

Brain-Inspired Knowledge-Growing System: Towards a True Cognitive Agent

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Abstract—Knowledge growing is one of intelligence characteristics possessed by human brain. In this paper we review some fundamental theories that are appropriate for emulating this kind of intelligence in order to develop an intelligent system in Artificial Intelligence (AI) field, called brain-inspired Knowledge-Growing System (KGS). The development of this system is approached from various fields, namely psychological, mathematical, social, and electrical engineering and informatics fields. Based on the review results, we have built this system along with mechanism for growing the knowledge that consists of a model of Human Inference System (HIS), Sense-Inference-Decide and Act (SIDA) cycle, and the mathematical formulation for growing the knowledge called Observation Multi-time Arwin-Adang-Aciek-Sembiring (OMA3S) information-inferencing fusion method. In conclusion, brain-inspired KGS is a cognitive agent which is equipped with knowledge growing mechanism as its intelligent characteristic.

Keywords—Artificial Intelligence; Brain-Inspired KGS; Cognitive Agent; Inferencing; Intelligent System; Knowledge-Growing; OMA3S

I. INTRODUCTION

Artificial Intelligence (AI) has been an attracting field for researchers who are interesting in emulating human intelligence into computer systems. There are many approaches, and similar approaches are put into the same groups. For examples, [1] puts Artificial Neural Networks (ANN), Evolutionary Computation (EC), Swarm Intelligence (SI), Artificial Immune System (AIS), and Fuzzy Systems (FS) are put into a group called Computational Intelligence (CI). Each paradigm models have distinct phenomenon of intelligence behavior displayed by humans and living things, but they all have the same basis for emulating it namely probabilistic techniques as depicted in Fig. 1.

Another field called Machine Learning (ML) which is concerned with the question of how to construct computer programs that automatically improve with experience [2] or program computers to optimize performance criterion using example data or past experience [3], has developed very matured learning techniques based on the famous Bayesian theory, statistical and estimation theory, clustering techniques, and so on. Some of ML techniques are ANN, Genetic Algorithm (GA), Decision Tree, Bayes Optimal Classifier, and Naive Bayes Classifier.

In designing an ML technique, some design choices have to be considered, namely the type of training experience, the target function to be learned, a representation for this target function, and an algorithm for learning the target function from training examples [2]. So, the fundamental matter of ML is that, the system has to learn in order to gain knowledge, and the learning process is carried out by giving it training experience or past data along with targets that it has to learn. It is called

supervised learning. There are also unsupervised learning techniques where the system gains knowledge without being given targets. Unsupervised learning usually uses competitive learning with winner-takes-all technique. Some techniques are also derived from probabilistic method such as Bayes theory, a special case in probability theory.

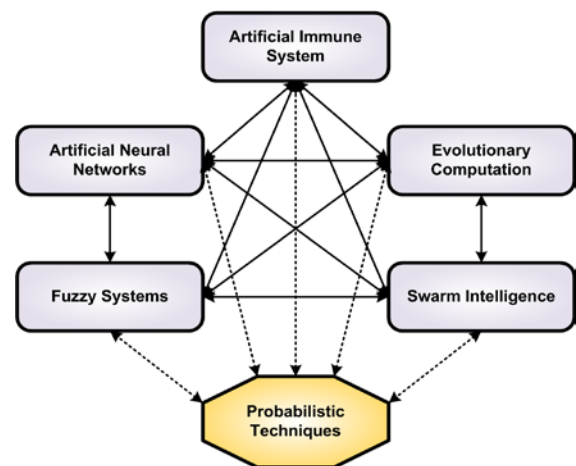


Fig. 1 CI paradigms [1]

In some cases, human derives conclusions after observing a phenomenon directly as the time passes. Based on the drawn conclusions, he gains knowledge as regard to that phenomenon, in other words, his knowledge about the observed phenomenon grows from nothing to some extent that is satisfied for him to recognize it. This is the mechanism that we call knowledge growing. It motivates us to carry out a research in order to construct an intelligent system called as Knowledge-Growing System (KGS). In a simple definition, KGS is a system that is capable of growing its knowledge along with the accretion of information it receives as the time passes. KGS is aimed to emulate the mechanism of knowledge growing within human brain. Our hypothesis is that, the growing of one's knowledge on a phenomenon is an inference of various information of the phenomenon from time to time.

To achieve that objective, in this paper we deliver the development of KGS based on a survey on some very relevant theories from multi-discipline perspectives that will become the basis for our KGS. Therefore the structure of the rest of the paper is as follows. In Section II we review some related theories from psychology, mathematical, and electrical engineering and informatics aspects. Based on our review, the model of KGS will be delivered and reviewed in Section III. In this section we also explain the knowledge growing mechanism based on Observation Multi-time Arwin-Adang-Aciek-Sembiring (OMA3S) information-inferencing fusion method. An example of how KGS carries out knowledge-growing to

obtain new knowledge will be delivered in Section IV. At the end of the presentation, we deliver some concluding remarks and further works in Section V.

II. FUNDAMENTAL THEORIES

Based on the hypothesis there are four important matters, namely inference, information, fusion, and time. In this section, reviews on fundamental theories from psychology, mathematical, social, and electrical engineering and informatics fields will be presented. The reviews will be the basis for building brain-inspired KGS.

The principle how knowledge is generated has been studied since a long time ago. The works in this field were done by earlier researchers such as Seymour Papert, Jean Piaget, and Lev Vygotsky. Although they have different perspectives on the way of knowledge generation in human brain, they share the same idea which is later called constructivism [4] [5]. On its very simple definition, constructivism is a theory of learning or theory of knowledge (epistemology) which states that humans generate knowledge and meaning from experiences and interactions. Fundamentally, constructivists believe that humans “construct” their own knowledge and understanding through ideas, content, events, etc. that they come in contact with [4]. This theory is used extensively in education field in order to obtain the most appropriate techniques in teaching and learning [6]. We try to bring it into AI field.

The term “knowledge generation” in constructivism is the basis for our term of “knowledge growing”. The important difference of those two terms is in the process of generating knowledge. Instead of being generated by experiences, the knowledge generation in knowledge growing term is carried out in just-in-time manner especially when humans are interacting with the world (environment). In the other words, the knowledge is grown from nothing to some extent that is satisfied for humans to understand the observed phenomenon. The initial knowledge that is stored in brain will serve as prior knowledge to be used for growing new knowledge once humans perceive new information about a phenomenon.

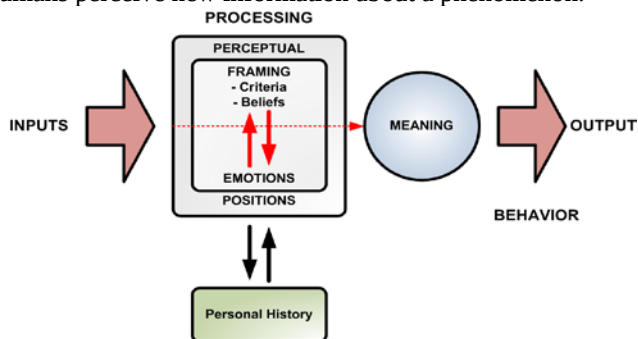


Fig. 2 An example of a model of how people think or human information processing model proposed by [7]

A. Psychological Perspective

From the psychological perspective we review some human thought models and try to find their relations to our concept of knowledge growing in order to apprehend how inference occurs in human brain. Therefore our primary aim is to obtain a Human Inference System (HIS) model. It is not easy to find literatures on such models. Most of the models found are models for human information processing such as one given by [7] depicted in Fig. 2. Human information processing models

are good starts to obtain our HIS model. Within the HIS model there is a mechanism of growing the knowledge that can be apprehended by using human thought models.

There are some models that we consider as human thought models that were proposed by some earlier and recent researchers as well as practitioners. These models are:

1) *Galileo Model*: Galileo modelled the way of human thinks to understand physical world into 4-step model which is called advancement of rational thinking that consists of (1) facts acquisition, (2) modelling, (3) conclusions, and (4) verifications with experiments [8]. In this model, the physical world is reflected as depicted in Fig. 3.

In this model, facts acquisition means diligently investigating the natures of a phenomenon. This step is followed by modeling that is aimed at carrying out experiments to find appropriate hypotheses. Conclusions step is to describe the nature of the phenomenon and draw conclusions on it. A verification with experiments does not mean trying to determine that phenomenon (before certain) unless that phenomenon can be aid in the experiment. Conclusions that have been verified can be considered as new knowledge.

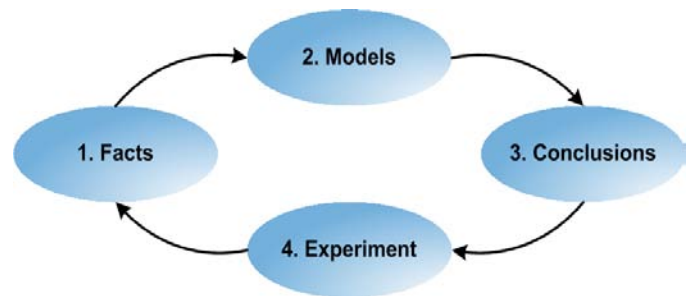


Fig. 3 The model of how human thinks viewed from Galileo's 4-step perspective

2) *Piaget Model*: Piaget theory is originated from a matter that is called schema, that is, an entity of behaviour and knowledge which interacts and evolves along with its environment and with other schemas [9]. In performing its activities, schema carries out intelligence basic processes that are divided into two parts, namely assimilation and accommodation. In assimilation, schema uses things within the world including other schemas within it. Assimilation is a part of its function. Accommodation is the modification of schemas in order to fit with newlies within the world. This modification process produces new knowledge regarding environment dynamics so the schema can always be able to adapt it well.

3) *Feynman Model*: Feynman noted that daily activities can be naturally considered as light model. He perfected Galileo model to become Feynman's 4-step model which consists of (1) models or laws, (2) principles or theories, (3) new predictions, and (4) experiments [8]. In this model, models or laws from an observation to a phenomenon will be obtained numbers that have to be measured and then law is obtained to summarize all of those numbers. The fundamental matter is to find the way of thinking. At the next step, from the emerged laws will be raised principle or theory regarding the phenomenon. New predictions is the application of principle or theory to law, which produce new prediction regarding the phenomenon. To ensure that the new predictions are correct, a sequence of experiment is carried out to test and prove their validities. The proven new predictions are considered as new knowledge. The Feynman's 4-step is depicted in Fig. 4.

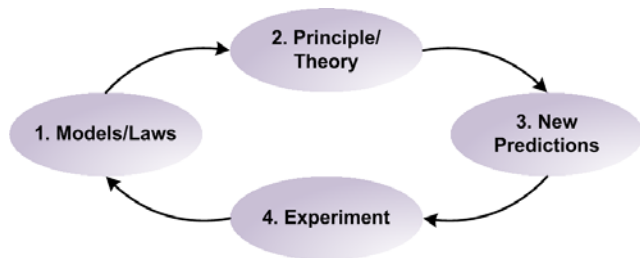


Fig. 4 The model of how human thinks viewed from Feynman's 4-step perspective

4) *Popper Model*: Sir Karl Popper modelled human's mental activity or intellectual process into "three worlds" as depicted in Fig. 5. World 1 is described as an environment along with process to percept it. Between World 1 and World 2 there is a transition called World 1½ because the part of sensory and effector are parts of schema. The sensory part senses if there is a stimulus from the environment that is processed by World 2 and then sends signals to the effector to activate certain parts. Meanwhile, World 2 that is also called thought-domain, which processes inputs from World 1½ to one instruction to World 1 to make them stable thought process within World 3.

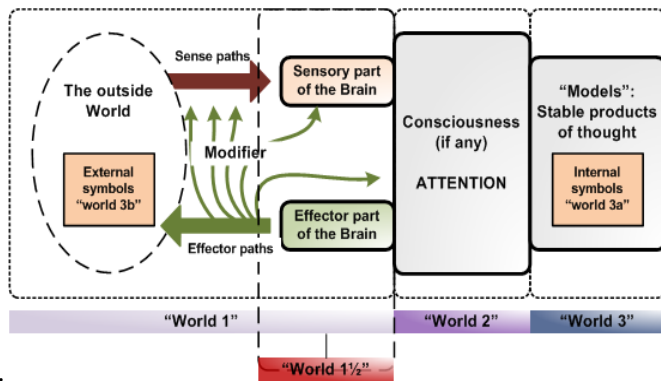


Fig. 5 Popper's human thought model [10]

World 3 is a domain that stores the products of thought processes which are called symbolic models (World 3a) that represent the situation of sensed environment (World 3b). These stable thinking products are also called models that can be considered as new knowledge.

5) *Cognitive Psychology Model*: The subject of cognitive psychology field is the main internal psychological processes that are involved in making sense of the environment and deciding what action that might be appropriate. As depicted in Fig. 6, from this view, thinking is a psychological process that involves action sensing the environment and deciding to carry out possible action that is presumed correct based on the assumptions as follows [11].

- Information provided by environment is processed by a sequence of processing system which consists of stimulus, attention, perception, thought processes, decision, and response or action.
- This processing system transforms or changes information in various ways.
- Specifying processes and structures that compose as basic cognitive performance.
- Human information processing mimics that occurs in computer.

Eventhough it is not stated clearly, from thought process will be produced new knowledge as the result of processing the information sensed from the environment. The product is then used as the basis for decision making or action.

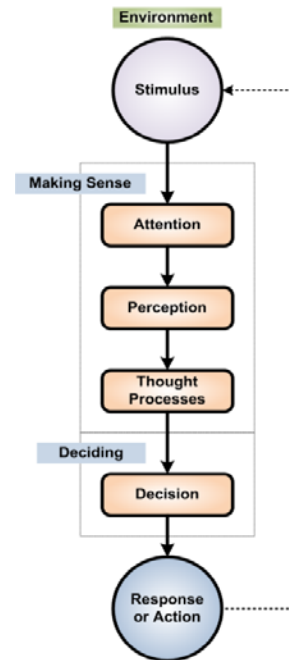


Fig. 6 The model of how human thinks viewed from cognitive psychology

6) *Decision Cycle Model*: Decision-making cycle Observe, Orient, Decide, and Act (OODA) is a cycle of how a perceived stimulus is processed and a formulation of a decision is obtained as the basis for decision-making. OODA cycle is a process that is carried out thousand times in a day [12] within human brain every time it receives a new stimulus.

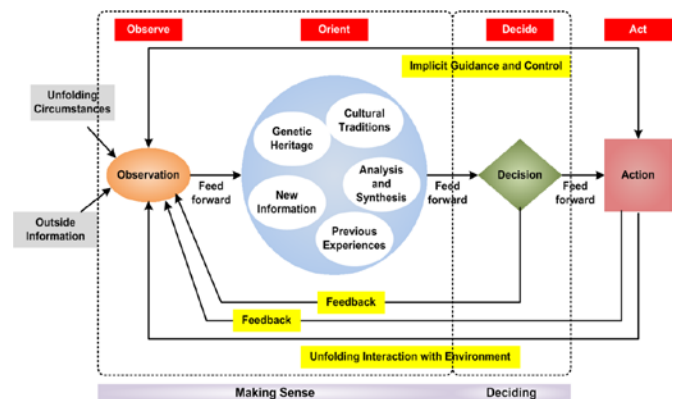


Fig. 7 The model of how human thinks viewed from John Boyd's OODA cycle perspective [13]

Phases in OODA cycle can be related to human thought process with explanations as follows.

- **Observation phase.** In this phase observation is done on phenomena in the environment by sensory organs or perception. Information collected by the sensory organs is delivered to brain to be processed further.
- **Orientation phase.** The received information will be processed automatically which one of the process is with the combination of the existing knowledge. If it is related with decision making, the products of the process will be appeared in the form of alternatives which can be selected in the next phase.

- Decide phase. The best alternative will be compared with the impacts of the alternative selection. In this phase human makes considerations by paying attention to received facts, indications, and signs, with the alternatives within his thought as the basis for taking the most appropriate alternative.

- Action phase. The implementation of the selected alternative will result impacts that can alter the environment dynamics. These alterations can be observed by the sensory organs to obtain new information to be processed in the next cycles.

In OODA model, thought process occurs in Orientation phase that involves the process of the existing new information from sensory organs that is combined with existing knowledge or previous experiences by considering culture and genetic aspects. The product of information processing is then analyzed and synthesized to produce new knowledge that will be used as basis for decision making to perform a correct action.

B. Artificial Intelligence Perspective

We view AI from its anatomy as the classification based on detail analysis on how AI techniques work. In this paper we focus on AI anatomy viewed from [14], Ahmad (2006) in [15], and [16].

1) *Russel and Norvig's Perspective*: In this perspective, the approaches are divided into two big categories, namely (1) to build systems that can think or act humanly, and (2) to build systems that can think or act rationally as depicted in Fig. 8. They approached AI from the perspective to build systems that can act rationally through agent approach, that is, a thing that performs actions. In order that systems can emulate the way of humans think on especially how to draw conclusions, a subject that we are trying to explain in this paper, an approach from cognitive modelling then is necessary.

Cognitive modelling is aimed at modelling the way of humans think which involves reasoning, learning, problem solving, and etc. that orifices to cognitive science and cognitive engineering. Cognitive science is aimed at developing computation model for apprehending human intellectual process or human cognition [11], while cognitive engineering is aimed at exploring computation models from reasoning, learning, planning, and coordination, and multi-agent control from human psychological milieu [17].

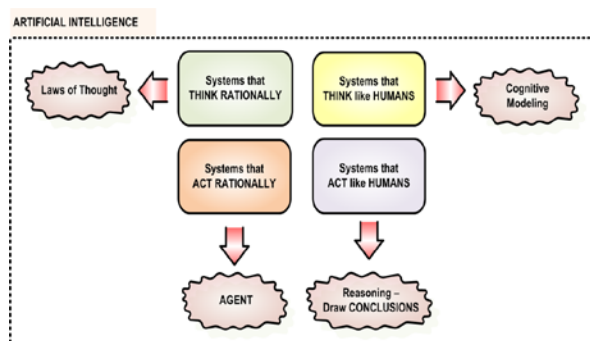


Fig. 8 Russel and Norvig's perspective on AI

In conclusion, cognitive science is focused on cognitive function models that take place in human brain, while cognitive engineering is focused on computation models to emulate cognitive function models as the representation of human intelligence or the commonly called cognitive modelling.

2) *Ahmad's Perspective*: Ahmad (2006) in [15] defines a topology on AI which can be divided into three categories, namely smart systems, knowledge-based system, and computational-based systems or computational AI as depicted in Fig. 5.

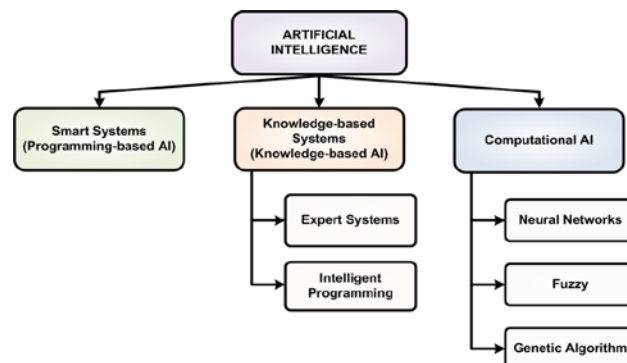


Fig. 9 AI topology proposed by Ahmad (2006)

Cognitive modelling which tries to model the computation mechanism within human thought process can be considered as a kind of knowledge-based systems, especially intelligent programming approach. This approaches the way of humans think that can be formulated in form of algorithms and implemented in form of computer software. The primary consideration of the approach is in knowledge acquisition process, which is necessary to provide a medium as the knowledge storage, and the stored knowledge can be used to solve problems or to update it in the presence of new information.

3) *Munakata's Perspective*: AI is grouped into two categories as follows.

- Symbolic AI. This category covers field such as knowledge-based systems especially Expert System (ES), symbolic machine learning, searching techniques and natural language processing.

- Biological AI. Approaches in this category are based on low-level microscopic biological models that are stressed on physiology or genetics. The approaches are ANN, GA or evolutionary computation, fuzzy systems, rough set theory, and chaotic.

	Microscopic, Primarily Numeric	Macroscopic, Descriptive and Numeric
Deductive	Chaos	Fuzzy Systems
Inductive	Neural Networks Genetic Algorithms	Rough Sets

Fig. 10 The characteristics of AI techniques based on the types of processed data and the types of information processing [16]

The primary matter in this perspective is the types of processed data and the mechanism of information processing either for symbolic AI or biological AI are classified in detail as depicted in Fig. 10.

By adopting these three perspectives in AI, our brain-inspired KGS has characteristics as follows.

- Capable of thinking, namely grows knowledge based on information sensed and perceived by its sensors in deductive manner.

- Knowledge growing based on information-inferencing fusion.
- Able to store new knowledge for the next stage of knowledge growing process.
- Able to act rationally, namely select the best alternative amongst available ones based on knowledge it has.
- Information processing is carried out in computation manner based on numerical data.

C. Mathematical Perspective

The way of human thinking in general is full of judgement and always takes into account any information before making decision. This way of thinking shows that the way of human brain processes information they receives in a probabilistic manner or with probabilistic thinking. Thinking involves finding and selecting amongst potential possibilities such as actions, beliefs, or possible personal objectives [18]. When thinking, the brain performs reasoning to form belief or certainty that is measured with a parameter called Degree of Belief (DoB) [14] or Degree of Plausibility [19], or Degree of Knowledge [20], or Degree of Certainty (DoC) [21].

Belief or certainty is a form of new knowledge which can be obtained directly through argumentation, reasoning which is carried out deductively or inductively. The method that is related with argumentation part is a probability theory because it treats different degrees (of belief) where the results are final or not [22]. The past practices also show that the most successful method up to now for handling uncertainties is the application of probability [23].

The most mature probability-based method that has been used in AI for a long time is Bayes Inference Method (BIM) that is formulated in (1).

$$P(B_j | A) = \frac{P(A | B_j) P(B_j)}{\sum_j P(A | B_j) P(B_j)} \quad (1)$$

Where $P(B_j | A)$ is posterior probability that hypothesis B_j is true given A ; $P(A | B_j)$ is prior probability that indication A is true given B_j ; $P(B_j)$ is prior probability that B_j is true; and $P(A) = \sum_j P(A | B_j) P(B_j)$. This mechanism can be called as multi-hypothesis single-indication problem [24].

There are strong reasons why we select BIM as the basis of our KGS. Firstly, humans' reasoning follows a complex version of BIM [25]; secondly, humans' thinking process is fundamentally a mathematical thinking process and its characteristic is probabilistic [18]; and lastly, Degree of Knowledge or Degree of Certainty is an epistemic perspective [19]. There are two ways to obtain the best B_j from all possible hypotheses produced by (1).

1) *Maximum A Posteriori (MAP) Technique or Point Estimation* [26]: BIM is commonly combined with MAP technique to obtain an inference from the results of its computation. BIM+MAP can only obtain point estimation, $P(B_j | A)$ or one estimation that is believed the most appropriate from the available hypotheses set as presented by

(2). $P(B_j | A)_{estimate}$ is the highest value of $P(B_j | A)$ that is called as DoC.

$$P(B_j | A)_{estimate} = \max_j \frac{P(A | B_j) P(B_j)}{\sum_j P(A | B_j) P(B_j)} \quad (2)$$

In practice, BIM+MAP combination has difficulty when faced with multi-indication multi-hypothesis problems that are always faced by humans in their everyday life. Suppose given two random variable sets, $A = \{A_1, \dots, A_i, \dots, A_n\}$ and $B = \{B_1, \dots, B_j, \dots, B_m\}$ that are two events with $P(A_i) \neq 0$ and $P(B_j) \neq 0$, and serially each one represents indication set and hypothesis set. Therefore, BIM equation for this phenomenon is presented in (3).

$$P(B_j | A_i) = \frac{P(A_i | B_j) P(B_j)}{\sum_j P(A_i | B_j) P(B_j)} \quad (3)$$

The problem is how to obtain $P(B_j | A_i)_{estimate}$. Why? Because by using (2), the selected $P(B_j | A_i)$ is hypothesis that is true given only one A_i not all indications, $A = \{A_1, \dots, A_i, \dots, A_n\}$. This problem is solved by using a new formula called Maximum Score of the Total Sum of Joint Probabilities (MSJP) that is introduced at the first time in [24].

2) *Maximum Score of the Total Sum of Joint Probabilities [MSJP] Method*: One of a posteriori information processing using BIM+MAP is the complexity if there is more than one potential hypothesis to be selected from more than one conditional data [28] to explain those hypotheses. MSJP method is the extension of Linear Opinion Pool (LOP) and BIM methods viewed from information combination from information multi-source or can be called as multi-indication. By considering the concept of total probability and generalization of LOP method, MSJP method is given in (4).

$$P(B_j | A_i) = \frac{1}{n} \sum_{i=1}^n P(B_j | A_i) \quad (4)$$

In this case, it is needed one condition so MSJP method fulfills norms in probability theory in order that $\sum_{j=1}^m P(B_j | A_i) = 1$ so that $P(B_j | A_i) \in [0, 1]$ or $0 \leq P(B_j | A_i) \leq 1$. The detail regarding this formula can be found in [28].

D. Social Perspective

Consensus theory is a social theory that is adopted to AI field. In its definition, consensus theory is a research field that involves procedures with an objective to combine single probability distribution to summarize estimations from experts or data sources with an assumption that the experts make decisions based on Bayes decision theory [29] [30]. One of the methods in consensus theory is opinion pool that can be traced back in 1961 when it was introduced [31] and it is now known as Linear Opinion Pool (LOP). This method is based on a condition where a joint decision is demanded in a group that consists of n experts or observers. Yet in agreement, each expert's opinion regarding a phenomenon may have different probabilities. This condition is formulated to a pooled density function as given in (5).

$$p_{s\lambda}(\theta) = \sum_{i=1}^k \lambda_i p_{si}(\theta) \quad (5)$$

with $p_{si}(\theta)$ is probability density function for i -th opinion. Weights are $\lambda_i \geq 0, i=1, \dots, k$ and $\sum_{i=1}^k \lambda_i = 1$. In order that the rule is democratic, all experts or observers will be assigned the same weight, so that $\lambda_i = \lambda_1 = \dots = \lambda_k = \frac{1}{k}$ [31].

There are other opinion pool methods, namely Independent Opinion Pool (IOP) or also called as Logarithmic Opinion Pool (LogOP), and Independent Likelihood Pool (ILP). However, the method that is often used is LOP method [32] and in AI field, LOP is the most common way to combine probabilities from different agents to produce single social probabilities [33].

III. CONSTRUCTING BRAIN-INSPIRED KNOWLEDGE-GROWING SYSTEM

In this section we will explain and review the construction of our brain-inspired KGS in a top-down approach. The first view is from HIS model, the second one is from the knowledge-growing cycle, and the last one is from the mathematical model of knowledge-growing mechanism.

A. HIS Model for KGS

Adopting the concept of human information processing models, our HIS as the basis for KGS is depicted in Fig. 11.

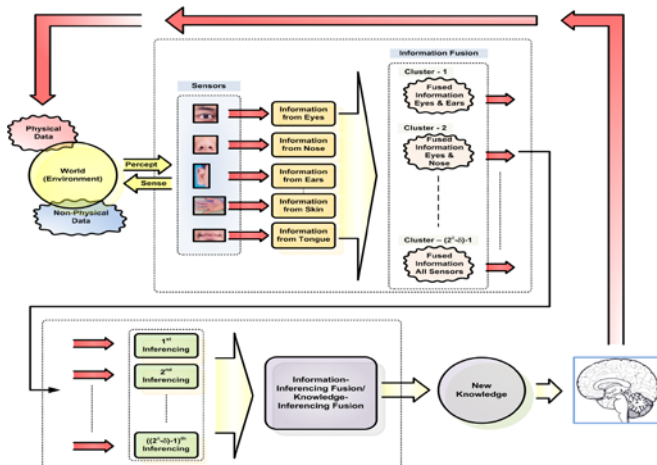


Fig. 11 HIS model as the basis for brain-inspired KGS

In this model we assume that any new information is a product of fused information that is perceived by two or more sensory organs or simply sensors. Based on this HIS concept, we generalize the model to a system that is equipped with a set on sensors $n=1, \dots, i, \dots, \delta$. Therefore, the number of fused information is λ , so the number of fused information can be obtained by using (6).

$$\lambda = (2^\delta - \delta) - 1 \quad (6)$$

Each of the fused information has an inferencing or a conclusion given information, data, events, facts, or indications perceived by the sensors. The inferencing becomes new knowledge if it is satisfied enough to describe the observed phenomenon in the environment. If not, the next process will be information-inferencing fusion after it receives new information at the next observation time. As an example

in case a HIS, $\delta = 5$ namely, eyes, ears, nose, skin, and tongue. Eyes and ears are considered as single sensor. Therefore, $\lambda = (2^5 - 5) - 1 = 26$. There will be 26 clusters that accommodate combination of information which comes from two or more sensors. Each combination will have an inferencing with total is 26 inferencing. Two or more inferencing, depending on the number of observation time, will be fused to obtain new knowledge of the phenomenon being observed. This cycle will be repeated until KGS concludes with an ultimate knowledge.

B. A Model for Knowledge-Growing Mechanism

Based on our study of human thought models delivered in Section II.A., we have developed our own human thought model called Sense-Inference and Decision Formulation-Decide and Act (SIDA) cycle as depicted in Fig. 12. It has three steps, namely Sense, Knowledge Growing, and Product. The core of the model is in Inference and Decision Formulation mechanism in Knowledge Growing step where the knowledge is grown during each cycle. In some respects, SIDA completes and simplifies the reviewed models. Table I shows the advantages of SIDA over other models which were already explained in Section II.A.

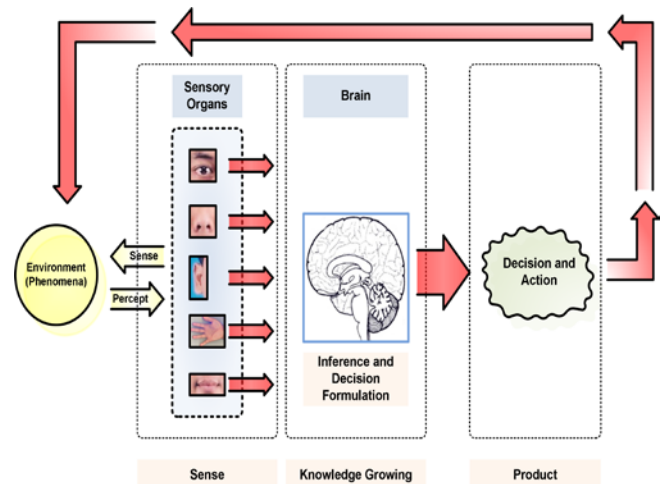


Fig. 12 SIDA cycle of HIS model for brain-inspired KGS

TABLE I. THE COMPARISON OF SIDA MODEL WITH OTHER MODELS

Model	Analogy with SIDA Model		
	Sense	Knowledge Growing	Product
Galileo	Facts	Model-Conclusions	Experiments
Feynman	Model-Laws	New Predictions	Experiments
Piaget	Assimilation		Accomodation
Popper	World 1	World 2 and World 3a	World 3b
Cognitive Psychology	Making Sense		Decision
Attention and PerceptionThought Process			
Decision and Action			
OODA	Observation		Orientation

Based on Fig. 11 and Fig. 12, we developed knowledge growing mechanism for the designed system and it is depicted in Fig. 13.

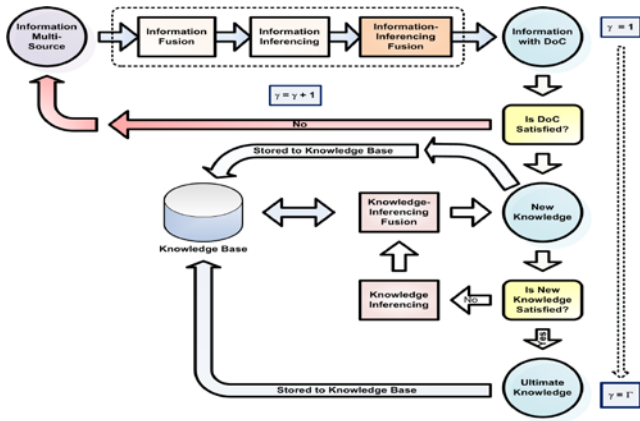


Fig. 13 Knowledge growing mechanism for brain-inspired KGS

C. A Simple Mathematical Model for Knowledge-Growing Mechanism

As we know, BIM faces complexity when there exist more than one potential hypotheses to be selected and more than one conditional data that produce those hypotheses. Our research has also come up with a method that is aimed at minimizing such problem called A3S (Arwin-Adang-Aciek-Sembiring) information-inferencing fusion method. A3S method is a refinement of Maximum Score of the Total Sum of Joint Probabilities (MSJP) method developed in 2008 [24]. The method views that all hypotheses are formed by the fusion of all conditional events, which means that each hypothesis is characterized by all events or indications. This schema is formulated in (7).

$$P(B_j | A_i) = \sum_{k=1}^n \left(\frac{P(A_i | B_j) P(B_j)}{\sum_{k=1}^n P(A_i | B_k) P(B_k)} \right) \quad (7)$$

where $P(B_j | A_i)$ is the probability of B_j is true given the presence of the fusion or combination of all events or indications A_i and MAP of A3S is determined by (8).

$$P(B_j \oplus A_i)_{estimate} = \max_{j=1, \dots, m} \left(\frac{P(B_j | A_i)}{n} \right) \quad (8)$$

If $P(v_i^j) = P(B_j | A_i)$, $P(\psi_i^j) = P(B_j \oplus A_i)$, and $n = \delta$ then (8) is simplified to become (9).

$$P(\psi_i^j) = \frac{\sum_{i=1}^{\delta} P(v_i^j)}{\delta} \quad (9)$$

where $P(\psi_i^j) \in \Psi$ and it is called as New Knowledge Probability Distribution (NKPDT) at observation time γ_1 . The inferencing or new knowledge at this point can be obtained by applying (10).

$$P(\psi_i^j)_{estimate} = \odot [P(\psi_i^j)] \quad (10)$$

where $\odot[\dots] = \max[\dots]$.

If at the first observation the system still does not have an indication of what exactly is the phenomenon it observes, it will do some observations during a significant period of time.

As the time passes, it will collect information regarding the phenomenon in form of NKPDT on each observation time, $P(\psi_1^j), \dots, P(\psi_{\gamma}^j), \dots, P(\psi_{\Gamma}^j)$. The inferencing of these distributions can be obtained by applying (11).

$$P(\phi_{\gamma}^j) = \begin{cases} 1, & \text{if } P(\psi_{\gamma}^j) > \frac{P(\psi_{\gamma}^j)}{\lambda} \\ 0, & \text{if } P(\psi_{\gamma}^j) \leq \frac{P(\psi_{\gamma}^j)}{\lambda} \end{cases} \quad (11)$$

where $P(\phi_{\gamma}^j) \in \Pi$ is inferencing of the each information to the distribution.

The information-inferencing fusion is performed by applying OMA3S method, a dynamic version of A3S method as presented in (9). The result is a new distribution called New Knowledge Probability Distribution over Time (NKPDT). The ultimate knowledge obtained after fusing all inferencing is obtained by applying (12) to NKPDT.

$$P(\theta_j) = \frac{\sum_{\gamma=1}^{\Gamma} P(\phi_{\gamma}^j)}{\Gamma} \quad (12)$$

$$P(\theta)_{estimate} = \odot [P(\theta_j)] \quad (13)$$

where $j = 1, \dots, \lambda$

D. Measuring System's Degree of Certainty

The system's certainty of the phenomenon it observes is measured by using Degree of Certainty (DoC) (14)

$$DoC = |P(\theta)_{estimate} - P(\phi^j)| \times 100\% \quad (14)$$

where $j = 1, \dots, \lambda$ and $P(\phi^j)$ is the knowledge in terms of probability value of the j best hypothesis at observation time γ_1 . This DoC is KGS' ultimate knowledge.

IV. KNOWLEDGE GROWING IN BRAIN-INSPIRED KGS

We have explained the steps in constructing our brain-inspired KGS. However, in order that the readers can have a comprehensive apprehending on how the knowledge growing in KGS, we will give an illustration with a simple example as follows.

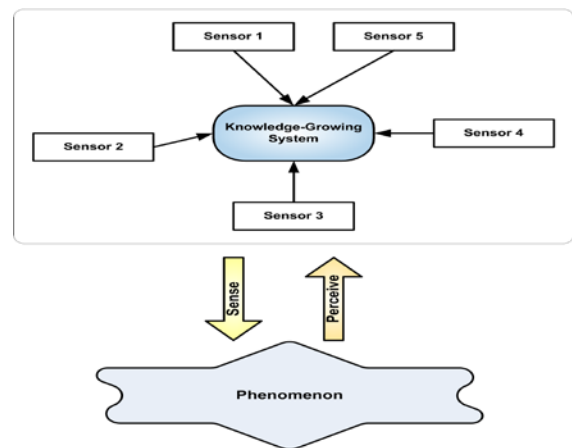


Fig. 14 An illustration of KGS with its five sensors

TABLE II. INFORMATION REGARDING THE PHENOMENON SENSED AND PERCEIVED BY KGS

i-th observation time	i-th information from Sensors	Multi-Hypothesis			
		H_1	H_2	H_3	H_4
γ_1	S_1	1	0	0	0
	S_2	1	0	0	0
	S_3	0	0	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_2	S_1	0	1	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_3	S_1	0	1	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_4	S_1	0	0	0	0
	S_2	0	0	0	1
	S_3	0	0	0	1
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_5	S_1	0	1	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_6	S_1	0	0	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_7	S_1	0	1	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0
γ_8	S_1	0	1	0	0
	S_2	0	1	0	0
	S_3	0	1	0	0
	S_4	0	0	0	0
	S_5	0	0	0	0

Assume a system with five sensors $\delta = 5$ namely $S_1, \dots, S_5$ as depicted in Fig. 15, is observing a phenomenon. Based on (6), so the system will have $\lambda = (2^5 - 5) - 1 = 26$ hypotheses where one of those can describe or explain the phenomenon being observed. In this example we only show four hypotheses ($H = 4$) namely $H_1, \dots, H_4$ with the number of observation time is $\Gamma = 8\gamma$, namely $\gamma_1, \dots, \gamma_8$. The observation results will be represented by two-value state, namely “1” which represents information regarding the

phenomenon sensed while “0” is the opposite situation as listed in Table II.

A. NKPD of KGS

The system's knowledge at each observation time is represented in the form of NKPD that is obtained by applying A3S method in (9) to the information listed in Table II. KGS inferencing at each γ_i is called new knowledge. Inferencing is the conclusion obtained through reasoning. These NKPD is listed in Table III.

TABLE III. KGS KNOWLEDGE AT INTERVAL TIME γ_1 TO γ_8

Knowledge at i-th observation time	Multi-Hypothesis			
	H_1	H_2	H_3	H_4
NKPD at γ_1	1	0	0	0
NKPD at γ_2	0	1	0	0
NKPD at γ_3	0	1	0	0
NKPD at γ_4	0	0	0	1
NKPD at γ_5	0	1	0	0
NKPD at γ_7	0	1	0	0
NKPD at γ_8	0	1	0	0

B. NKPD of KGS

To know how much knowledge grows in the system after carrying out observations from time to time, NKPD listed in Table III will be fused to obtain DoC of the observed phenomenon from time to time. Knowledge fusion is used to compare the system's knowledge at observation time γ_1 with the knowledge at $\gamma_{i \pm 1}$. For example, comparing the knowledge at γ_1 with the knowledge after the system senses new information at γ_2 and so on to γ_8 in order to obtain NKPD as listed in Table IV.

TABLE IV. KGS KNOWLEDGE FROM TIME TO TIME

System's Knowledge	Multi-Hypothesis			
	H_1	H_2	H_3	H_4
NKPD at γ_1	1	0	0	0
NKPD after 2γ	0.5	0.5	0	0
NKPD after 3γ	0.333	0.667	0	0
NKPD after 4γ	0.25	0.5	0	0.25
NKPD after 5γ	0.2	0.6	0	0.2
NKPD after 6γ	0.167	0.667	0	0.167
NKPD after 7γ	0.143	0.714	0	0.143
NKPD after 8γ	0.125	0.75	0	0.125

By observing the list of NKPD in Table IV there are two things can be explained as follows.

1) System's DoC that the phenomenon being observed is H_1 gradually decreased from 1 at γ_1 to 0.125 after carrying out observations for 8γ . In other words, information accretion has an impact on system's knowledge when the phenomenon being observed is not true H_1 .

2) System's DoC that the phenomenon being observed is true H_2 and gradually increases from 0 at γ_1 to 0.75 at γ_8 or after carrying out observations for 8γ . In other words,

information accretion influences system's knowledge when the phenomenon being observed is true H_2 .

C. KGS's DoC of the Phenomenon

The KGS' DoC for all hypotheses $H_1, \dots, H_4$ after carrying out observations at interval time $\gamma_1, \dots, \gamma_8$ is given by applying (13) and (14).

- The best hypothesis from NKPD

$$P(\theta)_{\text{estimate}} = \odot[0.125; 0.75; 0; 0.125] \\ = 0.75$$

with H_2 as the best hypothesis ($j=2$)

$$\text{DoC} = |P(\theta)_{\text{estimate}} - \phi_j^2| \times 100\% \\ = |0.75 - 0| \times 100\% \\ = 75\%$$

Based on the results of the computation above, it can be concluded that the system's DoC that the phenomenon being observed is hypothesis H_2 is 0.75 or 75%. The process of growing the knowledge is illustrated simply in Fig. 15.

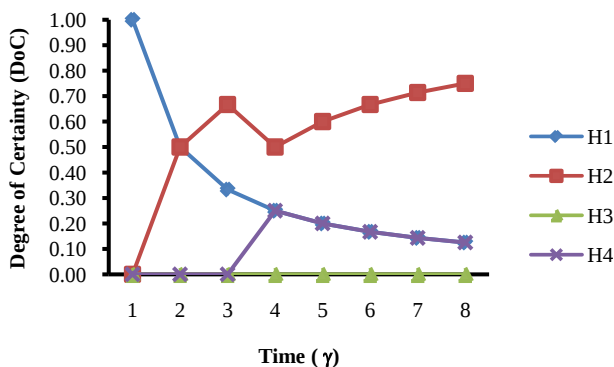


Fig. 15 KGS DoC to all hypotheses along with the accretion of information as the time passes

V. CONCLUDING REMARKS AND FURTHER WORKS

Humans generally learn in two ways, namely learning from experience and learning from interaction with the environment. ML approaches are focused on building systems that will become smarter or more intelligent after learning from the experiences either given targets (supervised) or form clusters autonomously (unsupervised) based on competitive learning. Almost similar to ML but viewed from different perspective, our KGS generates its knowledge when it interacts with the environment and its knowledge will grow to some extent that the ultimate knowledge it gains is satisfied enough to explain the phenomenon it perceives from the environment. It determines its own knowledge through Degree of Certainty obtained from NKPD it is obtained after carrying out numerical computation of probability values of information from the observed phenomenon perceived by its sensors. The ultimate knowledge of the system is obtained after carrying out observations at a certain interval time and produces NKPD.

We review some approaches from three perspectives that can be a strong basis for building KGS. The results of the review along with the explanations from each perspective by referring Fig. 16 are as follows.

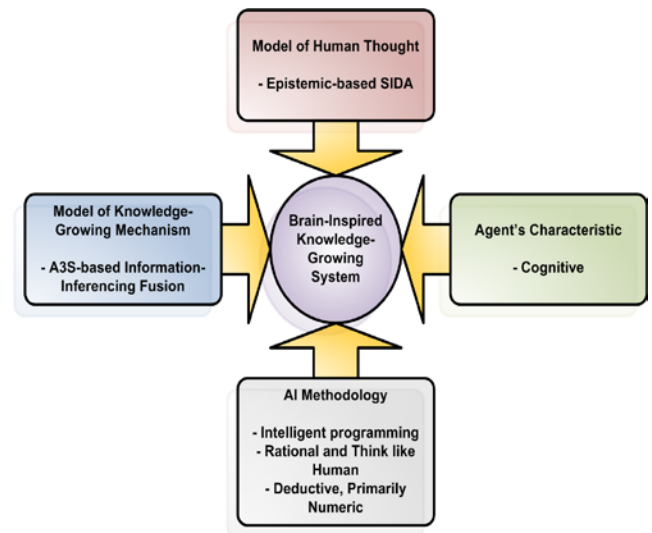


Fig. 16 The elements of the construction of the brain-inspired KGS

1) Psychology perspective gives epistemological basis for human thought model that is constructed in form of SIDA knowledge-growing cycle.

2) Social perspective gives a basis for developing better knowledge fusion that ends up with a new information-inferencing fusion method called A3S along with OMA3S method as its dynamic version. A3S/OMA3S method is the fundamental matter for generating knowledge in brain-inspired KGS.

3) Electrical engineering and informatics perspective, especially AI field, gives four matters, namely, (1) KGS is a kind of cognitive agent that is capable of growing its knowledge, (2) the knowledge-growing is performed by information-inferencing fusion using OMA3S information-inferencing fusion method, (3) the knowledge-growing mechanism is implemented through intelligent programming based on numerical data computation, and (4) the knowledge obtained by the system is represented in the form of NKPD, while the ultimate knowledge is obtained by taking the maximum value of NKPD.

4) Mathematical perspective gives a basis of the selection of the most appropriate method to represent the way of human brain knowledge grow given new information. The selection of A3S method and its dynamic version OMA3S, as the main engine is used for selecting the most appropriate hypothesis from multi-hypothesis given fusion of all conditional indications.

We understand that "Knowledge-Growing System" is a novel term in AI and it is our challenge to propose it to the society. What we have delivered in this paper is for enriching our insight that there is still a vast area in AI that we can explore for developing truly intelligent systems as aspire to AI earlier researchers. This work is a part of our research in Cognitive Science area. Knowledge growing mechanism is a kind of cognitive development that occurs naturally in human beings in their entire life. At this moment, DoC in (14) is the most appropriate measurement for knowledge obtained by KGS, but this matter will be one of our focuses in our further works. However, KGS has successfully caught the essential matter of the mechanism occurs in human's thought process, namely growing the knowledge along with the accretion of information as it interacts with a phenomenon as the time passes.

This research has also widened our insight that non engineering fields give uncountable contributions in the development of theories and methods as well as techniques in AI field. It has been shown that the involvement of consensus theory has yielded a new kind of method for combining knowledge from multi-agents.

Actually, we have applied KGS to find knowledge regarding genes behavior in a Genetic Regulatory System (GRS) in yeast 25 *saccharomyces cerevisiae* database [34] and knowledge-sharing in knowledge-growing-based system [35]. Closing the remarks, we state that brain-inspired KGS is a cognitive agent which is equipped with knowledge growing mechanism as its intelligent characteristic. We believe that this research is an important path towards a true cognitive agent.

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REFERENCES

- [1] A.P. Engelbrecht, Computational Intelligence: An Introduction, 2nd ed., John Wiley & Sons, England: Chichester, 2007.
- [2] T. Mitchell, Machine Learning, McGraw-Hill, 1997.
- [3] E. Alpaydin, Introduction to Machine Learning, Massachusetts: MIT Press, 2004.
- [4] K.C. Moore, (2004), "Constructivism & Metacognition". [Online]. Available: <http://www.tier1performance.com/Articles/Constructivism.pdf>.
- [5] E. Ackermann, (2002) "Piaget's Constructivism, Papert's Constructionism: What's the difference?." [Online]. Available: http://learning.media.mit.edu/content/publications/EA.Piaget%20_%20Papert.pdf.
- [6] S. Sjøberg, (2007), "Constructivism and learning". [Online]. Available: http://folk.uio.no/sveinsj/Constructivism_and_learning_Sjoberg.pdf.
- [7] B. Bostrom and V. Clawson, "How People Think: Human Information Processing", [Online]. Available: <http://www.terry.uga.edu/~bostrom/How%20People%20think.doc>.
- [8] R. Tomass, (2001), "Models - the Basics of Physical Thinking, Conclusions for Multimedia". [Online]. Available: http://www.fisica.uniud.it/girepseminar2001/CS03/ROMANOVKIS_08_FINAL.pdf.
- [9] G.L. Drescher, Made-up Minds: A Constructivist Approach to Artificial Intelligence Artificial Intelligence, Massachusetts: MIT Press, 1991.
- [10] R. R. Traill, (2007), "Thinking as Mental Model-Building: a Piagetian-cum-mechanistic Explanation of the 'Engram'". [Online]. Available: <http://www.ondwelle.com/OSM04.pdf>.
- [11] M.W. Eysenck, Principles of Cognitive Psychology 2nd ed., New York: Psychology Press Ltd., 2001.
- [12] T.A. Hightower, (2007), "Boyd's O.O.D.A Loop and How We Use It". [Online]. Available: <http://www.tacticalresponse.com/d/node/226>.
- [13] K.D. Senne and G.R. Condon, (2007), "Integrated Sensing and Decision Support", Lincoln Laboratory Journal, **16**(2), 237 – 243.
- [14] S.J. Russel and P. Norvig, Artificial Intelligence: A Modern Approach 2nd Edition, New Jersey: Prentice-Hall, 2002.
- [15] L.W. Panjaitan, Dasar-Dasar Komputasi Cerdas, Yogyakarta: Andi Offset, 2007.
- [16] T. Munakata, London: Spinger-Verlag, 2008. Fundamentals of the New Artificial Intelligence: Neural, Evolutionary, Fuzzy, and More 2nd Edition.
- [17] A. Konar and L. Jaim, Cognitive Engineering: A Distributed Approach to Machine Intelligence, London: Springer, 2005.
- [18] J. Baron, Thinking and Deciding 4th Edition, Cambridge: Cambridge University Press, 2008.
- [19] M.E. McIntyre, (2007), "On Thinking Probabilistically". [Online]. Available: <http://www.atm.damtp.cam.ac.uk/mcintyre/mcintyre-thinking-probabilistically.pdf>.
- [20] D. Howie, Interpreting Probability: Controversies and Developments in the Early Twentieth Century, Cambridge: Cambridge University Press, 2004.
- [21] D.M. Eddy, (1982), "Probabilistic Reasoning in Clinical Medicine: Problems and Opportunities, in D. Kahneman, P. Slovic, and A. Tversky, (Eds), Judgment under Uncertainty: Heuristics and Biases, Cambridge: Cambridge University Press, 1982.
- [22] J.M. Keynes, A Treatise on Probability, London: MacMillan, 1921.
- [23] C.W. Therrien and M. Tummala, Probability for Electrical and Computer Engineers, Boca Raton: CRC Press, 2004.
- [24] A.D.W. Sumari, A.S. Ahmad, A.I. Wuryandari, and J. Sembiring, (2008), "Pengembangan Teori Probabilitas untuk Fusi Penginferensian Informasi", Prosiding Seminar Nasional Matematika IV 2008, Institut Teknologi 10 Nopember Surabaya, 13 December, Surabaya, RSP53–60.
- [25] E.T. Jaynes, Probability Theory: The Science of Logic, Cambridge: Cambridge University Press, 2003.
- [26] K. Doya and S. Ishii, "A Probability Primer", in K. Doya, S. Ishii, A. Pouget, and N.R.P. Rao, (Eds), Bayesian Brain: Probabilistic Approaches to Neural Coding, Massachusetts: MIT Press, 2007.
- [27] A.D.W. Sumari, (2010), "Sistem Berpengetahuan-Tumbuh: Satu Perspektif Baru dalam Kecerdasan Tiruan", Doctor of Electrical Engineering and Informatics Dissertation, School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung.
- [28] D.L. Hall, Mathematical Techniques in Multisensor Data Fusion, Artech House, 1992.
- [29] J.A. Benediktsson, J.R. Sveinsson, K. Ersoy, and P.H. Swain, (1997), "Parallel Consensual Neural Networks", IEEE Transactions on Neural Networks, **8**(1), January, 54 – 64.
- [30] Y. Chen and D.M. Pennock, (2005), "Information Markets vs. Opinion Pools: an Empirical Comparison". [Online]. Available: <http://dpennock.com/papers/chen-ec-2005-market-vs-pool.pdf>.
- [31] M. Stone, (1961), "The Opinion Pool", Annals of Mathematical Statistics, **32**(4), 1339 – 1342.
- [32] G.J. Briem, J.A. Benediktsson, and J.R. Sveinsson, (2002), "Multiple Classifiers Applied to Multisource Remote Sensing Data", IEEE Transactions on Geoscience and Remote Sensing, **40**(10), October, 2291 – 2299.
- [33] C.P. Chambers, (2004), "An Ordinal Characterization of the Linear Opinion Pool", <http://www.hss.caltech.edu/~chambers/opinionpool.pdf>.
- [34] A.D.W. Sumari, A.S. Ahmad, A.I. Wuryandari dan J. Sembiring (2009), "The Application of Knowledge-Growing System to Multiagent Collaborative Computation for Inferring the Behavior of Genes Interaction", International Journal of Computer Science & Network Security (IJCSNS), **9**(11), Soongsil University, South Korea, November, 82 – 92.
- [35] A.D.W. Sumari, A.S. Ahmad, A.I. Wuryandari dan J. Sembiring, (2010), "Knowledge Sharing in Knowledge-Growing-based Systems", Proceedings of the First International Conference on Green Computing (ICGC-RCICT2010), Gadjah Mada University, 2-3 March, Yogyakarta, 329 – 333.



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