Cognitive Model of Brain-Machine Integration

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Abstract. Brain-machine integration is a new intelligent technology and system, which is a combination of natural intelligence and artificial intelligence. In order to make this integration effective and co-adaptive biological brain and machine should work collaboratively. A cognitive model of brain-machine integration will be proposed. Environment awareness and collaboration approaches will be explored in the paper.

Keywords: Brain-machine integration · Environment awareness · Collaboration · Motivation · Joint intention

1 Introduction

Machines have advantages that humans can't match in terms of search, computing, memory, etc. However, machines are far less intelligent and efficient than human intelligence in terms of perception, reasoning and learning. In order to realize artificial intelligence with common attributes, it is necessary to combine the advantages of machine intelligence and human intelligence to achieve deep integration of brain with machine. Brain-machine integration is a new intelligent technology and system generated by the interaction of human and machine. It combines the advantages of human and machines, and is the next generation of intelligent systems [1].

At present, brain-machine integration is an active research area in intelligence science. In 2009, DiGiovanna et al. developed the mutually adaptive brain computer interface system based on reinforcement learning [2], which regulates brain activity by the rewards and punishment mechanism. The machine adopts the reinforcement learning algorithm to adapt motion control of mechanical arm, and has the optimized performance of the manipulator motion control. In 2010, Fukayarna et al. control a mechanical car by extraction and analysis of mouse motor nerve signals [3]. In 2011, Nicolelis team developed a new brain-machine-brain information channel bidirectional closed-loop system reported in Nature [4], turn monkey's touch information into the electric stimulus signal to feedback the brain while decoding to the nerve information of monkey's brain, to realize the brain computer cooperation. In 2013, Zhaohui Wu team of Zhejiang University developed a visual enhanced rat robot [5]. Compared with the general robot, the rat robot has the advantage in the aspects of flexibility, stability and environmental adaptability.

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Brain-machine integration system has three remarkable characteristics: (a) More comprehensive perception of organisms, including behavior understanding and decoding of neural signals; (b) Organisms also as a system of sensing, computation body and executive body, and information bidirectional exchange channel with the rest of the system; (c) Comprehensive utilization of organism and machine in the multi-level and multi-granularity will achieve system intelligence greatly enhanced.

Supported by the project of National Program on Key Basic Research we are engaging in the research on Computational Theory and Method of Perception and Cognition of Brain-machine Integration. The main goal of the project is the exploration of cyborg intelligence through brain-machine integration, enhancing strengths and compensating for weaknesses by combining the biological cognition capability with the computer computational capability. In order to make this integration effective and co-adaptive, brain and computer should work collaboratively. We mainly focus on four aspects, environment awareness, cognitive modeling, joint intention and action planning, to carry out the research of cognitive computational model.

In this paper, a model of brain-machine integration is proposed. Environment awareness is an important for brain-machine integration and will be explored. The collaboration methods between brain and machine will be explored by motivation and joint intention. The conclusions and future works are given at the end.

2 A Model of Brain-Machine Integration

An effective approach to implementing engineering systems and exploring research problems in cyborg intelligence is based on brain-machine integration methods [6]. Using these methods, computers can record neural activity at multiple levels or scales, and thus decode brain representation of various functionalities, and precisely control artificial or biological actuators. In recent decades, there have been continuous scientific breakthroughs regarding the directed information pathway from the brain to computers. Meanwhile, besides ordinary sensory feedback such as visual, auditory, tactile, and olfactory input, computers can now encode neural feedback as optical or electrical stimulus to modulate neural circuits directly. This forms the directed information pathway from the computer to the brain. These bidirectional information pathways make it possible to investigate the key problems in cyborg intelligence.

How to interact between brain and computer is a critical problem in brain-machine integration. On the basis of the similarity between brain function partition and corresponding computing counterparts, a hierarchical and conceptual framework for brain-machine integration is proposed. The biological part and computing counterparts are interconnected through information exchange, and then cooperate to generate perception, awareness, memory, planning, and other cognitive functions.

For the brain part, abstracted the biological component of cyborg intelligence into three layers: perception and behavior, decision making, memory and consciousness shown in Fig. 1. We also divided the computer functional units into three corresponding layers: awareness and actuator, planning, motivation and belief layers. We also defined two basic interaction and cooperation operations: homogeneous interaction (homoraction) and heterogeneous interaction (heteraction). The former represents information exchange and function recalls occurring in a single biological or computing component, whereas the latter indicates the operations between the function units of both biological and computing parts. Homoraction is also modeled as the relationship between units within the same part. In the case of a single part in a brain-machine integration system, it will reduce to a biological body or computing device just with homoraction inside. Consequently, verifying the existence of heteraction is necessary for cyborg intelligent systems.

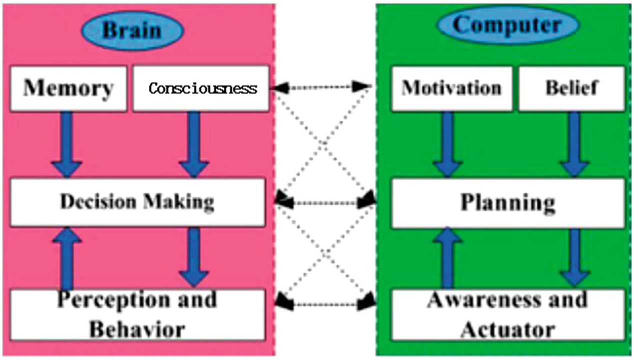

Fig. 1. Cognitive model of BMI

As typical Brain-machine integration system of "animal as the actuators", rat cyborgs [7, 8], were developed to validate how the animals can be enhanced by the artificial intelligence. Ratbots are based on the biological platform of the rat with electrodes implanted in specific brain areas, such as the somatosensory cortex and reward area [9]. These electrodes are connected to a backpack fixed on the rat, which works as a stimulator to deliver electric stimuli to the rat brain.

3 Environment Awareness

For brain-machine bidirectional information perception characteristics, the integration of visual features of the Marr visual theory and Gestalt whole perception theory in the wide range, research on the environment group awareness model and method by combination of brain and machine. The discriminative, generative and other methods are applied to analyze the features of environment perception information, mine perception information patterns and knowledge, generate high-level semantics, and understand well the environment awareness.

In 1995, Endsley proposed a classic theory of situational awareness, which is a three-level model. It is defined as the ability of people to perceive, comprehend and predict the various elements in the environment in a certain space and time [10]. In the three-level model of situational awareness, perception acquires information, and under high-load cognitive conditions, information acquisition mainly depends on the sensor of the machine, and then is presented to the operator through computer processing. The machine plays an important role in the perception phase in the three-level model. In the decision-making stage after the forecast, the collaborative judgment and analysis between machines and people is also needed. The integration of brain and machines in dynamic situational awareness is the key to achieving good performance in understanding the environment.

Awareness is the state or ability to perceive, to feel events, objects or sensory patterns, and cognitive reaction to a condition or event. Awareness has four basic characteristics:

– Awareness is knowledge about the state of a particular environment.
– Environments change over time, so awareness must be kept up to date.
– Agents maintain their awareness by interacting with the environment.
– Awareness establishes usually an event.

Based on the integration of Marr visual theory and Gestalt whole perception theory, applying statistic and deep learning and other methods to analyze environment information and generate high-level semantics, we can build the brain-machine awareness model.

The brain-machine awareness model is defined as 2-tuples: {Element, Relation}, where Element of awareness is described as follows:

(a) Who: describes the existence of agent and identity the role, answer question who is participating?
(b) What: shows agent's actions and abilities, answer question what are they doing? And what can they do? Also can show intentions to answer question what are they going to do?
(c) Where: indicates the location of agents, answer question where are they?
(d) When: shows the time point of agent behavior, answer question when can action execute?

Basic relationships contain task relationship, role relationship, operation relationship, activity relationship and cooperation relationships.

(a) Task relationships define task decomposition and composition relationships. Task involves activities with a clear and unique role attribute.
(b) Role relationships describe the role relationship of agents in the multi-agent activities.
(c) Operation relationships describe the operation set of agent.
(d) Activity relationships describe activity of the role at a time.
(e) Cooperation relationships describe the interactions between agents. A partnership can be investigated through cooperation activities relevance between agents to ensure the transmission of information between different perception of the role and tasks for maintenance of the entire multi-agent perception.

Agent can be viewed as perceiving its environment information through sensors and acting environment through effectors. As an internal mental model of agent, BDI model has been well recognized in philosophical and artificial intelligence area. As a practical agent existing in real world should consider external perception and internal mental state of agents. In terms of these considerations we propose a cognitive model through 4-tuple <Awareness, Belief, Goal, Plan>, and the cognitive model can be called ABGP model [11].

There are several methods developed for visual awareness. Here we describe how CNN is used for visual awareness. Convolutional neural networks (CNN) is a multiple-stage of globally trainable artificial neural networks. CNN has a better performance in 2 dimensional pattern recognition problems than the multilayer perceptron, because the topology of the two-dimensional model is added into the CNN structure, and CNN employs three important structure features: local accepted field, shared weights, sub-sampling ensuring the invariance of the target translation, shrinkage and distortion for the input signal. CNN mainly consists of the feature extraction and the classifier. The feature extraction contains the multiple convolutional layers and sub-sampling layers. The classifier is consisted of one layer or two layers of fully connected neural networks. For the convolutional layer with the local accepted field and the sub-sampling layer with sub-sampling structure, they all have the character of sharing the weights.

The architecture of ABGP-CNN agent is shown in Fig. 2. In the ABGP-CNN, the awareness module has been implemented by CNN, which is completely different from the original single pre-defined rule implementation. The parameters of CNN will become the knowledge in the belief library, and other modules have not changed. In Fig. 2, the ABGP-CNN based agent implements behavior planning through motivation-driven intentions, and the motivation drive adopts a series of internal events. Interesting to achieve planning choices. Each internal mental action of ABGP-CNN must be transformed into an event that drives introspective search to select the most interesting event planning method using novelty and interest. Events consist primarily of internal events (which occur inside the agent) and external events (from external scene perception or other agents). Often, the formation of motivation is motivated by demand and curiosity, but is primarily motivated by curiosity in the ABGP-CNN agent. A goal consisting of a motivational position drives an agent. Unlike most traditional BDI systems, ABGP-CNN does not simply target the target as a special set of events, nor does it assume that all targets must be consistent.

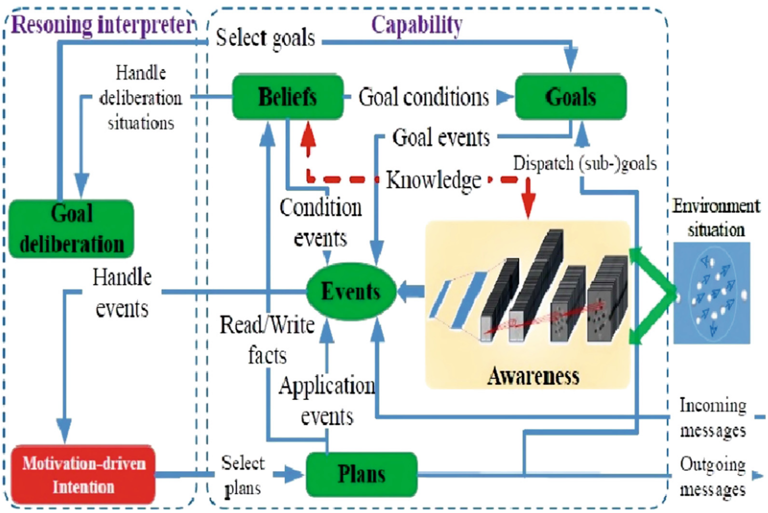

Fig. 2. ABGP-CNN agent

4 Collaboration

Collaborations occur over time as organizations interact formally and informally through repetitive sequences of negotiation, development of commitments, and execution of those commitments. Both cooperation and coordination may occur as part of the early process of collaboration, collaboration represents a longer-term integrated process. Gray describes collaboration as a process through which parties who see different aspects of a problem can constructively explore their differences and search for solutions that go beyond their own limited vision of what is possible [12].

In this project we propose multi-level collaboration for brain-machine integration [13]. Here we only introduce motivation-based collaboration and joint-intention based collaboration.

4.1 Motivation Based Collaboration

Motivation is defined by psychologists as an internal process that activates, guides, and maintains behavior over time. Maslow proposed hierarchy of needs which was one of first unified motivation theories [14]. Since it introduced to the public, the Maslow's theory has a significant impact to the every life aspect in people's life. Various attempts have been made to either classify or synthesize the large body of research related to motivation.

Curiosity is a form of motivation that promotes exploratory behavior to learn more about a source of uncertainty, such as a novel stimulus, with the goal of acquiring sufficient knowledge to reduce the uncertainty. In fact, most of curiosities are caused by novelty. Novelty detection is useful technology to find curiosity. Novelty detection is the identification of new or unknown data or signal.

Detecting novel events is an important ability of any signal classification scheme. Given the fact that we can never train a machine learning system on all possible object classes whose data is likely to be encounter by the system, it becomes important to differentiate between known and unknown object information during testing.

Interestingness is defined as novelty and surprise. It depends on the observer's current knowledge and computational abilities. The interestingness of a situation is a measure of the importance of the situation with respect to an agent's existing knowledge. Interestingness will make attention to an event, leading to collaborative work of brain and machine.

4.2 Joint Intention Based Collaboration

The abstraction concept of the joint intention is convenient to support describe and analyze the social behavior among the agents. A joint intention to perform a particular action is a joint commitment to enter a future state wherein the agents mutually believe the collaborative action is imminent just before they perform it.

In 1990, Bratman's philosophical theory was formalized by Cohen and Levesque [15]. In their formalism, intentions are defined in terms of temporal sequences of agent's beliefs and goals. In 1992, Jennings claimed the need to describe collectives as well as individuals [16]:

- Agents must agree on a common goal.
- Agents must agree they wish to collaborate to achieve their shared objective.
- Agents must agree a common means of reaching their objective.
- Action inter-dependencies exist and must be catered for in general terms.

In multi-agent systems, agents achieve a formula together. Joint intention embody all agents' joint activity selection, so the selective and joint are the basic factors. Intuitively, joint intention has the list properties:

- **Selective**: Intention is the choice of the agent about the future, it will have effect on its activities.
- **Joint**: Joint intention is that which all the team member want to achieve. As a team member, each one knows it specifically and needs collaboration to achieve.
- **Satisfaction**: The satisfaction makes the notion of a formula being true under an interpretation. Then intention is satisfiable means the intention is achievable.
- **Consistency**: Joint intention is the same as the single agent's intention. Different intentions among the team will make the joint intention conflict. What's more, one agent's belief and intention should be consistent.
- **Continuity**: Continuity is one of the properties of joint intention. All the agents will keep their intention until it is impossible to achieve or achieved.

Agent joint intention means agent wants to achieve a formula, which corresponds to agent's goal. For the joint intention, each agent has three basic knowledge: first each one should select ϕ as its intention; second, each one knows its neighbors who also select the intention ϕ; third, each one knows they are on the same team. Distributed dynamic description logic (D3L) is adopted to describe joint intention [17].

Since the brain-machine integration is a multi-agent system as a distributed system, the dynamic description logic is only suitable for processing isomorphic information, and can't provide a reasonable logical basis for multi-agent system. For this reason, D3L is proposed to extend the dynamic description logic for distributed, heterogeneous information integration. Distributed dynamic description logic is a unified representation and reasoning mechanism for studying multi-agent systems.

Distributed dynamic description logic propagates knowledge through bridge rules, but it only deals with the case where two local DDL ontology are connected by bridge rules, and the propagation of knowledge between ontology is not used for distributed reasoning. Knowledge dissemination is the main feature of D3L that is different from traditional dynamic description logic. In the case that multiple DDL agents form a chain between bridge rules, they do not always propagate in the expected way, so the combination consistency is introduced and distributed dynamic description logic supporting chain bridge rules is proposed (CD3L). The CD3L component is divided into three parts: a distributed TBox, a distributed ABox, and a distributed ActBox. Therefore, it can better provide a logic basis for multi-agent systems.

5 Simulation Experiment

ABGP-CNN as the detailed implementation for the conceptual framework of brain-machine integration, here we give a simulation application to significantly demonstrate feasibility of conceptual framework of brain-machine integration based ABGP-CNN Agent model. The following will mainly represent the actual design of the rat agent based on ABGP-CNN supported by the conceptual framework of brain-machine integration.

Under belief knowledge conditions, the goals (here mainly visual information) constantly trigger the awareness module to capture environment visual information, and the event module converts the visual information into the unified internal motivation signal events which are transferred to action plan module. Then the action plan module will select proper actions to response the environment.

In simulation application, we construct a maze and design a rat agent based on ABGP-CNN to move in the maze depending on the guidepost of maze path in Fig. 3. The task of the rat agent is to start moving at the maze entrance (top-left of maze), and finally reach the maze exit (bottom right of maze) depending on all guideposts.

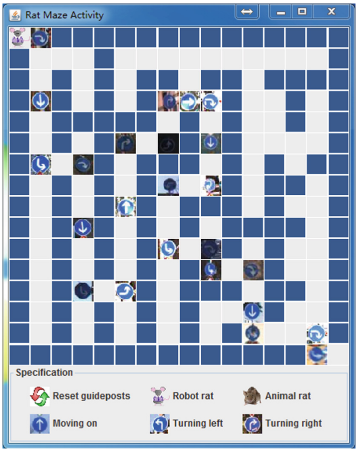

Fig. 3. Rat agent activities in maze

In order to fulfill the maze activity shown in Fig. 3, the rat agent is implemented all the three basic modules, <Awareness>, <Motivation>, <Action Plan>. In the rat maze activity experiment, the rat agent is designed to have 3 basic behaviors moving on, turning left and turning right in the maze. In order to guide rat's behaviors we construct a true traffic guidepost dataset means 3 different signals, moving on, turning left and turning right. The different signal corresponds to different guidepost images like in Fig. 4.

Fig. 4. Traffic guideposts in maze

When rat agent moves on the path, its goals constantly drive awareness module to capture environment visual information (here guideposts in the maze) and generate the motivation signal events to drive its behaviors plan selection. In the experiment, there are 3 motivation signals, moving on, turning left and turning right according to the guideposts in the maze path, which means the agent can response 3 types of action plans to finish the maze activities.

6 Conclusions

At present, brain-machine integration is an active research area in intelligence science. A cognitive model of brain-machine integration has been presented in this paper. The paper explained environment awareness. Motivation is the cause of action and plays important roles in collaboration. The motivation based collaboration has been explored in terms of event curiosity, which is useful for sharing common interest situations. Joint intention based collaboration is also discussed in terms of a sharing goal.

The future of brain-machine integration may lead towards many promising applications, such as neural intervention, medical treatment, and early diagnosis of some neurological and psychiatric disorders. The goal of artificial general intelligence (AGI) is the development and demonstration of systems that exhibit the broad range of general intelligence. The brain-machine integration is one approach to reach AGI. A lot of basic issues of brain-inspired intelligence are explored in details in the book [1].

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