only numerical computation, and is thus less complex than the uncertain logic

reasoning where many possible reasoning paths are heuristically searched. This has biological foundations. In real human cognition, rational deliberation represented by logic reasoning consumes more energy and is much slower than intuitive decision. For example, if you come across a mathematical theorem for the first time, try to prove its correctness. You will spend a great deal of time thinking with your own knowledge repository. When you are familiar with that theorem later, however, you will probably draw the conclusion as long as you see its assumptions. Although the proof steps can be reproduced via your achieved knowledge, you are inclined to omit such a detailed process. This example tells us that a human's explicit knowledge in system 2 tends to be converted into implicit knowledge in system 1, because it saves energy.

After the individual's cognitive model is constructed, the third step of building an ACS is to calibrate the model's parameters before application. Calibration and validation are essential, because they can help elevate the quality of the model, making the ACS approximate the real system. Many calibration methods can be used to complete this task. We refer readers to our previous work (Ye et al., 2021a) for further details.

3.2 Predictive cognition: computational deliberation experiments

The fuzzy logic rules of procedural knowledge representation can be converted into a causal graph, in which nodes and directed links stand for specific system states and causal relationships. The transfer condition (or strategy) between adjacent states is placed with the directed link. An example of a causal graph segment is shown in Fig. 4, with three system states as nodes and four directed links as transfer directions and conditions. Here, links construct cycles because the state transfer is bidirectional.

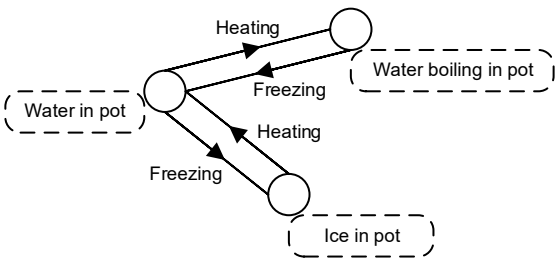

Fig. 4 An example of the causal graph segment

Given a collection of world states and procedural knowledge, reasoning can be modeled as a search process. When an agent perceives the current environment signals, the corresponding state nodes are activated, and the conditions satisfied (or strategies taken) will expand the causal graph by sequentially activating adjacent nodes until the desired world state is activated in the graph. This process will eventually create a reasoning tree with the current world state as its root and final achievable states as its leaves. Every path from the root to a particular leaf in the reasoning tree gives a strategy sequence to achieve the leaf state, and thus one sequence is for the desired goal leaf. Note that the reasoning path is uncertain and dynamically changeable because it is influenced by the agent's historical experience.

Ideally, all reachable paths from the current world state to the desired goal can be traversed to obtain all possible action sequence candidates, but this approach does not seem biologically plausible. On one hand, people tend to consider only a few choices rather than all possible candidates, due to the existence of "bounded rationality" (Campitelli and Gobet, 2010). Their decision-making greatly relies on their individual experience and personal habits. Thus, if they find a solution acceptable for the goals, then they are not inclined to make a change even if the solution is not optimal. On the other hand, when the reasoning tree is wide, the search process will be quite time-consuming. Unfortunately, this dilemma can hardly be avoided, because uncertainty is usually introduced. The uncertainty, in the form of membership degree and rule firing strengths, makes most action sequences possible, thus leading to a great spread of the generated reasoning tree. Such a spread makes traditional pruning or cut-off heuristics almost ineffective, and leads the final computational results to be temporally unacceptable. Therefore, a central issue for computational deliberation experiments is to select the reasoning path so that the achieved solutions are representative and the scale of the reasoning tree is controlled.

Reasoning path selection can be viewed as another hyper-parameter search problem. Reinforcement learning is typically adopted to investigate the action sequences with the largest "confidence." Here, confidence refers not only to the activation strength of an action, but also to the correlation with the anticipated actions the individual takes. The

correlation values are constantly learned during the parallel behavioral prescription, which will be discussed in detail in the next subsection. The whole computational deliberation experiments are illustrated in Fig. 5, where enormous deliberation paths are investigated and a most suitable prescription path is provided to the human user.

3.3 Prescriptive cognition: parallel behavioral prescription

Parallel behavioral prescription involves the dynamic bidirectional interaction between a real human cognitive system and an ACS. In the real-to-artificial direction, the ACS dynamically learns a human individual's cognitive features, reasoning paths, decision preferences, and so on, in an adaptive way, according to one's heterogenous actions. Based on the classic models from psychology and cognitive neuroscience, the learning fine-tunes them to distinct individual differences.

ACS learning of heterogeneous individual behaviors runs mainly in two modes. The first is to calibrate the parameters of psychological or neurological models. Combined with reinforcement learning, mentioned in the last subsection, the calibration adaptively adjusts the confidence of possible reasoning paths so that the search space in computational deliberation experiments is reduced to a more relevant area. Note that the calibration here is conducted constantly rather than only once. This is because in reality, human cognition and decisions may probably vary from time to time, as his/her knowledge and experience gradually accumulate. The second mode runs the incremental learning for the existing cognitive models, and aims to eliminate the bias of traditional models. Limited by the traditional "experiment–induction–modeling–validation" paradigm, cognitive models often come from a small number of typical subjects. Some uncommon patterns of thinking and decision-making in less popular groups are usually not covered by them. Therefore, ACS adaptive learning in this mode would inductively acquire new knowledge as supplements to the original cognitive knowledge base, and establish more accurate cognitive models for each particular individual.

In the artificial-to-real direction, behavioral prescription is implemented as the feedback control of one's environmental perception signals. Using a broad search of computational deliberation experiments, the ACS will find expected sequential states (of both machines and humans) as time goes on in the future via human-machine interaction. The optimal interaction pattern will determine the optimal perception signals to the individual to prescribe his/her appropriate actions. Basic perception signals contain visual image/video, audio instruction/warning, olfactory stimuli, tactile sense, and so on. The

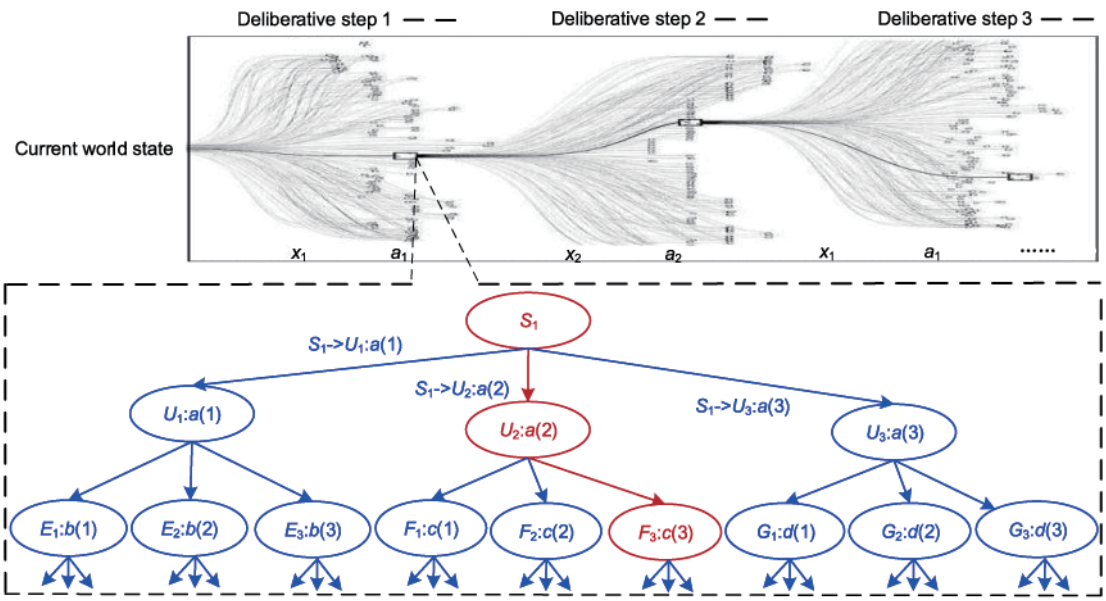

Fig. 5 Computational deliberative experiments

bidirectional interactions between two cognitive systems are iteratively running, with the ACS and its human counterparts co-evolving in synergy.

3.4 Adaptive deliberation learning

The objective of adaptive deliberation learning is to acquire heterogeneous behaviors and deliberative patterns of different individuals by exploiting the breakthrough of machine learning and AI. It is a potential solution for the limitation of traditional psychological studies. Based on the perceptive signals for a human participant and their responsive behaviors, machine learning can infer the cognitive reasoning process. Adaptive learning is composed of perception learning and reasoning learning. Perception learning aims to model the differences among individual perception abilities. These abilities are usually impacted by one's physiological factors such as age, vision, and active attention. In implementation, the results of perception are typically stored as a tuple like <agent$_i$, attr$_i$, value$_i$>, which represents the agent ID, the ith attribute's name, and value. The attributes may have linguistic values with firing strengths due to the discrete biological basis of human memory. During perception learning, each piece of knowledge of a particular agent in the ACS is iteratively updated through the perception network. Such updates take place in every human-machine interaction step via an on-line mode.

Fig. 6 gives an example of perception learning. Each attribute is encoded by a neural network segment. The input is the original perceptual signal (represented as in$_i$). The outputs are discrete linguistic values (s_{ij}) with a membership degree (μ_{ij}). Note that the figure omits the normalization of the membership, which is a usual operation in DNNs via a softmax function. Perception learning can be viewed as a fuzzification, which was implemented in our previous work (Wang and Kim, 1995) as a three-layered neural network with an input layer, a hidden layer, and an output layer, but a DNN is also applicable.

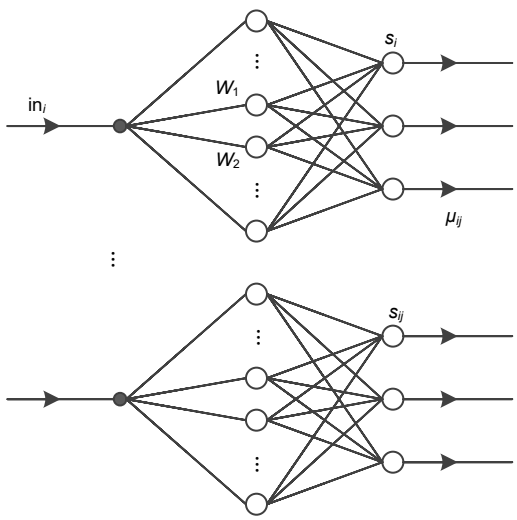

Fig. 6 An example of perception learning

With the precepted knowledge tuples as inputs, reasoning learning aims to adjust one's cognitive reasoning according to his/her environment signals and actions. The learning relies on the psychological decisions as a priori, and establishes their equivalent DNN (Fig. 7). The whole network can be viewed as three parts with their names marked (Kim and Wang, 1994). The pattern recognition network accepts the precepted knowledge and fuzzifies it into the values of predefined linguistic variables, which was introduced before. Memberships encoded as the outputs of a pattern recognition network are fed into a fuzzy reasoning DNN and converted into selection strengths of action candidates. The action selection network finally chooses a suitable action to conduct. This process can also be viewed as a de-fuzzification.

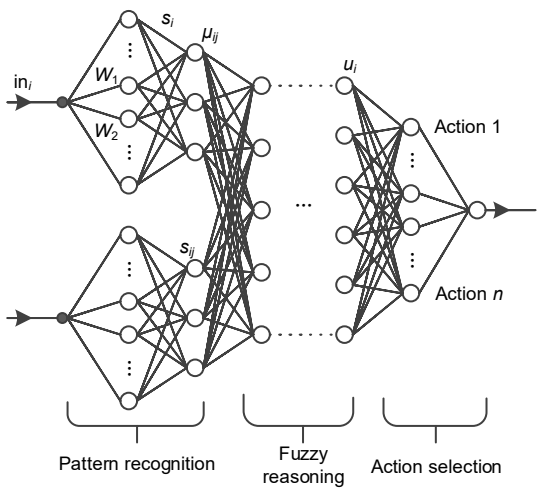

Fig. 7 Reasoning learning network

The reasoning learning network is trained using prior psychological decisions. It can be deemed as an approximation of the classical psychological decision modes. After training, the reasoning learning network can extract a decision rule from each record

in a data stream scenario. The real human's operation is used as the label, so the network can realize incremental learning. All the learned rules with frequencies are saved to a rule base for computational deliberation experiments. As the data stream comes one by one, the rule frequencies will be maintained dynamically. In this way, the decision modes in the ACS are adaptively adjusted.

4 Case studies

As mentioned before, parallel cognition is applicable for two main sorts of CPSS—the management of social group decisions and the promotion of a human-in-the-loop system in complex engineering. This section will give two typical case studies from these two fields.

4.1 Urban travel behavioral prescription

A representative scenario of social group decisions is urban transportation, in which the traffic situation is the aggregation of each traveler's behavior. To test the validity of travel behavioral prescription using parallel cognition, we established an experimental scenario in the central area of Qingdao in China, which includes about 263 traffic zones, 50 main roads, 20 variable message signs (VMSs), and so on. According to the census data, we synthesized 405 758 virtual travelers at the community level. Each agent chooses its travel schedule based on a classic disaggregate selection method by considering travel distance, congestion level, and familiarity. By default, the travel path is determined by

$$p_l^e = \frac{\exp(\frac{c_e}{L_l} + d_e \cdot F_{el} + \frac{f_e}{G_l})}{\sum_t \exp(\frac{c_e}{L_t} + d_e \cdot F_{et} + \frac{f_e}{G_t})},$$

where p_l^e stands for the probability that agent e selects the lth path. L_l is the length of the path. F_{el} is a fuzzy variable ranging from 0 to 10, and represents the agent's familiarity with the lth path. G_t is also a fuzzy variable ranging from 0 to 10, and represents the overall congestion level of the lth path. c_e, d_e, and f_e are coefficients. The corresponding learning DNN is shown in Fig. 8, where all the input signals are fuzzified with activation strengths. Here, OD stands for the travel origin and destination nodes in the road network. The output encodes all the path candidates and gives a selection strength for each one. After computational deliberation experiments, the expected optimal path is recommended to the travelers via official traffic websites, VMS, and applications in users' cell phones.

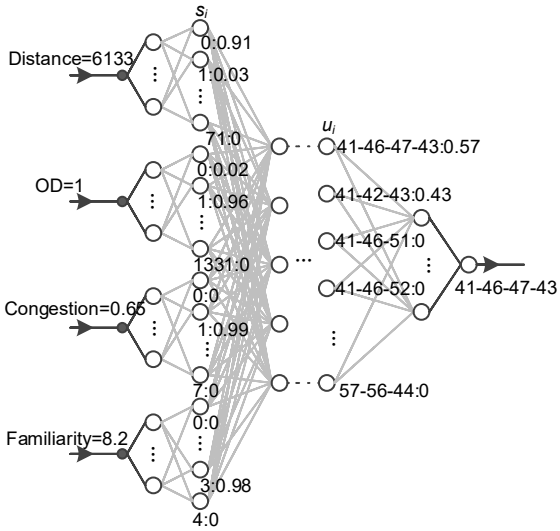

Fig. 8 Deep neural network for adaptive travel behavioral learning

Our preliminary test was conducted on May 11, 2020, and Fig. 9 demonstrates the comparison of queue length before and after the travel behavioral prescription. Note that May 11 and May 18 had similar traffic demand for the same weekday. In the east direction, the queue lengths decreased by 44.7%, 16.8%, and 8.7% during the whole day. The two other directions, south and north, also had reduced queue lengths, ranging from 21% to 33%. However, due to the low traffic volume, the queue length in the west direction increased slightly after our behavioral prescription. However, this did not impact the improvement of the overall performance. In addition, customized recommendations were served to over 85 000 drivers, indicating that our travel behavioral prescription is effective and valid.

4.2 Cognitive visual reasoning

A second test scenario comes from cognitive visual reasoning. In complex human-machine interactive systems, operators typically execute specific actions to ensure the successful completion of the task. Their decisions rely on the state information as inputs from machines via visual, audio, olfactory, and other perception channels. Among the channels, visual perception is the most important source of external information acquisition. The cognitive visual

reasoning task can effectively simulate the human decision process based on visual signal inputs.

Our experiment scenario was generated on the RAVEN dataset, which provides synthetic tasks for relational and analogical visual reasoning (Zhang C et al., 2019). The original dataset consists of 70 000 reasoning problems, with 60%, 20%, and 20% used for training, validation, and testing, respectively. As illustrated in Fig. 10, each problem contains eight images as inputs. Users need to select a suitable one from eight candidate images to complete the problem, so that the implicit decision rules are satisfied. The decision rule involves seven attributes as listed in Table 1, where the last four attributes correspond to the entities.

The part of our DNN was similar to Fig. 8 except that the raw image was processed by some convolutional and pooling layers (Fig. 11). The DNN was pre-trained with a given dataset, and during experiments, we dynamically selected the type of problem according to the user's learning preference. Our aim is to increase the subject's accuracy by learning what he/she is good at and what he/she is weak in. Fig. 12 shows the recognition errors of human participants, with each subfigure providing a particular attribute error. As can be seen, all the errors decreased with test iterations. In the early stage of experiments, visual reasoning problems were randomly given to the subjects. Thus, errors were relatively large. As human-machine interactions progressed, our ACS gradually learned the user's preference and chose the problems that he/she was good at according to computational deliberation experiments. This

Table 1 Attributes of cognitive visual reasoning

Attribute	Values	Value number
Structure	Singleton, ..., Out-In	4
Component	Grid, Left, ..., In	7
Layout	Cen.-Sin., ..., Dow.-Cen.-Sin.	10
Type	Cons., Prog., Arit., Dis.-3	4
Size	Cons., Prog., Arit., Dis.-3	4
Color	Cons., Prog., Arit., Dis.-3	4
Angle	Cons., Prog., Arit., Dis.-3	4

Cen.-Sin.: Center-Single; Dow.-Cen.-Sin.: Down-Center-Single; Cons.: Constant; Prog.: Progression; Arit.: Arithmetic; Dis.: Distribute

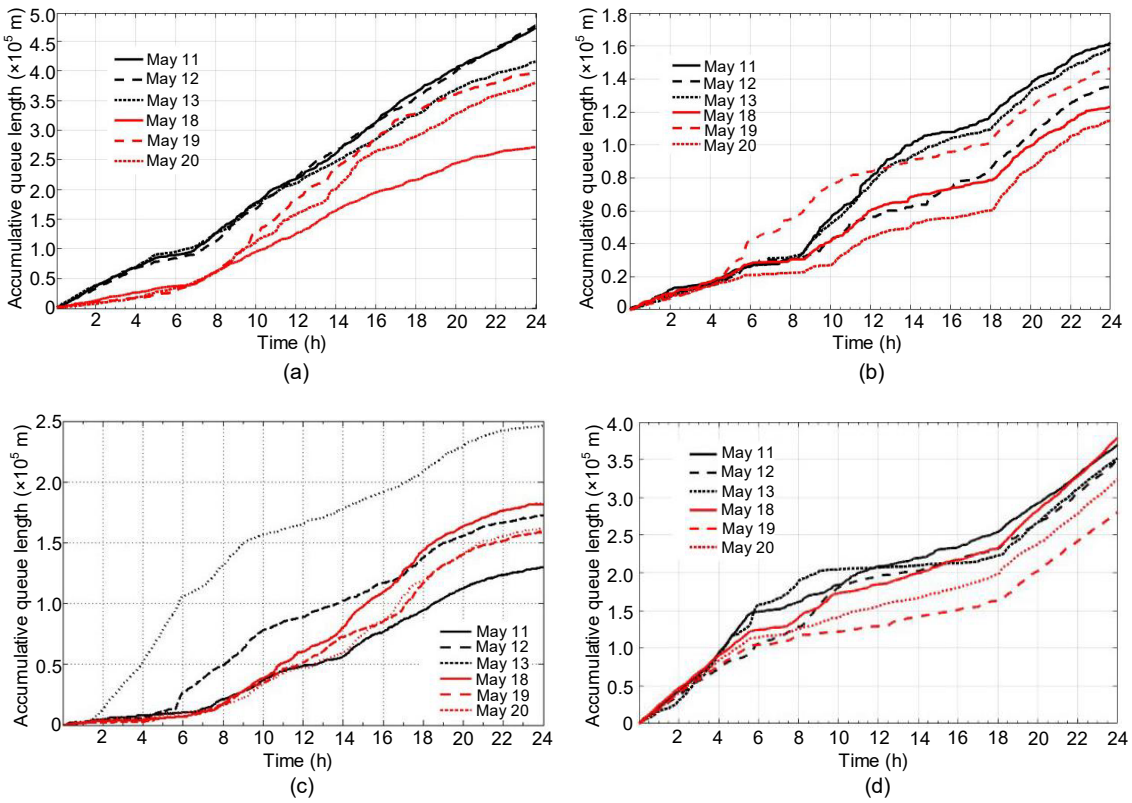

Fig. 9 Comparison of queue length before and after the travel behavioral prescription in the east (a), south (b), west (c), and north (d) directions (References to color refer to the online version of this figure)

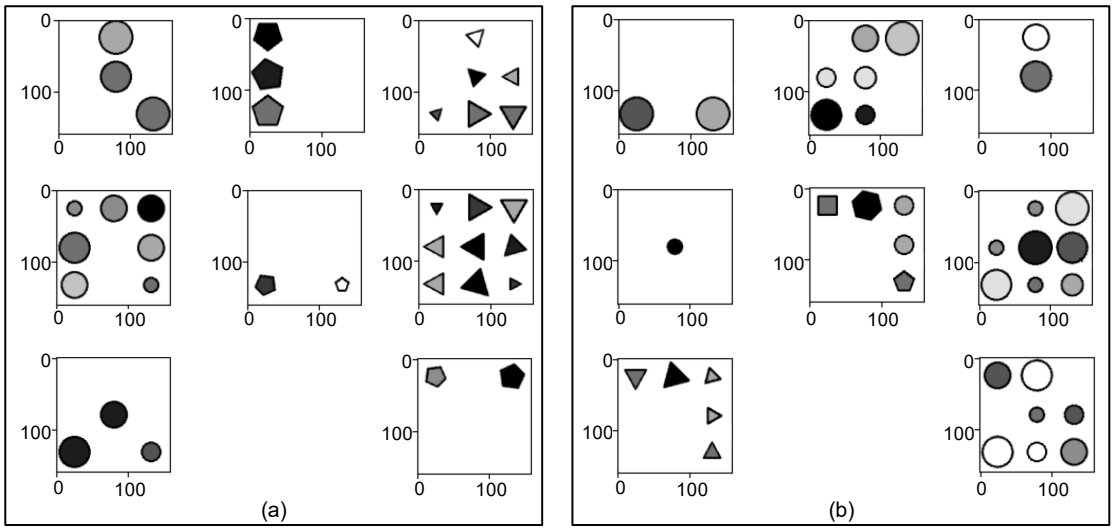

Fig. 10 An example of cognitive visual reasoning for a given problem (a) and candidates (b)

customization effectively led to a decrease in the average errors and finally reached a stable trend. Such a phenomenon could prove the effectiveness of our ACS and preliminarily validate the parallel cognition approach. A second phenomenon was that the overall image structure, component, and layout errors were smaller than those of other attributes. It is because these three attributes are global features, which can be more easily identified (the accuracies approached 100%). By contrast, type, size, color, and angle are local properties of each entity. Their values are usually confused by users, especially when an image includes several entities, bringing a heavy cognitive load to limited perception channels of the subject.

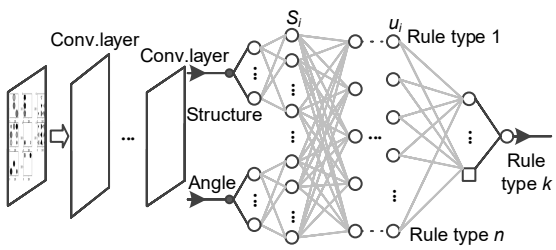

Fig. 11 Deep neural network for cognitive visual reasoning

Because conflict in real human-machine CPSSs usually results from a "wrong" action that the system "expects" the human operator to do, our ACS learns one's reasoning ability and selects suitable problems for the subject, so that his/her "correct" decisions can be increased as much as possible. This simulates the customized environment provided for the operator to reduce the risk of human-machine conflict. In this sense, this case study can test and validate our ACS.

Urban travel behavioral prescription and cognitive visual reasoning are two representative use cases for parallel cognition. Some other typical CPSSs are applicable as well. For instance, in complex social systems, this approach could be used to analyze regional economics (Gallegati et al., 2017), urban land use (Hosseinali et al., 2015), military strategies (Yun et al., 2015), public health (like COVID-19) (Nianogo and Arah, 2015), and the latest Metaverse. In the human-in-loop scenarios, driver assistant systems or autonomous vehicles are promising areas for parallel cognition techniques (Cunningham and Regan, 2015).

5 Conclusions and discussions

In this paper, we propose a new parallel cognition research paradigm with a hybrid learning method for individual cognitive knowledge. The objective of such an approach is to reduce the human-machine conflicts in CPSSs and harmonize their cooperation in human-centered interaction. The method was preliminarily tested and validated in urban travel behavioral prescription, a scenario of social group decision management, and cognitive visual reasoning, a scenario of individual operation prescription. Experiment results indicated that our

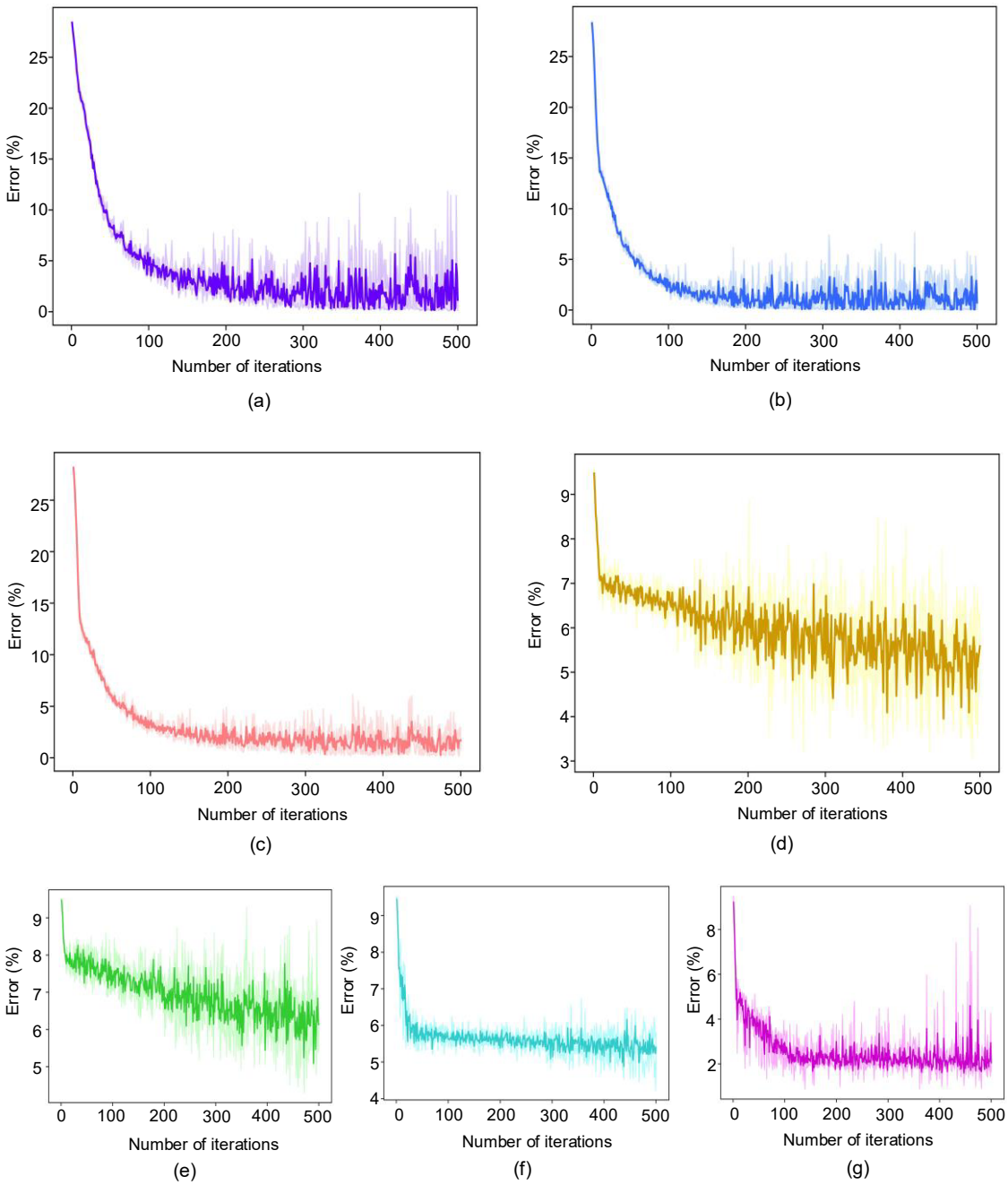

Fig. 12 Recognition errors of human participants: (a) structure; (b) component; (c) layout; (d) type; (e) size; (f) color; (g) angle

parallel cognition learning is effective and is probably feasible in representative applications.

The experiments in this paper are elementary. Our future improvements may address the following aspects: (1) Improve the accuracy of the learning method. Because the cognitive knowledge is simple in this paper, how to acquire more complicated cognitive knowledge in a data-driven mode is a focus of our next step. (2) Design distributed deliberation reasoning algorithms. When the ACS includes a large amount of cognitive knowledge, computational deliberation experiments will involve numerous reasoning paths. To ensure its time validity, we plan to introduce cloud computing for acceleration. Thus, designing distributed reasoning algorithms is an essential work for such a goal. (3) Validate the

approach in more application scenarios. The test experiment of cognitive visual reasoning in this paper addresses only simple polygons. To make the related methods more practical, complex recognition and reasoning in more open scenarios by jointly considering visual and textual information has already begun (Zheng et al., 2020, 2021). Such a hybrid use of image and text processing is another future direction.

Contributors

Fei-Yue WANG proposed the original idea for parallel cognition. Peijun YE designed the research and drafted this paper. Wenbo ZHENG helped design the experiments. Fei-Yue WANG, Xiao WANG, and Qinglai WEI helped organize the paper. Fei-Yue WANG revised and finalized the paper.

Compliance with ethics guidelines

Peijun YE, Xiao WANG, Wenbo ZHENG, Qinglai WEI, and Fei-Yue WANG declare that they have no conflict of interest.

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