AN INTRODUCTION TO KNOWLEDGE-GROWING SYSTEM: A NOVEL FIELD IN ARTIFICIAL INTELLIGENCE

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ABSTRAK

The essential matter of Artificial Intelligence (AI) is how to build an entity that mimics human intelligence in the way of learning of a phenomenon in a real life to gain knowledge of it and uses the knowledge to solve problems related to it. Based on the findings of intelligent characteristic displayed by the human brain in growing and generating new knowledge by fusing information perceived by sensory organs, we develop brain-inspired Knowledge-Growing System (KGS) that is, a system that is capable of growing its knowledge along with the accretion of information as the time passes. The essential matter of KGS is knowledge-growing method which is based on a new algorithm called Observation Multi-time A3S (OMA3S) information-inferencing fusion method. In this paper we deliver the development of KGS along with some examples of KGS application to a real-life problem. Based on the state-of-the-art of AI and approaches to construct OMA3S method as KG method as well as validations to assess the system performance, we state that brain-inspired KGS is a novel field in AI.

Keywords: AI, brain-inspired KGS, information-inferencing fusion, Knowledge-Growing, OMA3S.

1 INTRODUCTION

Human being is a very complex system that many scientists and engineers have been trying to understand the mechanism occurred in it. Human being is God's the most perfect creation that is already equipped with intelligence that is not possessed by other living things. Human intelligence is an abstract matter that has long attracted many people from diverse fields to study it, in order to apprehend how this matter works and try to emulate it to computing-based systems to build intelligent systems.

Building an intelligent entity that is capable of mimicking human intelligence in some aspects has been a challenging research all over the world. Moreover, studies and research in this field has been involving many science and engineering disciplines such as Philosophy, Psychology, Cognitive Science, Computer Science, Mathematics and Engineering as depicted in Figure 1. Of course, the approaches or techniques delivered by the diverse researchers to emulate human intelligence were difference because they modeled it based on their understanding of it combined with the science-and-engineering bases they had.

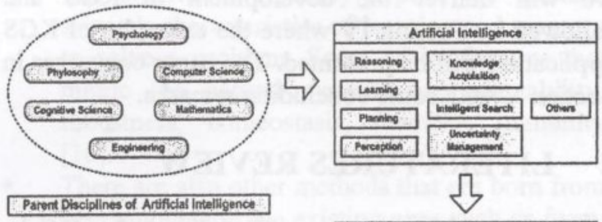

Figure 1. Science and Engineering disciplines of Artificial Intelligence (AI) [1]

The intelligence possessed by human beings has been there since they were born. With it, they can learn and have knowledge regarding the various phenomena occur in their environment and uses it to solve problems. In situations such these, human being always tries to find the most likely solutions that he has ever experienced in his life. These experiences are stored in brain in form of knowledge that is grown along with the accretion of information he sees, hears, etc from his environment as the time goes by.

Suppose, he is uncertain with the best available solutions, he will gather or collect more information in order to obtain comprehensive information regarding the problems. This mechanism is performed repeatedly by time to time until he ascertains with the best results to be taken as the basis for making a decision or an action. This is what is called as knowledge acquisition.

The illustration previously described shows that human being gets more intelligence when his knowledge grows from nothing to some extent that makes him able to apprehending the phenomena in his environment. Knowledge can be grown if there is information delivered to and processed by the brain. The comprehensive information can be obtained by combining or fusing information from all sensory organs by a technique called information-inferencing fusion. The comprehensive information will become his new knowledge regarding the phenomena he observes. The whole mechanism in obtaining the new knowledge is called as Knowledge-Growing (KG).

Our endeavor in this field has come up with an emulation of the KG in human brain called Knowledge-Growing System (KGS) with Observation Multi-time A3S (OMA3S) information-inferencing fusion method as the KG mechanism [2]. Regarding to this matter, the structure of the rest of the paper is as follows. Section II covers the literatures review regarding to the state-of-the-art of AI research especially that is related to the emulation of how brain obtains new knowledge. In Section III, we will deliver the development of KGS and followed by Section IV where the examples of KGS application will be presented. The paper converges in Section V with some concluding remarks.

2 LITERATURES REVIEW

In this section we will deliver what KG is, the state-of-the-art of AI, and the intelligent behavior of human brain in fusing information to obtain new knowledge.

2.1 What is Knowledge-Growing?

It is not easy to find any literature that defines or described what the term "Knowledge-Growing" is. The only research that used this term was done by [3] for industrial application. In this paper, [3] examined how the knowledge growing old in human brain and used the analogy of it for building a reconfiguration system for car application. They concentrated on the optimization of knowledge retrieval rather than emulating the way of human brain grows the knowledge over time and used actuality measurement to measure the knowledge that is very often used to solve an actual problem.

Up to the writing of this paper, there is no research that examines and develops an intelligent method for an intelligent system that emulates the mechanism how the human brain grows the knowledge from time to time. Our approach in developing KGS started from our observation of the intelligence characteristic displayed by human brain in performing such matter by fusing information perceived by human sensory organs and delivered it to the brain. This approach is discussed in detail in [4]. The original concept of information fusion, even though also adopted the mechanism occurs in living things' brain, just defines how to fuse the information for making estimation regarding a phenomenon, see [5] for the detail.

2.2 The Branches of AI

Back to the history, the work on AI was iniated by Alan M. Turing with his machine called as Turing machine. He also devised a test called Turing test to answer a question he raised if a machine can be intelligent [6][7]. Turing's works were then continued by other researchers such as Marvin Minsky, John McCarthy, etc to realize the dreams that machines can be as intelligent as human. In the summer in 1956, John McCarthy coined term AI [8] and since then this field has been grown with various methods and approaches with one aim to build intelligent machines.

In a particular view, AI technology is divided into two categories namely, the studies on the direction and the aim of the AI technology development. There are two matters that are raised as big issues namely, to build machines that can act or think rationally, or machines that can act or think humanly or like a human, or called as intelligent agent [9]. In 2006, Ahmad (2006) in [10] proposed the topology of AI that divides it into three big groups, namely smart systems, knowledge-based systems, and computational-based systems. The topology of AI is depicted in Figure 2.

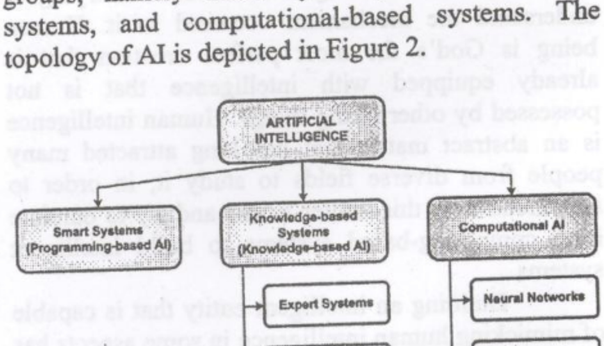

Figure 2. The Topology of AI

The model of human mind is approached from a field called Soft Computing (SC) [11]. SC is defined as a collection of techniques spanning many fields that fall under various categories in Computational Intelligence (CI). The main branches of SC are fuzzy systems, evolutionary computation, artificial neural computing, machine learning and probabilistic reasoning, belief networks, chaos theory, parts of learning theory and wisdom based expert system. The CI itself is defined as a study which is aimed to build intelligent systems or entities based on computational techniques [12]. CI in this case consists of five paradigms namely, artificial neural networks, evolutionary computation, swarm intelligence, artificial immune system, and fuzzy systems.

AI is a multidiscipline field where researchers from various backgrounds who work individually or in a team goes to one mission. This situation gave birth various methods and techniques which then caused the emergence of branches in AI. Each researcher has his own definition on AI branches. Such [13] divides into two categories. The first category is called as symbolic AI which covers areas such as knowledge-based systems, logical reasoning, symbolic machine learning, search techniques, and natural language processing. The second category is called as low level, microscopic biological models which are similar to the emphasis of physiology or genetics. The approaches in this category include neural networks and genetic algorithms or evolutionary computing, fuzzy systems, rough set theory, and chaotic systems.

2.3 A Brief Examination on the Existing Approaches in AI

All of approaches in AI modeled the human intelligence by mimicking or emulating the mechanisms in how the brain acquires knowledge and uses it to solve problems. We review some milestones in this field taken a brief from [14] with some addition as follows.

- McCulloch-Pitts viewed the human intelligence comes from the mechanism occurs in the human's nervous system. This view resulted in a model of human brain's neuron completed with the method of knowledge acquisition and repository as well as how to use the stored knowledge to solve problems. This approach gave birth to a technique called artificial neural networks.
- Lotfi Zadeh saw that human beings do not always think crisply that is, "yes" or "no", about a phenomenon but tend to think in between. Based on this reason he coined fuzzy set theory. In this approach the property of a phenomenon is valued with a degree of membership between 0 and 1.
- Human beings also have an ability to find the best compromise solution among several given alternatives and it is called as optimization problem. This perspective gave a birth to a new approach called as evolutionary computing where genetic algorithm is a part of it.
- Edward Feigenbaum and his colleagues initiated the development of an artificial system that is able to solve problems by using "if-then" formula. Their first work was Dendral that is considered as the first expert system ever built. This system is acquired the knowledge of human experts and uses it to work on the given problems.
- Another approach that comes purely from mathematics field is probabilistic reasoning which is defined as the utilization of mathematical probability and its related methods for modeling and emulating human intelligence in the existence of uncertainties.
- On the other side, machine learning is aimed to design and develop algorithms that allow computers to change behavior based on data. It is a programming computer to optimize a performance criterion using example data or past experience [15]. Major focus of machine learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on data. Expert system is a kind of knowledge-based system.
- Belief networks are also called as Bayesian Networks (BN) or Directed Acyclic Graph (DAG) model where the knowledge of the networks is stored in form on conditional dependencies amongst the variables connected in the networks.
- Artificial immune systems are adaptive systems, inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving. The algorithms typically exploit the immune system's characteristics of learning and memory to solve a problem. Some of its features that mimic the natural systems are adaptability, robustness, homeostasis, memory, immunity [16].
- There are also other methods that are born from the combination the existing ones such as fuzzy expert system, fuzzy neural system, etc.

2.4 The Intelligent Behavior of the Human Brain's Information-Inferencing Fusion

We did more deep investigation on the mechanism occurred during information fusion in the brain as depicted in Figure 2. We have concluded that there is an intelligent behavior performed by the brain when fusing the information gathered from the environment and delivered by the sensory organs which is in this case called as the information multi-source.

The mechanism of growing the knowledge in the brain can be viewed as a five-step process as follows.

- Fusing the information of a phenomenon perceived by the sensors to obtain fused information. It can be a combination of two or more information from two or more sensors.

There is no fusion for information delivered from single sensor.

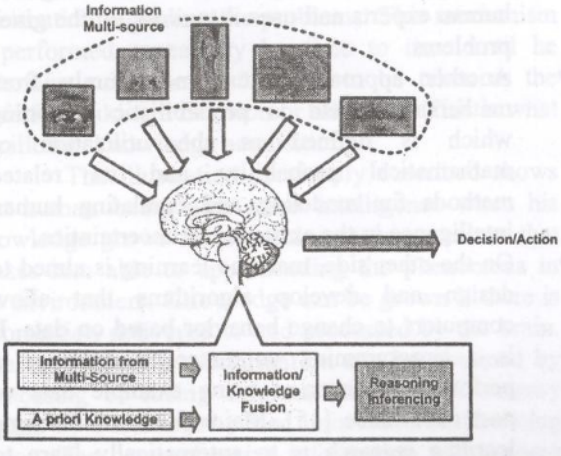

Figure 3. Human information-inferencing fusion system [17]

- Obtain the inferencing of the fused information. This inferencing can be regarded as the new knowledge if it is considered can explain the phenomenon.
- Fusing the information-inferencing of the fused information to obtain fused inferencing.
- Obtain the inferencing of the fused-inferencing to obtain knowledge regarding the phenomenon. This process is also called as knowledge inferencing.
- In order to obtain the ultimate knowledge, the brain performs knowledge-inferencing fusion as the final step of human thinking.

On the first process, information delivered from the sensory organs is fused to gain comprehensive information regarding the observed phenomenon. The result of this process is then reasoned to obtain the inferencing of the fused information. The inferencing at this stage is the inferencing regarding the phenomenon at the first observation or at time t. The next observation at the next subsequent time will result in inferencing at time t+1 and so on. The comprehensive information after some observation times is obtained by fusing the collection of the information-inferencing over time to become fused information-inferencing. This comprehensive information is called as new knowledge of the observed phenomenon.

3 THE DEVELOPMENT OF KGS

Before proceeding with KGS development, there will be some matters that have to be considered such as its features, what AI technology can be used to represent it, its modeling, the knowledge-growing mechanism, and the method for it. Refer to [18] the features of KGS are:

- It has ability to fuse information, information-inferencing, and knowledge-inferencing.
- It has ability to obtain inferencing from the fused information, and fused knowledge.
- It has a knowledge-base to store the new knowledge. The stored knowledge becomes prior knowledge to obtain the next new knowledge.

3.1 The Concept of Knowledge-Growing System

As the emulation of one aspects of human intelligence, KGS tries to mimic the process of human brain's KG mechanism in obtaining new knowledge from time to time and uses the acquired knowledge to make a decision or an action. Imagine that we do not have any knowledge about a phenomenon. At this point, assume at t_0, our knowledge has no information about it. At the subsequent times, we try to know it by utilizing our sensory organs – eyes, ears, nose, tongue, and skin.

Suppose at t_1 our eyes see it and deliver the information they gather to the brain. The brain still cannot have inferencing of what phenomenon that is. At the next time, t_2, our skin touches it and once more, delivers the information to the brain. This process will continue until the brain obtains comprehensive information that can be used to create inferencing regarding the phenomenon. This mechanism is depicted in Figure 4.

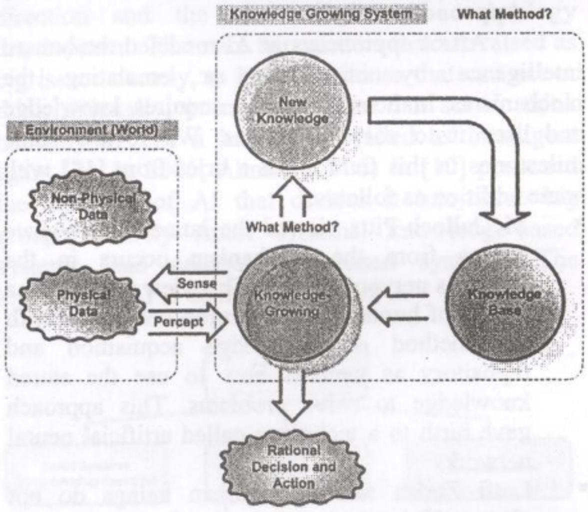

Figure 4. The Concept of Knowledge-Growing System

Refer to Section 1 the essential feature of KGS is KG mechanism that produces new knowledge after combining or fusing information received from the information multi-source with the information stored in system's Knowledge Base (KB). According to Figure 4, new knowledge will be stored in KB to be used to produce newer knowledge on the next KG process. The method for obtaining new knowledge will be delivered in the next section. Before that, we have to model the Human Inference System (HIS) which is the basis of the development of KGS.

3.2 The Model of Human Inference System and KG Mechanism [18]

Figure 5 illustrates how the KG mechanism works. In this illustration, we assume that the information delivered by the information multi-source is carried out in time by time manner started from information gathered by the eyes.

Suppose at time t_1, the brain receives information from the eyes. This information is then fused with the stored knowledge to obtain inferencing from the eyes regarding the observed object. Inferencing at this point is not enough to be used to decide what the observed object is. Therefore information from another information source is needed. At the next observation time, t_2, the brain receives information from the nose and uses it to obtain another inferencing.

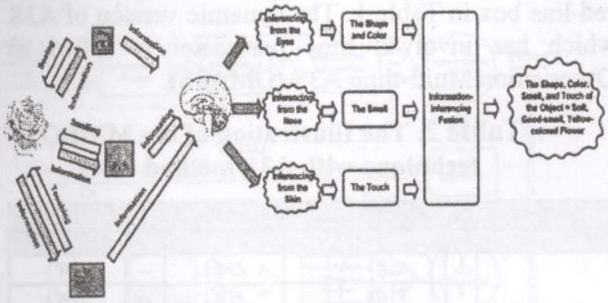

Figure 5. A simple illustration of KG mechanism

In order to have comprehensive information regarding the observed object, another information source namely the skin is also utilized and new inferencing is produced. Once more the brain does its job combining all information-inferencing to become comprehensive information regarding the object namely "soft, good-smell, yellow-colored rose flower". This information is then stored in the brain as the new knowledge.

3.3 The Mathematical Model of Knowledge-Growing Mechanism

To grow the knowledge, the requisites that have to fulfilled are there has to be a knowledge base and fusion mechanism. The fusion will be applied to the received information with the existing or prior information/knowledge. The knowledge is the result of the combination between the new information and the existing one which is called as after-processed information or posterior information.

Based on this examination, we find that there are two matters that have to be mathematical-modeled, that is:

- The first one is the model of the number of fused information;
- The second one is the model of knowledge-growing mechanism which consists two consecutive processes namely:
  - o Information-inferencing/knowledge fusion;
  - o Inferencing of the fused information-inferencing/knowledge.

For this purpose, we combine Figure 3 and Figure 5 to obtain comprehensive view of HIS as well as the process of growing the knowledge in Figure 6.

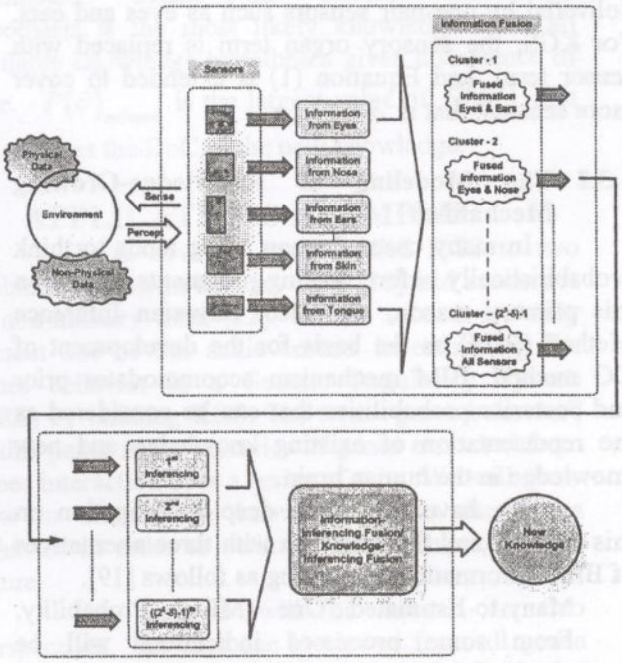

Figure 6. A simplified illustration of HIS along with KG mechanism

3.3.1 The Modeling of the Number of Fused Information

The model of HIS in Figure 6 is delivered ini Table 1.

Table 1. Possible Combinations of Information from Multi-Sensor

Information Source (Sensor)	The Possible Combination of Information from Multi-Sensor				
	1	...	i	...	λ
1	X		X		X
2		...		...	X
...		...	...	...	...
j	...	...	X	...	X
...		...	...	...	...
δ		...		...	X
Fused Information	1	...	i	...	λ

Observe Table 1, the number of fused information can be modeled as presented in Equation (1).

$$\lambda = \left(2^\delta - \delta\right) - 1 \qquad (1)$$

with λ is the number of fused information and n is the number of sensor. In the case of human being with $\delta = 5$ there will be $(2^5 - 5) - 1 = 26$ combinations of fused information or clusters. The number of combination is obtained under assumption that there is no information fusion for the information delivered by one-pair sensors such as eyes and ears. For KGS, the sensory organ term is replaced with sensor term, and Equation (1) is extended to cover more sensors, that is $\delta = 1, \ldots, n$.

3.3.2 The Modeling of Knowledge-Growing Mechanism

In many cases, human being tends to think probabilistically before making judgments. Based on this primary reason, we select Bayesian Inference Method (BIM) as the basis for the development of KG method. BIM mechanism accommodates prior and posterior probabilities that can be considered as the representation of existing knowledge and new knowledge in the human brain.

We have also done deep investigation on this method, and this came up with three alternatives of BIM' information processing as follows [19].

- Many-to-Estimated One (MEO) Probability. From some processed indications will be obtained information with a necessary certainty or called as Degree of Certainty (DoC), which directs to an inference regarding to the hypothesis being observed.
- One-to-Many-to-Estimated-One (OMEO) Probability. Given processed single indication will be obtained information regarding the DoCs of all available hypothesis which in turn directs to single hypothesis with the largest DoC.
- Many-to-Many-to-Estimated-One (MMEO) Probability. Given processed multiple indications will be obtained information regarding the DoCs of all available hypotheses which in turn directs to single hypothesis with the largest DoC. This is also called as multi-hypothesis multi-indication problem as depicted in Figure 7.

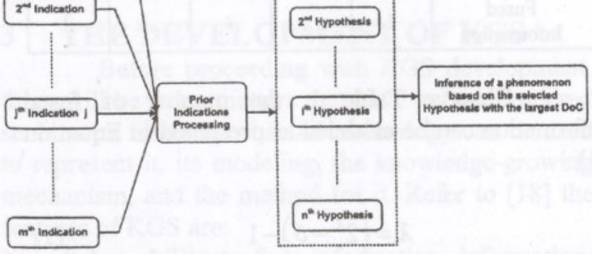

Figure 7. The Illustration of the MMEO technique [19]

If assumed that information perceived by sensors as indications or multi-indication of a phenomenon viewed from the sensors' perspectives, and the possible answers stored in form of knowledge in the brain are assumed as hypotheses or multi-hypothesis, we can see that this situation is a kind of a multi-hypothesis multi-indication problem which can be approached with MMEO technique.

We have also examined that BIM that is commonly combined with Maximum A Posteriori (MAP) cannot handle multi-hypothesis multi-indication phenomena. Based on that finding we have built a new method called Maximum Score of the Total Sum of Joint Probabilities (MSJP) [20]. MSJP became a fundamental method for developing a new KG method called Arwin-Adang-Aciek-Sembiring (A3S) information-inferencing fusion method [21]. The fusion mechanism in A3S method is depicted in red-line box in Table 1. The dynamic version of A3S which has involved time parameter is called as Observation Multi-time A3S (OMA3S).

Table 2. The Illustration of the MMEO technique with A3S method

B_j	Multi-Hypothesis, B_j					
A_i		1	...	j	...	λ
Multi-Indication A_i	1	$P(\vartheta_1^1)$	...	$P(\vartheta_1^j)$	...	$P(\vartheta_1^\lambda)$
	2	$P(\vartheta_2^1)$	...	$P(\vartheta_2^j)$	...	$P(\vartheta_2^\lambda)$
	...	...	...	...	...	...
	i	$P(\vartheta_i^1)$	...	$P(\vartheta_i^j)$	...	$P(\vartheta_i^\lambda)$
	...	...	...	...	...	...
	δ	$P(\vartheta_\delta^1)$	...	$P(\vartheta_\delta^j)$	...	$P(\vartheta_\delta^\lambda)$
A3S NKPD $P(\psi_1^j)$		$\frac{\sum_{i=1}^{\delta} P(\vartheta_i^1)}{\delta}$		$\frac{\sum_{i=1}^{\delta} P(\vartheta_i^j)}{\delta}$		$\frac{\sum_{i=1}^{\delta} P(\vartheta_i^\lambda)}{\delta}$
A3S + Maximum Score $P(\psi_1)_{estimate}$	$\max_{j=1,\ldots,\lambda}\left[\frac{\sum_{i=1}^{\delta} P(\vartheta_i^j)}{\delta}\right]$					

In its essential, A3S method consists of two equations. The first equation represents the information-inferencing/knowledge fusion in human brain, and the second one represents the mechanism to obtain the inferencing. Inferencing is new knowledge obtained from KG mechanism.

$$P(\psi_1^j) = \frac{\sum_{j=1}^{m} P(\vartheta_i^j)}{m} \tag{2}$$

$$P(\psi_1)_{estimate} = \max_{j=1,\ldots,\lambda}\left(P(\psi_1^j)\right) \tag{3}$$

with $P(\psi_1^j)$ is New-Knowledge Probability Distribution (NKPD) at time 1. $P(\vartheta_i^j)$ means hypothesis j where $j = 1, \ldots, \lambda$ at indication i $i = 1, \ldots, \delta$. The $P(\psi_1^j)$ is the representation of "fused probabilities" of all posterior probabilities from the same hypothesis at a certain observation time, while "estimated" means the selected hypothesis is the most likely hypothesis from all available hypotheses given indications at a certain observation time. $P(\psi_1)_{estimate}$ is the largest value of $P(\psi_1^j)$ that we call it as DoC of the selected hypothesis at time 1 that becomes new knowledge at time 1.

3.4 Knowledge-Growing with the Extension of A3S Information-Inferencing Fusion Method – OMA3S

The essential matter of KGS is time parameter as the indicator of the growing of the knowledge in KGS. Therefore we extended A3S method by involving this parameter and formed a new method called as Observation Multi-time A3S (OMA3S) as depicted in Figure 8.

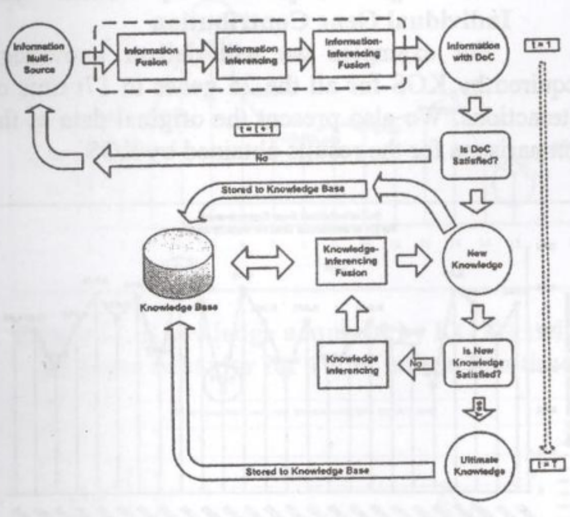

Figure 8. The Illustration of KG-mechanism in KGS [18]

The OMA3S method can be obtained as follows. We define a new term called New-Knowledge Probability Distribution over Time (NKPDT), $P(\Theta)$ with $\Theta = \{\theta_1, \theta_2, ..., \theta_\lambda\}$, as the collection of DoCs of the fused knowledge-inferencing obtained from OMA3S, which is the extension of A3S with the involvement of the time parameter. Equation (4) and Equation (5) present the OMA3S method as well as the mechanism to obtain the highest DoC as the most likely hypothesis that describes the observed phenomenon to become new knowledge.

$$P(\theta_t^j) = \frac{\sum_{t=1}^{\tau} P(\psi_t^j)}{\tau} \quad (4)$$

$$P(\theta)_{estimate} = \max_{j=1,...,\lambda}\left(P(\theta_t^j)\right) \quad (5)$$

with $P(\theta_t^j)$ is NKPDT, $P(\theta_t^j)$ means new knowledge j at time t where $t = 1, ..., \tau$. $P(\theta_t^j)$ is the representation of "fused probabilities" of all probabilities of the information-inferencing at each t from the same knowledge hypothesis. The term "estimated" means the selected knowledge hypothesis is the most likely knowledge from all available knowledge hypotheses given a sequence of time. $P(\theta)_{estimate}$ is the largest value of $P(\theta_t^j)$ that we call it as the DoC of the new knowledge.

4 APPLICATIONS EXAMPLES

Up to now we have applied KGS to two problems, one is in military field [20] and another is in non-military field [22]. In this section we only present one of our achievements in estimating the genes behavior in a Genetic Regulatory System (GRS) by utilizing KGS. The term "genes behavior" in this paper is the behavior of genes extracted from genes interaction over a series of time. We will show how to extract the knowledge from the genes behavior in order to estimate GRS behavior in the future.

The analysis will be viewed in two perspectives. The first one is viewed from all genes interaction over time and the second one is viewed from the contribution of individual gene over a time interval. For this purpose, we use data i.e. genes' interaction values database for yeast25-cdc28 taken from [23] as depicted in Table 3. In this database, there are 25 genes from ACE2 to SIC1 as listed in row 2 and row 22 in Table 3a and Table 3b respectively, with a time interval from t-1 to t-17 or 17t interaction times as shown in column A. Time parameter in this case is dimensionless.

Table 3a. Genes' interaction values of yeast25-cdc28 for ACE2-CDC21

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Time	ACE2	ASH1	FKH1	MBP1	MCM1	NDD1	STB1	SWI4	SWI5	SWI6	ALG7	CDC20	CDC21
2	t-1	-0.22	1,46	0,37	1,27	-0.8	0.89	-0.27	0,01	0.75	-0.31	-0.17	0.77	0,75
3	t-2	0,07	1,23	-0,63	-0,6	0	0.12	0,55	0,3	-0,1	0,26	-0,65	-0,42	0
4	t-3	-0,39	0,48	0,09	-1,12	-0.23	-0,08	0,05	0,3	-0,81	0,17	-0,69	-1,09	-0,01
5	t-4	-0,31	-0,23	-0,31	-1,63	-0,23	-0,24	0,15	0,24	-0,58	0,12	-0,41	-0,71	0,03
6	t-5	-0,92	-0,29	-1,41	-0,16	-0,34	-0,41	-0,11	-0,21	-1,82	-0,73	-0,47	-0,71	-0,49
7	t-6	-1,31	-0,86	-1,11	-0,3	0,09	-0,9	0,54	0,19	-1,35	-0,42	-0,94	0,62	0,51
8	t-7	-0,96	-1,21	-1,04	-0,33	0,3	0,16	1,42	0,86	-0,65	0,01	0,22	1,09	1,41
9	t-8	-0,42	-0,86	0,28	0,08	0,11	0,55	0,78	0,04	-0,67	0,28	0,32	0.45	1,23
10	t-9	0,19	-0,54	1,26	0,32	0,16	0,49	-0,64	-0,35	-0,4	0,32	0,19	-0,5	0,28
11	t-10	0,36	-0,51	1,34	0,27	0,13	0,56	-0,67	-0,39	0,34	0,29	0,03	0,14	-0,35
12	t-11	0,63	-0,92	0,72	0,27	0,02	0,2	-0,84	-0,51	0,57	0,09	0,29	0,05	-1,16
13	t-12	0,55	-0,34	0,36	0,03	0,22	0,06	0	-0,2	0,47	0,05	-0,26	-0,3	-1,38
14	t-13	0,72	0,78	0,28	-0,01	-0,24	-0,26	-0,17	0	0,51	-0,32	-0,11	-0,07	-1,16
15	t-14	0,51	2	-0,6	-0,54	0,38	-0,5	0,51	0,92	0,34	-0,1	-0,11	0,07	-0,51
16	t-15	-0,31	1,35	-0,3	-0,24	0,19	-0,38	0,73	0,77	0,12	0,12	0,17	0,17	1,03
17	t-16	-0,58	0,46	-0,22	-0,15	0	0,19	0,61	0,41	-0,25	-0,12	0,34	0,12	1,25
18	t-17	0,21	0,23	0,32	0,33	-0,53	0,38	0,22	0,14	0,08	0,09	0,59	0,2	1,06

4.1 Preparing The Inputs to KGS

One strategy to process the genes' interaction values listed in Table 3 is by converting them into binary numbers, and it will be done by using threshold value. In this case we use mean value as the threshold to obtain them. Because each gene has different characteristic, the mean value will be

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unique for each gene. The mean value is obtained by using Equation (6).

Table 4b. Genes' interaction values of yeast25-cdc28 for CDC5-SIC1

	A	B	C	D	E	F	G	H	I	J	K	L	M
21	Time	CDC5	CDC6	CLB2	CLB5	CLN1	CLN2	CTS1	EGT2	FAR1	HTA1	PCL2	SIC1
22	t-1	-0,46	-0,03	-0,07	0,24	-0,28	-0,21	1,8	1,58	0,83	-1,7	0,31	-0,4
23	t-2	0,2	0,44	-0,17	-0,11	-0,39	0,13	1,8	0,41	0,94	-0.72	0,71	1,63
24	t-3	-0,57	0.09	-0,91	-0,16	-0,31	0,13	2,32	0,41	0,59	-0,23	0,24	1
25	t-4	-0,23	-0,03	-0,91	-0,34	-0,29	0	2,24	-0,35	0,01	0,4	0,15	0,45
26	t-5	-1,59	-0,56	-1,35	-0,33	0	0	-0,06	-0,49	-1,18	-0,99	0	-0,3
27	t-6	-1,29	-0,79	-0,57	0,16	0,21	0,85	0,91	-0,15	-1,02	-0,71	0,86	-0,56
28	t-7	-1,54	0,25	-0,95	1,32	0,57	1,47	-0,57	-0,92	-1,74	0,38	1,14	-0,29
29	t-8	-0,75	0,19	-0,7	0,43	0,53	0,54	-1,16	-0,82	-1,69	0,21	-0,11	-0,5
30	t-9	-0,24	0,2	0,14	-0,1	0,14	0,03	-1,01	-0,35	-0,82	0,04	-0,32	-0,27
31	t-10	0,5	0,11	0,57	-0,2	0,16	-0,15	-0,31	-0,11	-0,19	-0,36	-0,26	-0,29
32	t-11	1,08	-0,01	1,06	-0,59	-0,34	-0,28	-0,41	-0,76	-0,31	-0,04	-0,84	-0,56
33	t-12	1,22	0,03	1,24	-0,32	-0,66	-0,5	-0,95	-1,09	0,72	-0,58	-1,11	-1,04
34	t-13	0,89	0,09	0,84	-0,63	-1,49	-1,57	-1,41	-0,1	0,76	-0,78	-0,24	0,32
35	t-14	-0,12	0,5	0,01	0,78	0,35	-0,18	1,01	1,63	1,75	0,2	0,61	1,57
36	t-15	-0,24	0,15	-0,35	0,91	1,05	0,52	1,67	1,31	1,43	0,33	1,23	0,9
37	t-16	-0,36	-0,24	-0,64	-0,13	0,62	0,86	1,03	1,23	0,44	0	0,54	0,45
38	t-17	0,32	0,08	-0,11	-0,12	0	0	0	0	0	-0,17	0,02	0,17

$$\phi_t^j = \begin{cases} 1, & \text{if } \psi_t^j < \dfrac{\sum_{i=1}^{\tau} \psi_t^j}{\tau} \\ 0, & \text{if } \psi_t^j \geq \dfrac{\sum_{i=1}^{\tau} \psi_t^j}{\tau} \end{cases} \qquad (6)$$

with $\phi_t^j \in \Pi$ is a binary number that represents an interaction value for gene j at time t. ψ_t^j is the value of interaction for gene j at time t, while τ is the number of t where the observations are carried out.

The result of the application of Equation (6) to list of interaction values in Table 3 is a set of binary-sequence numbers (Π) with size of $\tau \times \lambda$. The rule applied here is if the interaction value is lower than threshold value, it will be coded with '1'. The opposite condition will be coded with '0'. According [23], the lower the interaction value, the more active the gene is in the interaction. The result is delivered in Table 4.

Table 5a. Binary-sequence numbers of genes' interaction values of yeast25-cdc28 for ACE2-CDC21

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Time	ACE2	ASH1	FKH1	MBP1	MCM1	NDD1	STB1	SWI4	SWI5	SWI6	ALG7	CDC20	CDC21
2	t-1	1	0	0	0	1	0	1	1	0	1	1	0	0
3	t-2	0	0	1	1	0	0	0	0	0	0	1	1	1
4	t-3	1	0	0	1	1	1	1	0	1	0	1	1	1
5	t-4	1	1	1	1	1	1	1	0	1	0	1	1	1
6	t-5	1	1	1	1	1	1	1	1	1	1	1	1	1
7	t-6	1	1	1	1	0	1	0	0	1	1	1	0	0
8	t-7	1	1	1	1	0	0	0	0	1	0	0	0	0
9	t-8	1	1	0	0	0	0	0	1	1	0	0	0	0
10	t-9	0	1	0	0	0	0	1	1	1	0	0	1	0
11	t-10	0	1	0	0	0	0	1	1	0	0	0	0	1
12	t-11	0	1	0	0	0	0	1	1	0	0	0	0	1
13	t-12	0	1	0	0	0	0	1	1	0	0	1	1	1
14	t-13	0	0	0	0	1	1	1	1	0	1	1	1	1
15	t-14	0	0	1	1	0	1	0	0	0	1	1	0	1
16	t-15	1	0	1	1	0	1	0	0	0	0	0	0	0
17	t-16	1	0	1	1	0	0	0	0	1	1	0	0	0
18	t-17	0	0	0	0	1	0	0	1	0	0	0	0	0

4.2 Extracting Knowledge of the Genes Behavior

The knowledge in this case is the GRS behavior viewed from genes interactions over time that will be used as the basis for making an estimation regarding their interactions in the future. The ultimate aim of this effort is by apprehending the GRS behavior we can suppress or inhibit the genes that cause poor offspring quality and support the genes that produce good offspring quality.

Table 6b. Binary-sequence numbers of genes' interaction values of yeast25-cdc28 for CDC5-SIC1

	A	B	C	D	E	F	G	H	I	J	K	L	M
21	Time	CDC5	CDC6	CLB2	CLB5	CLN1	CLN2	CTS1	EGT2	FAR1	HTA1	PCL2	SIC1
22	t-1	1	1	0	0	1	1	0	0	0	1	0	1
23	t-2	0	0	1	1	1	0	0	0	0	1	0	0
24	t-3	1	0	1	1	1	0	0	0	0	0	0	0
25	t-4	1	1	1	1	1	1	0	1	1	0	1	0
26	t-5	1	1	1	1	0	1	1	1	1	1	1	1
27	t-6	1	1	1	0	0	0	0	1	1	1	0	1
28	t-7	1	0	1	0	0	0	1	1	1	0	0	1
29	t-8	1	0	1	0	0	0	1	1	1	0	1	1
30	t-9	1	0	0	1	0	1	1	1	1	0	1	1
31	t-10	0	0	0	1	0	1	1	1	1	1	1	1
32	t-11	0	1	0	1	1	1	1	1	1	0	1	1
33	t-12	0	0	0	1	1	1	1	1	0	1	1	1
34	t-13	0	0	0	1	1	1	1	1	0	1	1	0
35	t-14	0	0	0	0	0	1	0	0	0	0	0	0
36	t-15	1	0	1	0	0	0	0	0	0	0	0	0
37	t-16	1	1	1	1	0	0	0	0	0	0	0	0
38	t-17	0	0	0	1	0	1	1	1	1	0	1	0

4.2.1 Knowledge Acquired by KGS for Individual Gene Contribution

For examples we will deliver knowledge acquired by KGS for all the 25 genes in 17t time of interactions. We also present the original data as the comparisons for the results obtained by KGS.

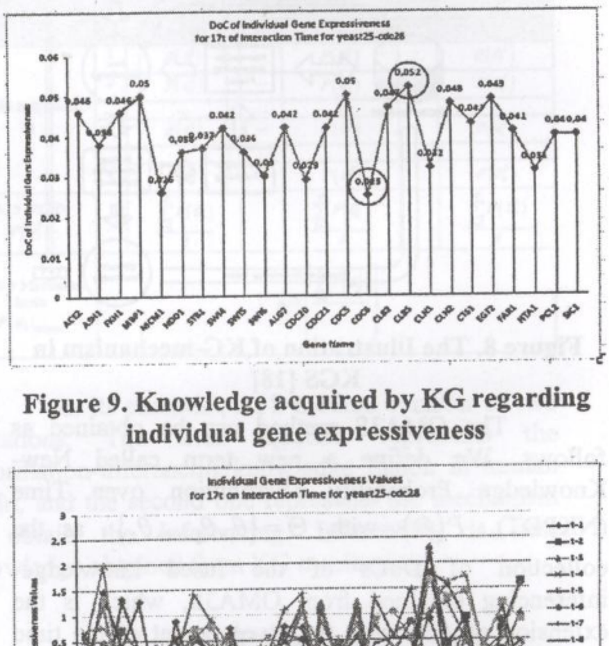

Figure 9. Knowledge acquired by KG regarding individual gene expressiveness

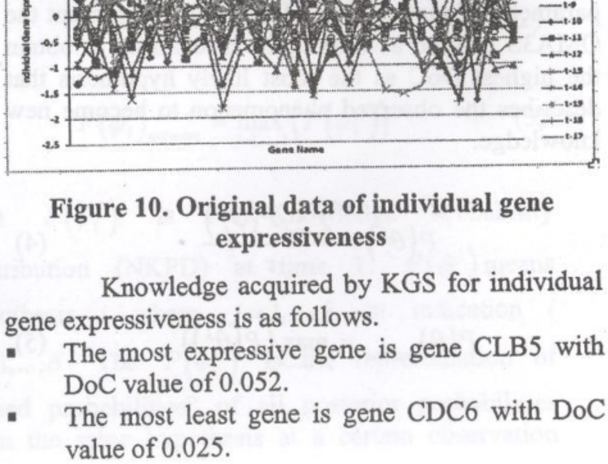

Figure 10. Original data of individual gene expressiveness

Knowledge acquired by KGS for individual gene expressiveness is as follows.

- The most expressive gene is gene CLB5 with DoC value of 0.052.
- The most least gene is gene CDC6 with DoC value of 0.025.

4.2.2 Knowledge Acquired by KGS for All Genes Contribution

In this view, KSG will acquire knowledge regarding all genes behavior from time to time during their interaction for 17t of interaction time. This phenomenon is the estimation of the behavior of biological GRS. The knowledge acquired by KGS is depicted in Figure 11, while the original data is depicted in Figure 12.

Knowledge acquired by KGS for genes behavior is as follows.

- The time when the interaction reaches its highest peak is at *t-5* with DoC value of 0.116.
- The time when the interaction reaches its lowest peak is at *t-15* with DoC value of 0.028.

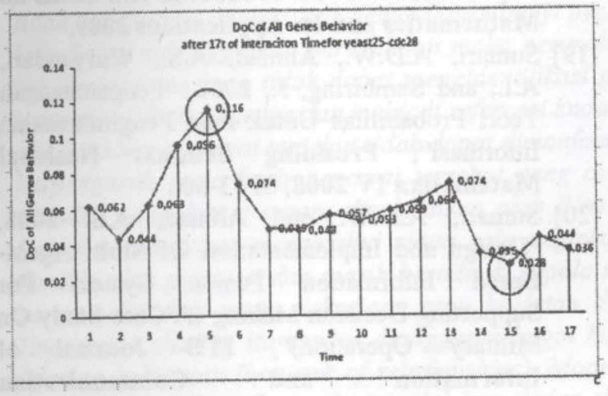

Figure 11. Knowledge acquired by KG regarding all genes behavior for 17t of interaction time

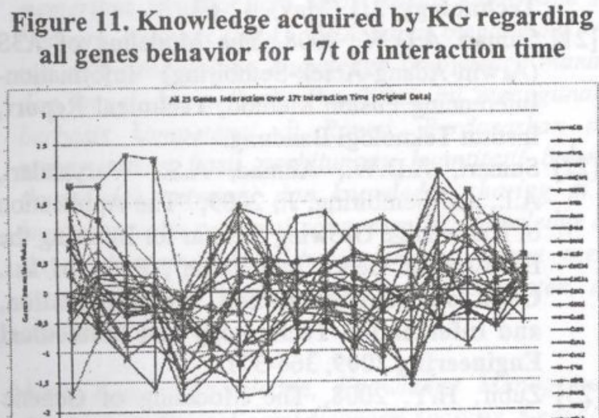

Figure 12. Original data of all genes behavior for 17t of interaction time

4.3 Estimation Based on KGS Knowledge

Based on the knowledge acquired by KGS, the estimations regarding the phenomena in GRS for the next interaction time is as follows.

- The most probable expressive gene is gene CLB5. If we look at in online genes information [24], this gene function is as promoter to begin transition in cell cycle progression and initiation of DNA replication. If this gene causes bad product, we can suppress or inhibit this gene.
- The most probable time when the interaction reaches its highest peak is at *t-22*.
- The most probable time when the interaction reaches its lowest peak is at *t-32*.

5 CONCLUDING REMARKS

Emulating human intelligence is not an easy task in AI technology. It is not only human being has various intelligence, but also what approach that is suitable to emulate it. Diverse approaches that have been devised and implemented came from diverse science-and-engineering basis and each of approach has its own strength and weakness.

In this paper we build a new method based on the observation of how human brain grows new knowledge from information perceived by his sensory organs. This intelligent mechanism is called as Knowledge-Growing (KG) that is based on information-inferencing fusion. The new system constructed from this mechanism is called as Knowledge-Growing System (KGS) that is defined as a system that is capable of growing its knowledge along with the accretion of information as the time passes.

The application of KGS to GRS has shown that this system is capable of acquired knowledge regarding two matters, that is : (1) individual gene expressiveness and (2) genes behavior in 17t of interaction time. The knowledge is used as the basis for making estimation of genes behavior in biological GRS.

The essential matter of KGS is KG mechanism, and it is built from the combination or fusion of probabilistic technique, intelligent programming to emulate the way of human thinks, and intelligent agent. The fusion results in a new KG method called Observation Multi-time A3S (OMA3S). From this consideration we state that brain-inspired KGS is a novel perspective in AI as depicted in Figure 13.

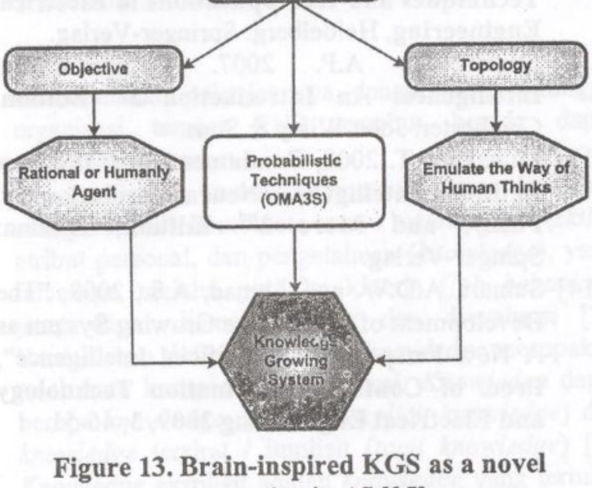

Figure 13. Brain-inspired KGS as a novel perspective in AI [25]

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