DOI: 10.3969/j.issn.1673-5188.2015.02.001
http://www.cnki.net/kcms/detail/34.1294.TN.20150521.1608.002.html,published online May 21, 2015

I^2oT: Advanced Direction of the Internet of Things

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Abstract

The Internet of Things (IoT) is still in its infancy because of the limited capability of its embedded processor. In the meantime, research on artificial intelligence (AI) has made plenty of progress. The application of AI to IoT will significantly increase the capabilities of IoT, and this will benefit both economic and social development. In this paper, the elementary concepts and key technologies of AI are explained, and the model and principle of intelligent IoT, denoted I^2oT, resulting from the integration of AI and IoT are discussed. I^2oT will be the most promising version of IoT. Finally, recommendations for further study and standardization of I^2oT are made.

Keywords

Internet of Things; artificial intelligence; knowledge producing; strategy formulation; intelligent internet of things

1 Introduction

There are two main motivations for expanding the Internet to the Internet of Things (IoT). The first motivation is to expand the amount of information shared by databases and objects in the real world. The second motivation is to enable users not only to share information but also control objects in the real world. These make IoT much more attractive in society. In other words, IoT is a good advancement of the conventional Internet.

In terms of technological development, however, IoT is still in its infancy and can be greatly improved by endowing IoT functions with much more intelligence [1]. Significant progress has been made in artificial intelligence (AI) over the past decade. All AI technologies needed to make IoT more intelligent and evolve into I^2oT are now feasible. The main concern at the moment is how to understand and effectively apply AI technologies to current IoT systems.

2 A Brief Description of IoT

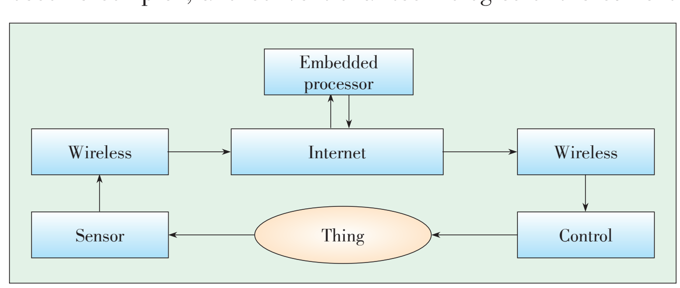
The purpose of IoT is to expand the functions of existing Internet and make it more useful. With IoT, users can share not only information provided by humans and contained in databases but also information provided by things in physical world. The simplified functional model of IoT is shown in **Fig. 1**.

As in Fig. 1, IoT has sensors, for acquiring information about the state of things; an embedded processor, for producing orders that regulate the state of things; wireless technology, for transferring information from sensors to Internet and Internet to controller; and control unit, for executing human orders regulating the state of things.

Take IoT for maintaining room temperature for example. A standard room temperature is designated in advance, and the actual room temperature is acquired by the sensor(s) and transferred via wireless to Internet. After receiving the actual room temperature, the embedded processor compares it with the designated value and generates an order to regulate the room temperature and keep it within a certain range. This order is immediately sent to the control unit via the Internet and wireless unit and is executed by the actuator of the control unit.

If information about the state of the thing concerned can be acquired by sensors and controlled by actuators, and if the function performed by the embedded processor is not too complicated, the IoT technology is feasible.

If physical things and their environment in IoT become complex, the functions of the required embedded processors also become complex, and conventional technologies of the current



▲Figure 1. Simplified functional model of IoT.

IoT will no longer be satisfactory.

Unfortunately, problems with complex factors are very often important to economic and social development. A typical example is air pollution over a large area. Another typical example is global warming. People want to know information about the air quality and weather conditions and control them in certain ways. Therefore, efficiently dealing with complex problems is an unavoidable responsibility of scientists.

The most promising approach to handling such complex problems is artificial intelligent. The reason for this proposal is the fact that central need for solving complex problems is the learning ability.

3 Fundamental Concepts and Principles of Artificial Intelligence

In a narrow sense, AI has traditionally implied the simulation of logical human thinking using computer technology. Within this framework, the fields of artificial neural networks (ANNs) [2]–[4] and sensor-motor systems (SMSs) [5]–[7] were considered extraneous, even though both fields have been concerned with simulating the functions of the human brain. ANN and SMS had to form a new discipline called computational intelligence (CI). Computational intelligence has become the other approach to AI. It is more reasonable for the term AI to encompass both AI in narrow sense and CI. In the contemporary sense, AI is now re-termed unified AI [8]–[9].

In this paper, AI means unified AI, a general term representing the theory and technology related to simulating intellectual abilities of human being, including the ability to understand and solve problems. What follows is a brief explanation of how AI can handle complex problems [10]–[12].

What AI simulates and offers is not anything else but the learning ability of human beings, i.e., learning to understand and solve the problem. Therefore, learning is the central feature in AI and learning-technology is the key to handling problems.

The simplest model for AI is roughly abstracted in **Fig. 2**.

Ontological information (OI) in Fig. 2 is information about the state and pattern of the state variance that are presented by the object in the environment of the outside world and that are the resources and clues for learning to understand the problem. On the other hand, the subject's action or reaction applied to the object can be learnt based on an understanding of the problem.

A more specific functional model of the technologies in AI is shown in **Fig. 3**. In Fig. 3, AI technologies are interconnected and interact with each other.

3.1 Categories of AI Technology

3.1.1 Perception

This technology is used to acquire the OI about the object or problem in its environment. It is also the technology for converting OI to epistemological information (EI).

Epistemological information is information perceived by the subject about the trinity of the form (syntactic information), content/meaning (semantic information), and utility/value (pragmatic information) concerning OI.

Unlike the traditional concept of information proposed by Claude Shannon, EI comprises the trinity of the form, content/meaning, and utility/value and is the basis of learning. This is why EI is also often called comprehensive information.

The essential function of perception is to convert OI to EI. This is the first class of information conversion in AI.

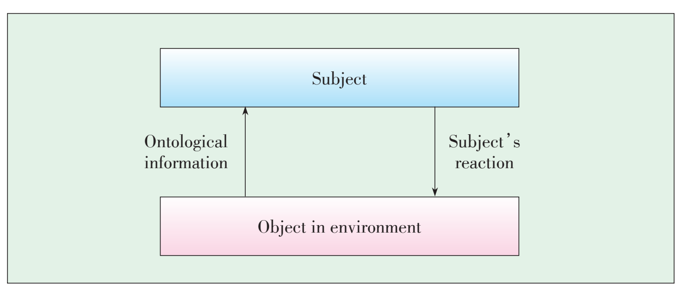
3.1.2 Cognition

The main function of cognition technology is to convert EI, which is perceived by the subject from OI, into the corresponding knowledge about the object. This is the second class of information conversion needed in AI. The only possible approach to converting EI to knowledge must be learning— there is no other way.

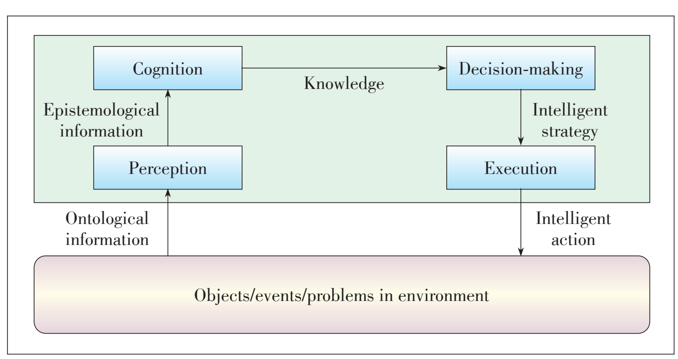
3.1.3 Decision-Making

The technology used in decision-making converts EI to intelligent strategy (IS) based on knowledge support and is directed by the goal of problem solving. The strategy is just the procedural guidance for problem-solving. This is the third class of information conversion in AI.

The radical function of decision-making technology is learning to find the optimal solution for a given problem. There are usually a number of ways of achieving the designated goal from



▲Figure 2. A simplified functional model for AI.



▲Figure 3. A more specific functional model of AI.

a starting point expressed by EI. A decision should be made through intelligent use, via learning, of the relevant knowledge provided.

3.1.4 Strategy-Execution

This technology is used to convert the IS into intelligent action (IA) that will solve the problem.

3.1.5 Strategy-Optimization

Because of various non-ideal factors in all sub-processes in Fig. 3, there are often errors when intelligent action is applied. These errors are regarded as new information and are fed back to the input of the perception of the model. With this new information, the knowledge can be improved via learning, and the strategy can be optimized. Such an optimization process might continue many times until the error is sufficiently small.

In sum, all the AI technologies hereto mentioned are learning-based, and this is why AI is powerful.

3.2 Implementation Issues for the Three Classes of Information Conversion

Perception technology can be implemented using the model in **Fig. 4**, which converts OI to EI, the trinity of X, Y and Z, and is the first class of information conversion.

Fig. 4 shows that the ontological information (denoted S) is applied to the input of the perception model and mapped to the corresponding syntactic information (denoted X). Next, the pragmatic information (denoted Z) can be retrieved from the knowledge base, in which many X-Z pairs, $\{X(i), Z(i)\}$, are stored. When X is matched with $X(i_0)$, then $Z(i_0)$ is regarded as the pragmatic information corresponding to X. In case no math can be found, the equation can be used to find Z;

$$Z = \mathrm{Cor}\,(X, G) \tag{1}$$

where X and G are expressed as vectors; and Cor is the correlation operation. Because X and Z are now available, the semantic information Y can be inferred from:

$$Y = \lambda\,(X, Z)\ \varepsilon S \tag{2}$$

where S is the space of semantic information, and λ is the logic operation mapping the pair of (X, Z) to Y in S. This means that Y is a subset of S when both X and Z are simultaneously valid. In other words, Y is determined by the joint conditions of X and Z (**Fig. 5**).

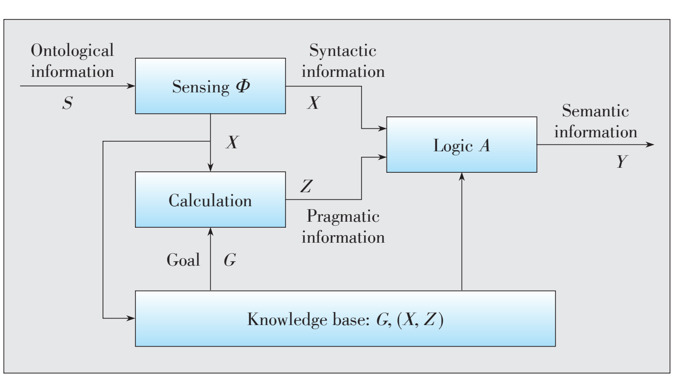
As a result, OI is converted into EI, which is the trinity of X, Y and Z, via the model in Fig. 4. This technology is completely feasible in practice.

Cognition technology can be implemented using the model in **Fig. 6**, with which EI is converted to knowledge. This is the second class of information conversion.

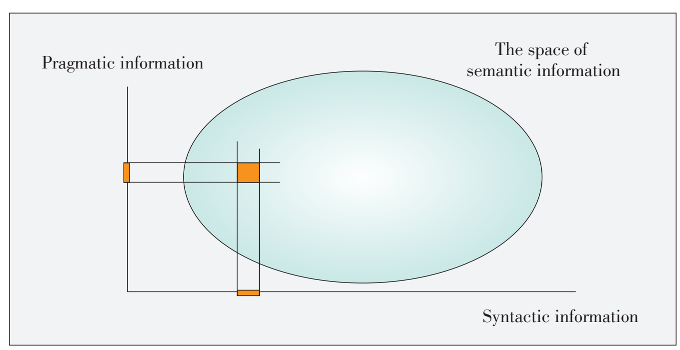
According to the definitions of information and knowledge, information is the phenomenon in nature and knowledge is the essence in nature. Thus, knowledge can be established using inductive-type algorithms (Fig. 6). In Fig. 6, comprehensive information is another name for EI.

The technology for decision-making can be implemented using the model in **Fig. 7**, which converts EI to IS based on the support of the related knowledge and guided by the goal of problem solving given beforehand.

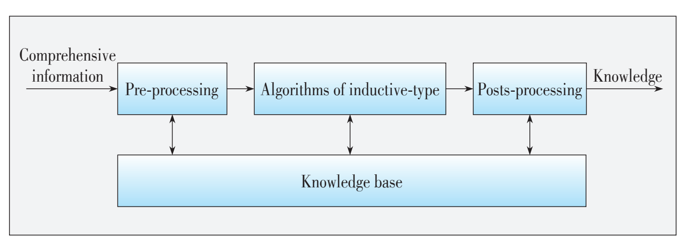
The model in Fig. 7 is quite similar to that in Fig. 6; however, the big difference between them is the principal algorithms. In Fig. 6, the algorithms are inductive type whereas in Fig. 7 they are deductive type.



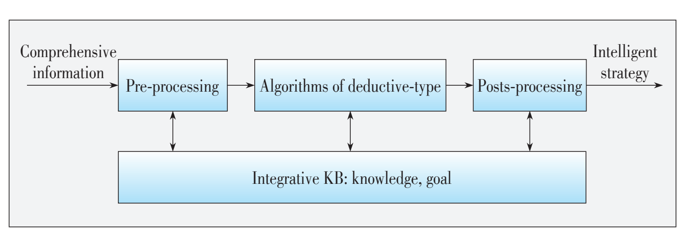
▲Figure 4. Model of the first class of information conversion.



▲Figure 5. $Y = \lambda\,(X, Z)$.



▲Figure 6. Model of second-class of information conversion.



▲Figure 7. Model of third class of information conversion.

In AI theory and technology, the three classes of information conversion (IC) are the nucleus and novelty. Nevertheless, the sub-process of strategy execution is a kind of normal technology, converting the intelligent strategy into intelligent action, and therefore is not necessary to explain here anymore.

In sum, the key issue in AI theory and technology is to successively derive the EI (first class of IC) and knowledge (second-class IC) in order to deeply understand the object concerned and then produce an intelligent strategy (third-class IC) based on OI, EI, knowledge, and the goal of the system in order to regulate the object.

4 A Conceptualized Model of I^{2}oT

The functioning ability of IoT is mainly limited by the performance of the embedded processor, which often fails to produce a strategy that is intelligent enough to deal with complex problems. Therefore, strengthening the embedded processor is the key to improving IoT.

Because the intelligent strategy can be derived from the three classes of IC in AI, it is feasible to use these three classes of IC to replace the embedded processor in IoT and transform IoT into I^{2}oT, which is a much more intelligent version of IoT (**Fig. 8**).

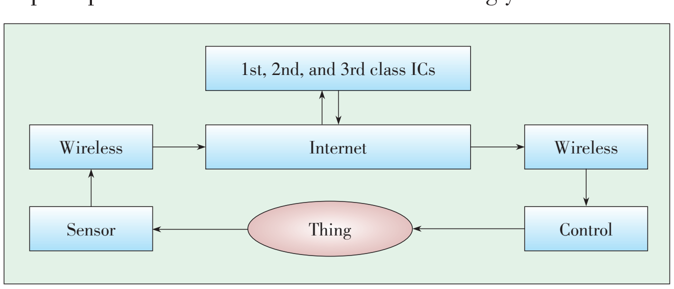
Comparing the conceptual model in Fig. 8 with that in Fig. 1, there is almost no difference between these two models except the replacement of embedded processor by the nucleus of AI technology, i.e., first, second and third class of IC. This is the most effective way of transforming IoT into I^{2}oT.

Because of the strong learning abilities offered by the three classes of IC in AI, the I^{2}oT will be much more powerful than the conventional IoT and will be able to handle the complex problems mentioned in section 2. The intelligent strategy needed to tackle complex problems can, in principle, be derived from the three classes of IC based on OI, EI, relevant knowledge, and the designated goal for solving problems in a manner similar to humans.

5 Conclusion

In conclusion, the following two points are emphasized:

1) IoT will have to be capable of intelligently handling complex problems. This will be an increasingly serious challenge. It is strongly recommended that the embedded processor be replaced by the three classes of IC technology in AI. In this way, IoT will become I^{2}OT and meet the demands of applications for economic and social development.
2) Broadly speaking, the real significance of AI is that it implements the great law of information conversion and intelligence creation, according to which information is the means and intelligence creation is the purpose. This is the radical law that governs all information activities in the information era. Arguably, this law will be more significant than the law of energy conversion and conservation in physical science in industrial era.



▲Figure 8. Simplified functional model of I^{2}oT.

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Manuscript received: 2015-04-11

Biography

Yixin Zhong (zyx@bupt.edu.cn) received the BS and MS degrees from Beijing University of Posts and Telecommunications (BUPT) in 1962 and 1965. From 1979 to 1981, he was an academic visitor to the Department of Electrical Engineering, Imperial College of Science and Technology, London. He is now a professor in the Department of Intelligence Science, School of Computing, BUPT. From 1993 to 2005, he was an associated editor of *IEEE Transactions on Neural Networks*. From 2001 to 2002, he was chair of APNNA. From 2001 to 2010, he was president of the Chinese Association for Artificial Intelligence. From 2007 to 2009, he was vice-president of WFEO and the chair of WFEO-CIC. He has also been the general chair or program chair for a number of international conferences on communications, information science, and artificial intelligence. He is now the honorary president of International Society for Information Studies.
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He has published more than 450 papers and 18 books in related fields.