Progress and Challenge of Artificial Intelligence

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Abstract Artificial Intelligence (AI) is generally considered to be a subfield of computer science, that is concerned to attempt simulation, extension and expansion of human intelligence. Artificial intelligence has enjoyed tremendous success over the last fifty years. In this paper we only focus on visual perception, granular computing, agent computing, semantic grid. Human-level intelligence is the long-term goal of artificial intelligence. We should do joint research on basic theory and technology of intelligence by brain science, cognitive science, artificial intelligence and others. A new cross discipline intelligence science is undergoing a rapid development. Future challenges are given in final section.

Keywords artificial intelligence, visual perception, machine learning, agent computing, semantic web, intelligence science

1 Introduction

Artificial Intelligence (AI) is generally considered to be a subfield of computer science that is concerned to attempt simulation, extension and expansion of human intelligence. The nominal birth of AI is considered to have occurred at a conference held at Dartmouth College in the summer of 1956. The conference was organized by Marvin Minsky, who later helped found the AI laboratory at MIT and currently at the MIT Media Laboratory and is famous for his work the Society of Minds. McCarthy who is a creator of the LISP programming language proposed the field artificial intelligence for funding purposes at that time. During the mid 50s of last century, Herbert Simon and Allen Newell had already implemented an automatic theorem proving program at the Rand corporation called the Logic Theorist. These four people are considered the grandfathers of AI.

Artificial intelligence has enjoyed tremendous success over the last fifty years. Its tools and techniques are in the mainstream of computer science and at the core of so many systems. For example, the computer beats the world's chess champ, commercial systems are exploiting voice and speech capabilities, there are robots running around the surface of Mars. We have made significant headway in solving fundamental problems in representing knowledge, in reasoning, in machine learning, and more.

The long-term goal of artificial intelligence is human-level intelligence, but it is still not directly definable[1]. For the long-term goal we should do joint research on basic theory and technology of intelligence by brain science, cognitive science, artificial intelligence and others. Brain science explores the essence of brain, research on the principle and model of natural intelligence in molecular, cell and behavior level. Cognitive science studies human mental activity, such as perception, learning, memory, thinking, consciousness etc. In order to implement machine intelligence, artificial intelligence attempts simulation, extension and expansion of human intelligence using artificial methodology and technology[2]. Sometimes we call the cross discipline intelligence science which dedicates to research on basic theory and technology of intelligence.

In 1991 Kirsh pointed out five foundational issues for AI: (1) Core AI is the study of conceptualization and should begin with knowledge level theories. (2) Cognition can be studied as a disembodied process without solving the symbol grounding problem. (3) Cognition is nicely described in propositional terms. (4) We can study cognition separately from learning. (5) There is a single architecture underlying virtually all cognition[3]. Newell *et al.* claim that cognition is basically the product of running programs in a single architecture. According to Newell, too much of the research in AI and cognitive science aims at creating independent representational and control mechanisms for solving particular cognitive tasks. In Society of Mind[4], Minsky has argued that intelligence is the product of hundreds, probably thousands of specialized computational mechanisms the terms agents. There is no homogenous underlying architecture. In the society of mind theory, mental activity is the product of many agents of varying complexity interacting in hundreds of ways. The very purpose of the theory is to display the variety of mechanisms that are likely to be useful in a mind-like system, and to advocate the need for diversity. There is no quick way to justify the assumption of architecture homogeneity.

Cognitive science is an interdisciplinary field that has arisen from the convergence on a common set of questions by philosophy, computer science, artificial intelli-

Survey

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gence, linguistics, psychology, and neuroscience. Cognitive scientists view the human mind as a complex system that receives, stores, retrieves, transforms, and transmits information. Each discipline makes its own distinctive contribution to the goal of formulating a computational theory of the human mind. Previously, each discipline sought to understand the mind from its own perspective, benefiting little from progress in other fields because of different methods employed. With the advent of cognitive science, however, common interests and theoretical ideas have overcome methodological differences, and interdisciplinary interaction has become the hallmark of this field.

Cognitive science is the interdisciplinary study of mind and intelligence, embracing philosophy, psychology, artificial intelligence, neuroscience, linguistics, and anthropology. Its intellectual origins are in the mid-1950s when researchers in several fields began to develop theories of mind based on complex representations and computational procedures. Its organizational origins are in the mid-1970s when the Cognitive Science Society was formed and the journal, Cognitive Science, began. Since then, more than sixty universities in North America and Europe have established cognitive science programs and many others have instituted courses in cognitive science. In recent 50 years, the foundation of Cognitive Science can be regarded as one of the most important event.

Cognitive scientists study an enormous variety of topics under the headings of memory and learning. Events affect humans, other animals, and machines in many ways, and sometimes enduring changes in the respective systems result, altering actual and possible future behaviour.

The International Human Frontier Science Program Organization (HFSP) was founded in October 1989 in Strasbourg, France. HFSP supports basic research focused on elucidating the complex mechanisms of living organisms[5]. Emphasis is placed on novel, innovative, interdisciplinary approaches to basic research that involve scientific exchanges across national boundaries. In particular, HFSP encourages research into biological problems involving approaches and knowledge from different disciplines such as chemistry, physics, mathematics, computer science, engineering, material sciences, because significant new ideas, techniques and discoveries often arise at the boundaries between disciplines.

The convergence of nanotechnology, biotechnology, information technology, and cognitive science (NBIC) is sponsored by the National Science Foundation and the Department of Commerce of United States of American in 2001. NBIC converging technique is referring to the combination of the four rapid developing fields: Nanotechnology, Biotechnology, Information technology, and Cognitive science (NBIC). To be more specific, the cognitive scientists recognize it; the nano-scientists create it; the bio-scientists use it and the information scientists control it. NBIC converging technique has several major applications, such as expanding human cognition and communication, improving human health and physical capabilities, enhancing group and societal outcomes, strengthening national security, and unifying science and education. NBIC converging technique is really an opportunity for China in the science area.

In this paper, we mainly focus on the progress and challenge of AI, as well as related topics of Cognitive Science. In Section 2, visual perception, which is a sophisticated perceptual process through which people gather information from the physical world, is discussed, and related work is introduced. Granular computing will be discussed in Section 3. Section 4 will describe agent-based computing. In Section 5, the topic about semantic grid is discussed. Agent grid intelligence platform will be discussed in Section 6. The future challenge of AI will be presented in Section 7. The last section is the conclusion of this paper.

2 Visual Perception

2.1 Representation of Perception

Perception is a cognitive activity that permits us to make sense of the physical world in which we live. Our ability to meaningfully experience and to react to the physical events around us depends upon proper functioning of the sensory organs and their associated neural pathways. The 5 traditional senses (vision, hearing, touch, smell, taste) work in concert with other less well-known senses (vestibular, pain, kinesthesia) to provide the means by which physical events become known. This module concentrates on vision because it is a sophisticated perceptual process through which people gather information from the physical world, and it is the sense modality that has the most substantive body of research.

There are mainly four representations of perception. First, the direct perception is proposed by Gibson. He claims that information from the visual world is sufficient to permit perception without the involvement of internal representations — focus on "bottom-up" processing. Gibson's ecological approach that believes there is no mediation from the mind between the object of perception and the perception event itself. The function of perception is thus one of adaptation and therefore the purpose of perception is then to adapt the organism to its environment. The main points of ecological approach are listed below:

- "optic array" contains all necessary visual information;
- layout of objects in space given by texture gradients, optic flow patterns, and affordances (implied meaning of objects);
- perception involves "picking up" information through "resonance";
- has had historical impact in restoring interest in the perceptual environment;
- has been criticized as being underspecified, and neglects role of knowledge in stimulus exploration.

The second perception theory is Marr's computational theory in which perception is seen from the neuropsychological level. Marr in fact compares the human visual system to a computer system and called "Reconstructionist" Approach. Marr stated that the process of visual perception has three stages of representation: the Primal sketch, which consists of two stages: the two-dimensional raw primal sketch, which records the incoming information of differing intensities of light, and the full primal sketch, which is the resulting image of that information; the 21/2-D sketch, which takes into account visual information of motion, shading, shape and texture; and the 3-D model representation, which is the concluding image[6].

The third is Gestalt theory that addresses directly the more global, holistic processes involved in perceiving structure in the environment. Gestalt principles consist of the following points:

• *Figure-ground*. When perceiving a visual field, some objects (figures) seem prominent, and other aspects of field recede into the background (ground).

• *Proximity*. We tend to perceive objects that are close to each other as forming a group.

• *Similarity*. We tend to perceive objects that are similar to each other as forming a group.

• *Continuity*. We tend to perceive smoothly flowing or continuous forms rather than the disrupted of discontinuous ones.

• *Closure*. We tend to perceptually close up, or complete, objects that are not, in fact, complete.

In 1982 Lin Chen proposed the Theory of Topological Perception in Science[7]. During the last two decades, challenged the dominating theory of "From Local to Global" on the fundamental problem of "where perception begins" by systematically developing a comprehensive theory of Topological Perception, which asserts "From Global to Local".

Lin Chen and his colleagues made a series of experiments with honey bees which demonstrate their small brains nevertheless possess the ability for topological perception. Bees rapidly learned to discriminate patterns that are topologically different, and they generalized the learned cue to other novel patterns. By contrast, discrimination of topologically equivalent patterns was learned much more slowly and not as well. Thus, although the global nature of topological properties makes their computation difficult, topology may be a fundamental component of the vocabulary by which visual systems represent and characterize objects[8].

2.2 Perceptual Learning

Perceptual learning should be considered as an active process that embeds particular abstraction, reformulation and approximation within the Abstraction framework. The active process refers to the fact that the search for a correct data representation is performed through several steps.

After Hubel and Wiesel[9,10] first showed that nerves in mammalian primary visual cortex (V1) were optimally stimulated by bars and edges, a large part of experimental, computational, and theoretical studies have been concerned with exploring the response characteristics of neurons in V1 and in higher visual areas.

2.2.1 *Processing of Sensory Data*

Low level vision represents the sensory response created when rod and cone cells respond to the presence of light. Research questions center on the kinds of real world information that are extracted from the retinal image (see Fig.1). Although we are beginning to understand the biological actions that occur when receptor cells are stimulated, there are a number of lingering questions regarding the exact nature of the information taken from the retinal image. The next section, which considers how sensory data are interpreted, and addresses some of these issues.

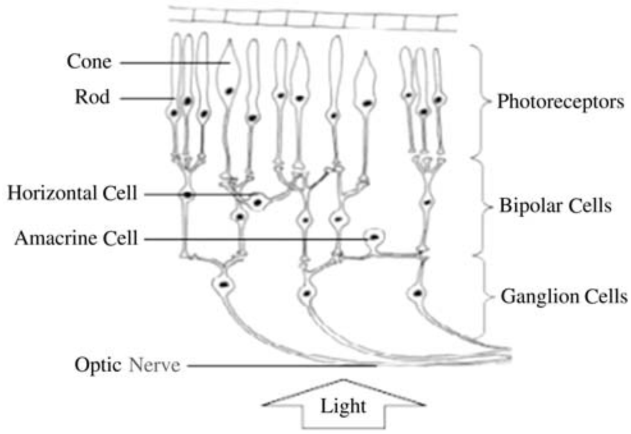

Fig.1. Layers of the retina.

As the sites of sensory transduction, receptor cells serve to excite adjacent cells and in this way information is conducted through the layers of the retina. Information passes from the receptor cells to the bipolar layer through to the ganglion layer of the retina. Fibers of the ganglion layer gather at the blind spot to form the optic tract, a sensory pathway that conducts information from the eye to the cortex. As information passes through the layers of the retina, a number of receptor cells activate a given bipolar and a number of bipolars activate a given ganglion cell. Such convergence of information suggests that neighboring cells interact as information is processed and sent to the brain. Receptive field studies[9,10] investigate low level vision by identifying the characteristics of regions on the retina that influence a ganglion cell's firing rate.

Kuffler[9] used the technique of single cell recording to investigate ganglion cell activity in an anesthetized cat. His results showed that the ganglion cell fired readily when light was projected onto the retina closest to it, but the cell would also respond if the light fell anywhere within a circular region around that point. The region on the retina that influences a cell's firing rate is called a receptive field. Fig.2 shows the cell types identified by Kuffler. In the On-Center cell, the center area is marked with pluses to indicate the "on" response. The on response is a marked increase in the cell's firing rate when a spot of light covers the center area of the receptive field. The surround is marked with minuses to designate the "off" response. The off response is a decrease in the cell's firing rate with a spot of light and a marked increase in the firing rate when the light is turned off. When the spot of light covers both center and surround, the two responses neutralize and the cell's response is quite weak. The Off-Center cell is quite similar except that the center yields the off response and the surround on response.

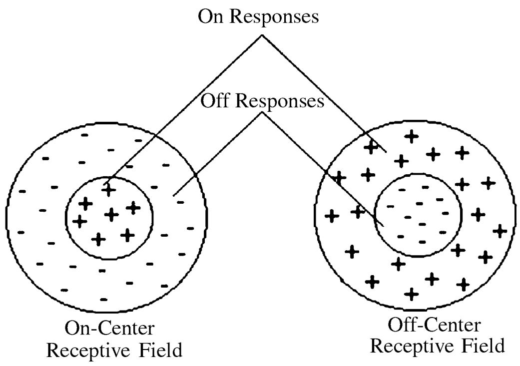

Fig.2. Receptive fields of the retina.

Hubel and Wiesel[10] extended Kuffler's work by recording from cells higher in the sensory pathway. When recording from the lateral geniculate cells (thalamus), receptive fields showed similar characteristics to the ganglion cells. The same On-Center cell types were found but with an enhanced capacity of the surround to cancel the effects of the center. Such a finding suggests that the lateral geniculate cells may be even more specialized than the ganglion cell responding to spatial differences in retinal illumination.

When Hubel and Wiesel[10] recorded from cells in the cerebral cortex, a complex organization of cells was identified and cells were of three types.

- Simple cells displayed on/off responses in areas that were side by side. Line stimuli such as slits, dark bars and edges seemed particularly effective in activating the simple cells. These cells were orientation specific which meant that to activate the cell the stimulus orientation needed to match the orientation of the receptive field.
- Complex cells also responded to bars, slits and edges at specific orientations provided that the stimulus was moving.
- Hypercomplex cells responded to a combination of stimulus features such as angles between lines, length of lines, width of the stimulus.

Receptive field studies are important because they map out the excitatory and inhibitory regions of the retina and show that the probability that a cell will fire depends upon the presence/absence of light as well as some spatial characteristics. Fig.3 shows the receptive fields in the visual cortex. The receptive field allows you to explore the most effective stimulus for a cell. It shows that a spot of light will vary in effectiveness depending upon where it falls on the center/surround portion of the receptive field and its size, that is, whether it covers the whole receptive field or just a portion.

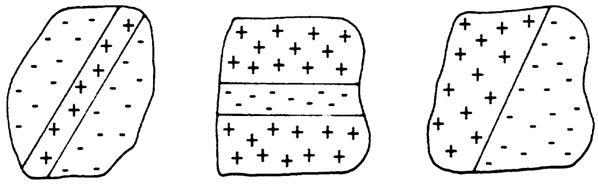

Fig.3. Receptive fields in the visual cortex.

Hubel and Wiesel won the Nobel prize in 1981 because their finding of a complex cell organization when recording from higher order cells in the cat's visual pathway revolutionized our thinking about sensory processing. Follow-up work with the single cell recording technique and a number of other less invasive techniques (PET scans, Functional MRI) have provided a more complete mapping of cells at each synaptic layer in the visual pathway. For example, we know that the lateral geniculate nucleus contains six layers of cells stacked on top of one another and each layer is organized in such a fashion that it maintains a topographic map of the visual field. This means that cells that carry information from adjacent areas of the retina connect with geniculate cells that are neighbors as well. The striate cortex (area V1) is also layered like the lateral geniculate but it has a vastly more complex organization of cells. Cells of a particular orientation specificity are aligned in columns and the visual field is represented in an orderly, topographic fashion. It is known that 80% of the cells in the visual cortex are devoted to representing the central 10 degrees of the visual field. This overrepresentation of the center of the visual field in the striate cortex is called cortical magnification.

2.2.2 *Model of Attention-Guided Visual Sparse Coding*

Vision attention mechanism is an active strategy in information processing procedure of brain, which has many interesting characteristics, such as selectivity, competition. Attention is everywhere in the visual pathway[11]. A typical scene within the neuron's classic receptive field (CRF) contains many different patterns which compete for neural representation because of the limited processing capacity of neurons in the visual system.

Besides, sparse coding theory demonstrates that the neurons in primary visual cortex form a sparse representation of natural scenes in the viewpoint of statistics, but a typical scene contains many different patterns (corresponding to neurons in cortex) compete for neural representation because of the limited processing capacity of the visual system. We propose an attention-guided sparse coding model[12]. This model includes two modules: nonuniform sampling module simulating the process of retina and data-driven attention module based on the response saliency. Our experimental results show that the model notablely decreases the number of coefficients which may be activated and retains the main vision information of the same time.

Response saliency is the response extent for a neuron compared with a group of neurons that respond to the same stimulus. The purpose of the response saliency is to represent the conspicuity for every neuron in the same perception level for a stimulus and to guide the selection of attended neuron, based on the value of response saliency[13]. The neuron response that has great response saliency value will be chosen to further process. On the contrary, the neuron that has small value will be omitted.

In the framework of sparse coding, the simple cells in the primary visual cortex (V_1) produce sparse code for the input stimuli. That is to say, simple cell takes very small (absolute) values or very large values often; to compensate, it takes values inbetween relatively more rarely. The sparse code focuses on the possibility distribution of response. Intuitively, the response value itself provides very useful information: the response value is bigger, the information represented by the neuron is more important; otherwise, the information is less important. Obviously, the response value gives a foundation for the attention mechanism. Supposed here that A_i represents simple cell i, and R_i represents the simple cell's response.

Every simple cell (corresponding to the Character of A in (1)) carries a specific pattern. Furthermore, every such pattern is selective for location, orientation and frequency. Based on Gestalt similarity perception principle and Hebb rule, we can get that the neurons with similar selectivity increase the response values; on the contrary, the neurons with different selectivity decrease the response values. So we can suppose that the response saliency value of a neuron, which has great discrepancy among a group of neurons responding to the same stimulus, will decrease; and the value for a neuron that has small discrepancy will increase relatively. The neuron set responding to the same stimulus assumes as S, $S = \{A_1, , A_2, \ldots, A_m\}$; the discrepancy between A_i and A_j is represented as $D(A_i, A_j)$, and the value for $D(A_i, A_j)$ is a function of simple cell's selective characteristics: location (L), orientation (O) and frequency (F). The equation is as below:

$$D(A_i,A_j) = W_1 \times N(\sqrt{(L_{ix} - L_{jx})^2 + (L_{iy} - L_{jy})^2}) + W_2 \times N(|O_i - O_j|) + W_3 \times N(|F_i - F_j|), \tag{1}$$

$$\mathit{Diff}(A_i, S) = \sum_{A_j \in S} (1 - D(i,j) \times R_j)/\mathrm{Count}(S) \tag{2}$$

where operation $N(\cdot)$ represents the normalization operator which makes the values between 0 and 1, and $0 \leqslant W_1, W_2, W_3 \leqslant 1$ represents the weights, $W_1 + W_2 + W_3 = 1$.

Then, the response saliency (RS) value is the weighted sum of norm response value and neuron discrepancy as following:

$$RS(A_i) = N(|R_i|) + \lambda \times \mathit{Diff}(A_i, S) \tag{3}$$

where λ is a weight that determinates the importance of each component.

2.3 Stereoscopic Vision

Stereoscopic vision infers 3D scene geometry from two images with different viewpoints. Jian Sun and Nan-Ning Zheng *et al.* formulate the stereoscopic problem as a Markov network and solve it using Bayesian belief propagation[50]. The stereo Markov network consists of three coupled Markov random fields: a smooth field for depth/disparity, a line process for depth discontinuity, and a binary process for occlusion. After eliminating the line process and the binary process by introducing two robust functions, apply the belief propagation algorithm to obtain the maximum a posteriori estimation in the Markov network.

3 Machine Learning

3.1 Learning Algorithms

As a broad subfield of artificial intelligence, machine learning is concerned with the development of algorithms and methods which aims to mimic intelligent abilities of humans by machines. Machine learning research has been extremely active in the last few years. The result is a large number of very accurate and efficient algorithms that are used for data mining and automate tasks.

In general, machine learning can be divided into supervised learning, unsupervised learning and reinforcement learning. In supervised learning, there is a label associated with each example. If the label is discrete, then the task is called classification problem, otherwise, for real valued labels is called regression problem. Decision tree, k-nearest neighbor classifier, support vector machine, boosting are frequently used as classification algorithms.

Unsupervised learning tries to uncover hidden regularities in the data, such as clustering. The clustering could be defined as the process of organizing objects into groups whose members are similar in some way. Clustering algorithms may be classified as exclusive clustering, overlapping clustering, hierarchical clustering, probabilistic clustering.

Reinforcement learning, different from supervised learning, is the kind of learning studied in most current research in machine learning, statistical pattern recognition, and artificial neural networks. In interactive problems it is often impractical to obtain examples of desired behavior that are both correct and representative of all the situations. Reinforcement learning is the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment. Reinforcement learning usually consists of four components: policy, reward function, value mapping and model of environment. There are four different families of reinforcement learning algorithms: temporal difference learning, dynamic programming, Monte Carlo methods and Q-learning.

3.2 Granular Computing

Granular computing is a general computation theory for effectively using granules such as classes, clusters, subsets, groups and intervals to build an efficient computational model for complex applications with huge amounts of data, information and knowledge. Though the label is relatively recent, the basic notions and principles of granular computing, though under different names, have appeared in many related fields, such as information hiding in programming, granularity in artificial intelligence, divide and conquer in theoretical computer science, interval computing, cluster analysis, fuzzy and rough set theories, neutrosophic computing, quotient space theory, belief functions, machine learning, databases, and many others. In the past few years, we have witnessed a renewed and fast growing interest in granular computing. Granular computing has begun to play important roles in bioinformatics, e-Business, security, machine learning, data mining, high-performance computing and wireless mobile computing in terms of efficiency, effectiveness, robustness and uncertainty.

3.2.1 Quotient Space Theory of Problem Solving

It is well known that one of the basic characteristics in human problem solving is the ability to conceptualize the world at different granularities and translate from one abstraction level to the others easily, i.e., deal with them hierarchically[14]. In order to analyze and understand the above human behavior, Bo Zhang and Ling Zhang presented a quotient space model in [15]. The model they proposed was intended to describe the worlds with different grain-size easily and can be used for analyzing the hierarchical problem solving behavior expediently. Based on the model, they have obtained several approaches in heuristic search, path planning, etc. since the approaches can deal with a problem at different grain sizes so that the computational complexity may greatly be reduced. The model can also be used to deal with the combination of information obtained from different grain-size so that the computational complexity may greatly be reduced. The model can also be used to deal with the combination of information obtained from different grain-size worlds (different views), i.e., information fusion.

3.2.2 Tolerant Relation Based Granular Computing Model

Human problem solving involves the perception, abstraction, representation and understanding of real world problems, as well as their solutions, at different levels of granularity[16−18]. The consideration of granularity is motivated by the practical needs for simplification, clarity, low cost, approximation, and tolerance of uncertainty[19]. As an emerging field of study, granular computing attempts to formally investigate and model the family of granule-oriented problem solving methods and information processing paradigms[20].

Information granules, as the name itself stipulates, are collections of entities, usually originating at the numeric level, that are arranged together due to their similarity, functional adjacency, indistinguishability, coherency or alike[21]. The entities on data layer usually belong to two types: symbolized data or consecutive real value data. Many models and methods of granular computing[15,19,22] have been proposed and studied. However, most of them discuss symbolized data or consecutive real value data respectively. In their theories, attributes are usually represented by symbols, which are calculated from the real value features by some methods such as feature extraction, feature reduction, classification or discretion. That means symbolized feature and real value feature can be generated from each other. So, it is time to construct a uniform model to study some important problems in pattern recognition and machine learning, such as feature extraction, feature reduction, discretion and classification, etc.

Nowadays, many researchers study equivalence relation based granular computing theory, such as B. Zhang and Y.Y. Yao[15,23] indicate that granule is closely related to quotient space. In reality, tolerant relation is a broader relation. So, our work[24,25] mainly discuss about the tolerant relation based granular computing theory. Besides, in our research, we present a definition of granules granule is not only a cluster (or set) of objects as some existent granular theories, but also an abstraction of the cluster (or set). Therefore, we denote a granule with two parts: the intension and the extension.

In 1962, Zeeman proposed that cognitive activities could be viewed as some kind of tolerance spaces in a function space. The tolerance spaces, which are constructed by distance functions based tolerance relations, is used for stability analysis of dynamic system by Zeeman. In this paper, tolerance spaces based on distance functions are developed for the modeling and analysis of information granulation, which is defined as tolerance relation granulation in the following part.

Suppose the triplet (OS, TR, NTC) describes a tolerance relation based granular space TG, where OS denotes an object set system; TR denotes a tolerance relation system; NTC denotes a nested tolerance covering system. For the detail definitions you can see paper [25].

4 Agent Computing

Agent is an atomic software entity operating through autonomous actions on behalf of the user without intervention. The agent computing paradigm has following features:

- Autonomy — agents operate without intervention;
- Social ability — agents interact each other using an agent communication language;
- Goal driven — agents exhibit goal-directed behavior;
- Reactivity — agents perceive and respond to their environment.

4.1 Multi-AGent Environment MAGE

MAGE[26] (Multi-AGent Environment) is designed for developing multi-agent systems. It can integrate legacy systems and enables interoperability between distributed heterogeneous systems. It facilitates the rapid design and development of new multi-agent applications by abstracting into a toolkit the common principles and components underlying many multi-agent systems. MAGE is compliant with FIPA[27], and its framework conforms to FIPA Agent Management Specification. It is a logical reference model for the creation, registration, location, communication, migration and retirement of agents.

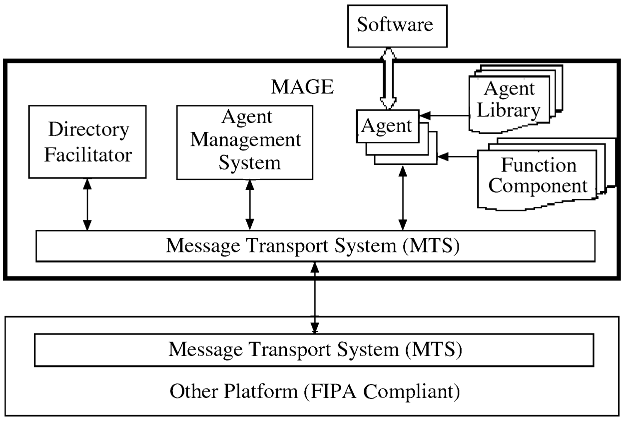

Fig.4. Architecture of MAGE.

Fig.4 illustrates the architecture of MAGE. It mainly consists of four subsystems: Agent Management System, Directory Facilitator, Agent, and Message Transport System. Agent Management System is a mandatory component of MAGE. It maintains a directory of AIDs (Agent Identifiers), which contain transport addresses for agents registered in MAGE and offer white pages services to other agents. Directory Facilitator (DF) is an indispensable component of MAGE. It allows agents to publish one or more services they provide so that other agents can find and successively exploit them. Agents may register their services with the DF or query the DF to find out which services are offered by other agents. Message Transport Service (MTS) is the default communication approach between agents on different FIPA-Compliant agent platforms. It uses FIPA ACL as the standard communication language. Agent is the fundamental actor in MAGE, which combines one or more service capabilities into a unified and integrated execution model that may include access to external software, human users and communications facilities. Software represents all non-agent, external components accessible to an agent. For example, agents may add new services or acquire new communication/negotiation protocols, etc.

Fig.5 is the extensible architecture of a generic MAGE agent. Agent kernel consists of the following parts. Sensor perceives the outside world. Function Module Interface makes an effect to the outside world. Communicator handles communications between the agent and other agents. Coordinator makes decisions concerning the agent's goals, and it is also responsible for coordinating the agent interactions with other agents using given coordination protocols and strategies. Scheduler plans the agent's tasks based on decisions taken by the Coordination Engine and the resources and task specifications available to the agent. Resource ontologies maintains a list of ontologies describing the semantic content of resources that are owned by and available to the agent. Task ontologies provide logical descriptions of tasks known to the agent. Plug-In Manager manages the components provided by MAGE or by users that can be plugged into agent kernel.

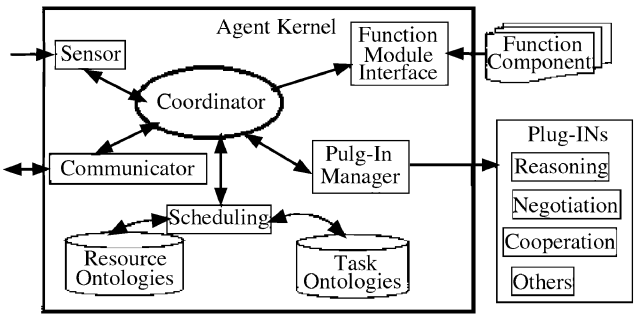

Fig.5. Architecture of the generic MAGE agent.

4.2 Mobile Agent

A Mobile Agent is specialized in that in addition to being an independent program executing on behalf of a network user, it can travel to multiple locations in the network. As it travels, it performs work on behalf of the user, such as collecting information or delivering requests. This mobility greatly enhances the productivity of each computing element in the network and creates a uniquely powerful computing environment well suited to a number of tasks.

Jian Lv *et al.* developed a mobile agent environment HOOPE and applied it to software coordination[28].

4.3 Agent-Oriented Software Engineering

Agent-Oriented Software Engineering (AOSE) is a novel and systematic theory, which aims to analyze, design and build complex software systems. It is based upon three strategies for addressing complex systems: decomposition, abstraction, and organization. In 1998 Zhong-Zhi Shi proposed Common Agent Request Broker Architecture (CARBA) according to COBAR idea. In terms of CARBA we have designed and implemented VAStudio, which provides a friendly interface for supporting agent design and programming. VAStudio is not only a programming environment, but also an agent-oriented design and programming environment. VAStudio provides many kinds of graphical interface wizards to help generating agent. At the same time, VAStudio provides a series of reusable component tools, such as component management tool, simple certainty FSM (Finite State Machine) edit tool, ADL (Agent Description Language) parsing and ontology edit tool, etc. VAStudio mainly contains four functional modules: VAStudio design platform, VAStudio programming platform, VAStudio runtime platform and VAStudio Toolkits[26].

For requirements analysis and design of multi-agent system, we extend UML into AUML which consists of four components, that is, system function modeling, behaviour modeling, agent modeling, system deployment modeling. Based on AUML system modeling method AUMP has been built at the Intelligence Science Laboratory[30].

5 Semantic Web

5.1 Knowledge Representation

WWW (World Wide Web) has been one of important channels from which people acquire information and services, but most web pages are only used by human at present, and these pages cannot be processed and understood automatically by computers. The semantic web is an essential reformation of Web. The main objective of the semantic Web is to enrich Web with semantics and be understood by computers, in order to communicate and cooperate between people and computer. The key of the semantic Web research is how to represent Web information, thus make them be understood by computers, i.e., the information possesses semantics[31].

The problem of semantics representation of the semantic web must be solved firstly, i.e., the problem of knowledge representation and ontology of semantic web, in order to let computer understand the information of the semantic web automatically. XML and RDF are two kinds of important knowledge representation languages which can be used to develop the semantic web. XML is a kind of tool which defines markup, and it has strong function and may be used easily, and these are outstanding characteristics of XML. RDF expresses meanings through triple tuple (predicate, subject, object), which forms Web. Because RDF codes information in RUI, so RUI insures that the related concepts are not only some words, and RUI relates these concepts to its unique definition in Web. Semantic web utilizes ontology to express its semantics. A typical ontology has a taxonomy and a group of reasoning rules in semantic web, where taxonomy defines class of objects and relationship between these objects, and these reasoning rules provide certain reasoning capability for semantic web. Ontology usage needs a kind of well-designed, well-defined language compatible with web ontology, which describe domain structure. All these structures may be described by certain concept (class) and attribute (relation), and ontology consists of axioms which these structures represent. Because description logic has some strongpoint in semantics, decidable property and object oriented taxonomy, so general ontology language may be built based on description logic, for example, ontology language DAML+OIL[32] and OWL[33] (including OWL Lite, OWL DL, and OWL Full) and so on. Because there exists a corresponding relationship between these ontology languages (DAML+OIL, OWL Lite, and OWL DL) and description logics, some scholars regard description logic as logical foundations for semantic web. For example, Ian Horrocks proves ontology language DAML+OIL is equal to description logic SHOIQ(D)[34]. Ian Horrocks and P F Patel-Schneider proves ontology language OWL DL is equal to description logic SHOIN+(D)[35]. Therefore they regard description logic SHOIQ(D) or SHOIN+(D) as logical foundations for semantic web. Franz Baader *et al.* point out description logic may be used as ontology language of semantic Web, so description logic may provide essential logical foundations for semantic web[36].

5.2 Dynamic Description Logic DDL

Semantic web not only needs to provide static information, but also needs to provide dynamic services (semantic web services)[37]. So logical reasoning of semantic web not only includes static knowledge (ontology) reasoning, but also includes dynamic knowledge (services) reasoning. But description logic mainly represents and reasons static knowledge, and it cannot represent and reason dynamic knowledge. So description logic (for example, SHOIQ(D) and SHOIN+(D)) cannot provide reasonable logical foundations for semantic Web, i.e., using description logic to act as logical foundations for semantic Web is insufficient.

Based on aforementioned reason and according to the characteristics and requirement of semantic Web, a kind of new description logic[38], i.e., dynamic description logic (DDL), is presented. The representation and reasoning of static knowledge and dynamic knowledge is integrated in this description logic theory. So DDL is a kind of formally logical framework which can process static knowledge and dynamic knowledge. The DDL has clear and formally defined semantics. It provides decidable reasoning services, and it can support effective representation and reasoning of the static knowledge, dynamic process and running mechanism. DDL generalizes description logic (add action representation and reasoning), therefore, the DDL provides reasonable logic foundation for semantic Web, and overcomes the insufficiency of using description logic to act as logical foundations for semantic Web.

5.3 Semantic Web Services

Semantic web services use ontologies as underlying data model to support Web service and data interpretation. **S**ervice **D**escription **L**anguage with **S**emantics and **I**nheritance and Supporting **N**egotiation (SDLSIN) based on DDL is proposed. The core of SDLSIN is DDL, and we implement SDLSIN in Java. This language considered not only semantic service description of agent, but also the inheritance and negotiation mechanism of agent service description, agent state language, and data types. SDLSIN is a kind of framework language with slots, and its formal criterion is in the following.

⟨asdl-descr⟩::=
(**ctype**
:**service-name** name
:**context** context-name+
:**types** (type-name = ⟨modifier⟩type)+
:**isa** name
:**inputs** (variable: ⟨modifier⟩put-type-name)+
:**outputs** (variable: ⟨modifier⟩put-type-name)+
:**precondition** (DL formulae)
:**effects** (head/body)*
:**concept-description** (ontology-name = ontology-body)+
:**attributes** (attributes-name : attributes-value)+
:**text-description** name
)
ctype ::= capability | task
context-name ::= name⟨*ontology-name⟩
type-name ::= name
modifier ::= listof | setof
type ::= (name : name⟨*ontology-name⟩)+
put-type-name ::= (type-name | name⟨*ontology-name⟩)+
variable ::= name⟨*ontology-name⟩
DL formulae ::= null | (DL formulae), (DL assertion)*
head ::= null | (DL assertion)
body ::= DL formulae
ontology-body ::= (expression in concept-language)
attributes-name ::= name ⟨*ontology-name⟩
attributes-value ::= name
name ::= String
ontology-name ::= name

In the formal criterion of SDLSIN, the meaning of each component is the following: **ctype** has two values, i.e., capability and task, where capability is the identifier which service provider (SP) registers its capability to the middle agent, while task is the identifier with which service requester (SR) requests services from the middle agent; **service-name** denotes the name of service (i.e., identifier); **context** uses several keywords (from domain ontologies) to describe the main characteristics of service and it may be used in (syntax based or semantics based) service matchmaking; **types** denote the definition of the data types (i.e., Integer, Real, and String) used in the service description; **isa** allows the name of a service from which this service will inherit the description; **inputs** denote input variable declarations for the service; **outputs** denote output variable declarations for the service, i.e., the outcome of invoking service; **precondition** denotes the executability of service; **effects** denote the effects of performing the service; **concept-description** denotes the meaning of words used in the service description, i.e., some terminologies defined in a given local domain ontology; **attributes** mainly support for service negotiation and its values include cost, quality of service, style of service, and performance of service etc; **text-description** is mainly used to descript the service in natural language; except for attribute service-name, all of these attributes are optional.

Currently, many research and development activities have focused on agent service description. Sycara *et al.*[41] studied and developed LARKS — an agent capability description language that took the trade-off between Quality of Service (QoS) and efficiency of service, but it did not consider the inheritance mechanism of service description and agent state language and the negotiation mechanism between services. G. J. Wickler[42] studied and developed the agent capability description language CDL, which did not consider the negotiation mechanism of services and did not support the definition of data types. K Arisha *et al.*[43] also presented a kind of agent service description language SDL which used hierarchy mechanism and synonym dictionary to infer the semantics of service description. As to all of these agent capability (or service) description languages, there exist corresponded service matchmaking algorithms.

6 Agent Grid Intelligence Platform

6.1 Architecture of AGrIP

Agent Grid Intelligence Platform (AGrIP) is a highly open software environment whose structure is capable of dynamical changes. It is a loosely coupled computer network of ever expanding size and complexity. It can be viewed as a large, distributed information resource, with nodes on the network designed and implemented by different organizations and individuals with widely varying agendas. Any computer system that must operate on the platform must be capable of dealing with these different organizations and agendas, without constant guidance from users (but within well-defined bounds). Such functionality is almost certain to require techniques based on negotiation or cooperation, which lies very firmly in the domain of multi-agent systems. The four-layer model for AGrIP from the implementation point of view is illustrated in Fig.6, where:

- data resources consist of various resources distributed in Internet, such as web pages, databases, knowledge bases etc., running on Unix, NT and other operating systems;
- multi-agent environment is the kernel of AGrIP, which is responsible to resources location and allocation, authentication, unified information access, communication, task assignment, agent library and so on;
- middlewares provide developing environment, containing agent creation, information retrieval, data mining, case base reasoning, expert system etc., to let users effectively use grid resources;
- application services automatically organize agents for specific purpose application, such as power supply, oil supply e-business, distance education, e-government.

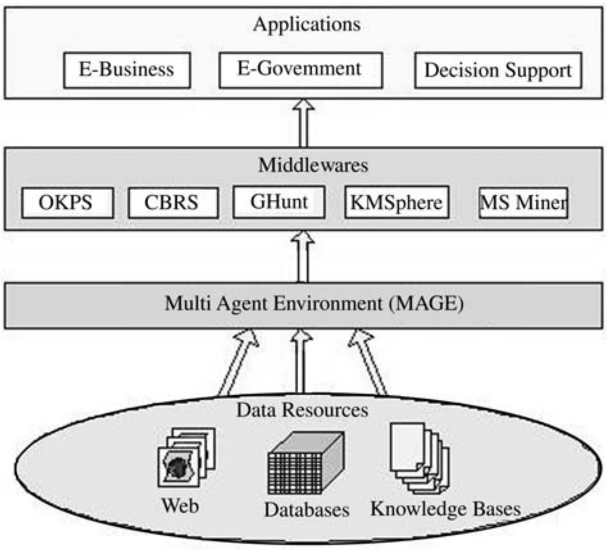

Fig.6. Implementation-oriented model for AGrIP.

Middleware layer provides developing environment, containing information retrieval, data mining, case based reasoning, expert system, knowledge management etc., to let users effectively use agent grid resources. In this section, we only expound the information retrieval and data mining because of page limits. Please refer to [39] for more information.

6.2 Intelligent Search Engine

GHunt (http://www.intsci.ac.cn/research/ghunt.html), from the function aspect, is an all-sided solution for information retrieval on the Internet. When it runs on the Internet, a parallel, distributed and configurable Spider is used for information gather; a multi-hierarchy document classification approach combining the information gain initially processes gathered web documents; a swarm intelligence based document clustering method is used for information organization; a concept-based retrieval interface is applied to user interactive retrieval. Since huge original information is crucial in a decision support system, it was integrated as a module of the AGrIP platform, which provides a powerful information retrieval function.

GHunt is composed of five key procedures. A parallel, distributed and configurable Spider is used for information gather. By applying text mining, GHunt constructs conceptual semantic space. A multi-hierarchy document classification approach combining the information gain initially processes gathered web documents. A swarm intelligence based document clustering method is used for information organization. GHunt has the special procedure to automatically generate abstracts and event traces. Image processing is used for building image space in GHunt. A concept-based retrieval interface is applied to user interactive retrieval. GHunt is an all-sided solution for information retrieval on Internet.

6.3 Data Mining

MSMiner is a generic multi-strategy data mining tool. The functions of the system include database access, data modeling, data preprocessing, data mining, and data visualization[40]. MSMiner has an open interface for adding data preprocessing function and can access a variety of databases such as SQL Server, Oracle, and Informix.

MSMiner can collect information from web, text, database and multimedia database. After data cleaning, they are stored in the data warehouse for data mining. Since it is a multi-strategy data mining tools, we integrated machine learning algorithms, such as C4.5, association rules, SVM, rough set, case-based reasoning, neural networks and so on in the algorithms library that provides a strong data mining tool to transform information into knowledge.

6.4 Knowledge Management

Ontology-based knowledge management system KMSphere aims to integrating ontologies with the grid and providing uniform mechanisms for ontology access and mediation. The KMSphere architecture explores important aspects of service-oriented and ontology-driven knowledge management on the grid. Ontologies aim to capturing consensual knowledge of a given domain that can be reused and shared across applications and by groups of people. In KMSphere, each term in ontologies is linked either to a data collection that have common features in certain attributes related to that term, or to the attributes commonly used within a related data collection. Through these linkages, ontologies construct a distributed knowledge space on top of data resources. Then KMSphere emphasizes how to organize, discover, utilize, and manage the knowledge resources in that space and brings the following advantages:

• discovering data objects via the knowledge space can work much more effectively and efficiently than via the huge namespace, since the knowledge space has meaningful content and is far smaller in size than the namespace;

• semantic-based data integration becomes feasible;

• semantic interoperability can be presentedto grid applications.

7 Future Challenges

7.1 Employment Test

The long-term scientific goal of Artificial Intelligence is human-level intelligence. Alan Turing claimed that it was too difficult to define intelligence. Instead he proposed Turing test in 1950. But the Turing test does not constitute an appropriate or useful criterion for human-level Artificial Intelligence. Nilssson suggested we replace the Turing test by "employment test"[44]. To pass the employment test, AI programs must be able to perform the jobs ordinarily performed by humans. Systems with true human-level intelligence should be able to perform the tasks for which humans get paid. One can hope that the skills and knowledge gained by a system's education and experience and the habile-system approach toward human-level AI can be entered at whatever level.

7.2 Learning

Introspective learning is a learning approach that improves reasoning by considering intelligence system's method of knowledge processing and reasoning, finding problem from failure and low-efficiency, and forming learning aim at repairing itself. Different with the other learning mechanisms, it pays more attention to the repair of system's reasoning. Introspection is essential to effective learning.

An ordinary introspective process involves three parts that are blame assignment, explain failure and repair failure. The blame assignment is a process of finding out errors. The explain failure is a process of looking for reasons and forming aims of introspective learning. The repair failure is the process that the system makes and performs learning strategy according to learning aim. It needs a representation to record and track reasoning. The meta-level reasoning representation is exactly in accordance with the requirement. Reasonable taxonomy of failure is one of important factors of affecting the abilities of introspective learning. The multi-layer taxonomy of failure corresponding to the system's reasoning can improve introspective efficiency. Case-based reasoning is important means of introspective learning, also an important application area of introspective learning. Based on these, a case representation and case retrieval mechanism appropriate to introspective learning are developed by us[45], which make it available to combine case-based reasoning and introspective learning further.

The introspection should not only pay attention to performance failure or reasoning failure, but also involve low-efficient performance and reasoning process. The realization approach of introspective learning process and quantitative introspection has become better direction of research. They include the confirmation and maintenance of introspective criteria, formation and performance of repair strategy, quantitative method of evaluation, etc.

The term implicit learning was coined by Reber to refer to the way people could learn structure in a domain without being able to say what they had learnt[46]. Reber first proposed artificial grammars to study implicit learning for unconscious knowledge acquisition. It will help us to understand the learning mechanism without consciousness. Since the mid 1980's, implicit learning become an active research area in psychology.

7.3 Memory

A brain has distributed memory system, that is, each part of brain has several types of memories that work in somewhat different ways, to suit particular purposes. According to the stored time of contents memory can be divided into long term memory, short term memory and working memory. Research topics in memory exist coding, extract and retrieval of information. Current working memory attracts more researchers to involve.

Working memory will provide temporal space and enough information for complex tasks, such as understanding speech, learning, reasoning and attention. There are memory and reasoning functions in the working memory. It consists of three components: that is, central nervous performance system, video space primary processing and phonetic circuit.

Memory phenomena have also been categorized as explicit or implicit. Explicit memories involve the hippocampus-medial temporal lobe system. The most common current view of the memorial functions of the hippocampal system is the declarative memory[47]. There are a lot of research issues that are waiting for us to resolve. What is the readout system from the hippocampal system to behavioral expression of learning in declarative memory? Where are the long-term declarative memories stored after the hippocampal system? What are the mechanisms of time-limited memory storage in hippocampus and storage of permanent memories in extra-hippocampal structures?

Implicit memory involves the cerebellum, amygdala, and other systems. The cerebellum is necessary for classical conditioning of discrete behavioral responses under all conditions. It is learning to make specific behavioral responses. The amygdalar system is learning fear and associated autonomic responses to deal with the situation.

7.4 Language

Language is a fundamental means for social communication. Language is also often held to be the mirror of the mind. Chomsky developed transformational grammar that cognitivism replaced behaviorism in linguistics[48].

Through language we organize our sensory experience and express our thoughts, feelings, and expectations. Language is particularly interesting from cognitive informatics point of view because its specific and localized organization can explore the functional architecture of the dominant hemisphere of the brain.

Recent studies of human brain show that the written word is transferred from the retina to the lateral geniculate nucleus, and from there to the primary visual cortex. The information then travels to a higher-order center, where it is conveyed first to the angular gyrus of the parietal-temporal-occipital association cortex, and then to Wernicke's area, where the visual information is transformed into a phonetic representation of the word. For spoken word the auditory information is processed by primary auditory cortex. Then the information input to higher-order auditory cortex, before it is conveyed to a specific region of the parietal-temporal-occipital association cortex, the angular gyrus, which is concerned with the association of incoming auditory, visual, and tactile information. From here the information is projected to Wernicke's area and Broca's area. In Broca's area the perception of language is translated into the grammatical structure of a phrase and the memory for word articulation is stored[49].

7.5 Consciousness

The most important scientific discovery of the present era will come to answer how exactly do neurobiological processes in the brain cause consciousness? The question "What Is the Biological Basis of Consciousness?" is selected as one of 125 questions, a fitting number for *Science*'s 125th anniversary[51]. Recent scientifically oriented accounts of consciousness emerging from the properties and organization of neurons in the brain. Consciousness is the notions of mind and soul.

Consciousness should not be confused with knowledge, it should not be confused with attention, and it should not be confused with self-consciousness. Many states of consciousness have little or nothing to do with knowledge. Memory and prediction play crucial roles in creating consciousness.

8 Conclusions

Artificial intelligence is generally considered to be a subfield of computer science that is concerned to attempt simulation, extension and expansion of human intelligence. Artificial intelligence has enjoyed tremendous success over the last fifty years. Human-level intelligence is the long-term goal of artificial intelligence. We should do joint research on basic theory and technology of intelligence by brain science, cognitive science, artificial intelligence and others. A new cross discipline intelligence science is undergoing a rapid development.

Let researchers on brain science, cognitive science, artificial intelligence work together to solve different level scientific problems, such as molecular, cell, behaviour. The efforts on learning, memory, language and so on will give us new idea to find new approaches for artificial intelligence. Nilsson proposed "employment test" maybe provide a feasible criteria for evaluation intelligent behaviour.

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