2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)
Banff Center, Banff, Canada, October 5-8, 2017

Building Cognitive Knowledge Bases Sharable by Humans and Cognitive Robots

Yingxu Wang, *Senior Member, IEEE*, Omar A. Zatarain, and Merhdad Valipour

International Institute of Cognitive Informatics and Cognitive Computing (ICIC)
Dept. of Electrical and Computer Engineering
Schulich School of Engineering and Hotchkiss Brain Institute
University of Calgary
2500 University Drive NW, Calgary, Alberta, Canada T2N 1N4
Email: yingxu@ucalgary.ca

Abstract — One of the fundamental means for interaction and coordination between humans and cognitive robots is knowledge sharing in general and formal concept comprehension in particular. A cognitive knowledge base (CKB) is introduced as a formal structure of collective knowledge embodied by a weighted hierarchical concept network. This paper formally describes a CKB based on concept algebra and semantic algebra. An Algorithm of CKB Generation (ACKBG) is developed for autonomous machine learning from complex human knowledge and semantic expressions. A set of experiments demonstrates applications of ACKBG in brain-machine interfacing via a sharable CKB in cognitive computing, semantic computing, and machine learning.

Keywords — *Cognitive systems, brain-machine interface, cognitive knowledge base, machine knowledge acquisition, machine learning, algorithms, computational intelligence.*

I. INTRODUCTION

Knowledge engineering for enabling machines to understand humans is a fundamental challenge in brain-machine communications. It is recognized that autonomous knowledge acquisition and comprehension are centric in brain-machine interfaces and interactions based on the latest development in cognitive computing [2, 8, 10] and cognitive robotics [3, 5]. Formally sharable knowledge and semantics are pervasively underpinned almost all forms of multimedia brain-machine interfaces of cognitive systems.

Classic approaches to knowledge engineering for cognitive robots are ontology-based and rule-based knowledge bases [1]. The former are a branch of metaphysics dealing with the nature of being as a manually-built taxonomic hierarchy of knowledge represented by lexical terms and syntactic relations [3, 4]. The latter are reflexive behavioral knowledge bases for dealing with imperative and adaptive intelligence [9]. Conventional knowledge bases were used to be manually built for modeling small-scale knowledge, which were often tedious, complicated, subjective, redundant, non-quantitative, unrigorous, inconsistent, and incomplete in practice.

A *cognitive knowledge base* (CKB) is a novel structure of formal knowledge base that represents and manipulates knowledge as a dynamic concept network mimicking human knowledge processing [7]. CKB is sharable by humans and machines generated by deep machine learning. In order to rigorously improve the structure and methodology of CKB theories, a mathematical model of *formal concept* [6] is created that denotes the basic unit of human knowledge as a triple of sets of attributes, objects and relations. Based on the mathematical model of concepts, a formal methodology for manipulating knowledge is enabled known as *concept algebra* [6], which provides a rigorous methodology for formal knowledge manipulations by a set of algebraic operators on abstract concepts. Concept algebra enables the quantification of concepts by semantic weights and the measurement of knowledge by the basic unit of *binary relation* (*bir*) [7] in knowledge science and engineering.

This paper presents a formal methodology for the generation of a CKB for supporting multimedia–based semantic interfaces among humans and cognitive robots. The mathematical model of CKB is created in Section II. A cognitive algorithm for autonomous CKB generation by machine learning is developed in Section III. A set of experimental results is reported in Section IV with case studies and applications in cognitive computing and brain-machine interactions.

II. MATHEMATICAL MODELS OF THE COGNITIVE KNOWLEDGE BASE

The *universe of discourse of knowledge* is a triple, $\mathfrak{U} \triangleq (\mathfrak{O}, \mathfrak{A}, \mathfrak{R})$, where $\mathfrak{O}$ denotes a finite set of *objects*, $\mathfrak{A}$ a finite set of *attributes*, and $\mathfrak{R}$ a finite set of *conceptual relations*. On the basis of $\mathfrak{U}$, an item knowledge is represented by a formal concept, while the entire knowledge base is embodied by a weighted concept network.

Definition 1. A *formal concept, C*, is the basic structural unit of knowledge and a unique model of cognitive semantics, which is a 5-tuple in the universe of discourse of knowledge $\mathfrak{U}$, i.e.:

$$C \triangleq (A, O, R^c, R^i, R^o) \qquad (1)$$

where A is a finite set of *attributes* of C, $A \subset \text{Þ}\mathfrak{A} \sqsubset \mathfrak{U}$, Þ represents a power set and $\sqsubset$ denotes that a set is a substructure of a given hyperstructure; O a finite set of *objects* of C, $O \subset \text{Þ}\mathfrak{O} \sqsubset \mathfrak{U}$; $R^c = O \times A$ is a finite nonempty set of *internal relations*, $R^c \subset \text{Þ}\mathfrak{R} \sqsubset \mathfrak{U}$; $R^i \subseteq C' \times C$, a finite set of *input relations* where C' is a set of external concepts, $C' \subset \text{Þ}\mathfrak{O} \sqsubset \mathfrak{U} \wedge C' \neq C$; and $R^o \subseteq C \times C'$ a finite set of output relations.

The semantic relations among formal concepts in cognitive linguistics can be classified in the categories of *synonym* (SN), *partial synonym* (PS), *hypernym* (HE) / *hyponym* (HO), and *holonym* (HL) / *meronym* (MR).

Definition 2. The *entire knowledge,* $\mathfrak{K}$, is a Cartesian product among all formal concepts C_i in the universe of discourse of knowledge $\mathfrak{U}$, i.e.:

$$\mathfrak{K} \triangleq \mathop{\mathcal{R}}_{i=1}^{n} C_i \times \mathop{\mathcal{R}}_{i=1}^{n} C_i = \mathop{\mathcal{R}}_{i=1}^{n} \mathop{\mathcal{R}}_{j=1}^{n} (C_i, C_j) \;\; [bir] \tag{2}$$

where the unit of knowledge is a binary relation (*bir*) [7].

In knowledge engineering and cognitive linguistics, knowledge as a complex system can be formally embodied by a cognitive knowledge base as a hierarchical concept network.

Definition 3. The *cognitive knowledge base*, CKB|H, is a hyperstructure (H) of knowledge denoted by a set of hierarchically connected concepts C weighted by the strength of their semantic relations, i.e.:

$$\begin{array}{ll}
\boldsymbol{CKB}|\text{H} \triangleq \mathop{\mathcal{R}}_{i=1}^{n} C(i)|\text{SM}, \;\; n = |\,CKB|\text{H}\,| & \\
= \mathop{\mathcal{R}}_{i=1}^{n} (<ID_i: \text{S} \mid C_i|\text{SM}.ID_i|\text{S} \sqsubset CKB|\text{SM}>, & // \text{Identifier} \\
\quad <A_i^*: \text{SM} \mid A_i^*|\text{SM} = C_i|\text{SM}.HE_j|\text{S}, \; w_{ij}|\mathbb{I})>, & // \text{Collective attribute} \\
\quad <A_i: \Xi \mid A_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{|HO_i|\Xi|} (A_{ij}|\text{S} = (C_i|\text{SM}.HO_j|\text{S} \wedge A_{ij}|\text{S} \notin O_i|\Xi), \; w_{ij}|\mathbb{I})\}>, & // \text{Attributes (intension)} \\
\quad <O_i: \Xi \mid O_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{|PS_i|\Xi|} (O_{ij}|\text{S} = (C_i|\text{SM}.PS_j|\text{S} \wedge C_i|\text{SM}.MR_j), \; w_{ij}|\mathbb{I})\}>, & // \text{Objects (extension)} \\
\quad <SN_i: \Xi \mid SN_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (SN_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge w_{ij}|\mathbb{I} = 1, \; w_{ij}|\mathbb{I})\}>, & // \text{Synonym} \\
\quad <PS_i: \Xi \mid PS_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (PS_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge \theta \le w_{ij}|\mathbb{I} < 1, \; w_{ij}|\mathbb{I})\}>, & // \text{Partial synonym} \\
\quad <HE_i: \Xi \mid HE_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (HE_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge C_i|\text{SM}.A|\Xi \supset C_j|\text{SM}.A|\Xi & \\
\qquad\qquad \wedge\, 0 < w_{ij}|\mathbb{I} < \theta, \; w_{ij}|\mathbb{I})\}>, & // \text{Hypernym} \\
\quad <HO_i: \Xi \mid HO_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (HO_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge C_i|\text{SM}.A|\Xi \subset C_j|\text{SM}.A|\Xi & \\
\qquad\qquad \wedge\, 0 < w_{ij}|\mathbb{I} < \theta, \; w_{ij}|\mathbb{I})\}>, & // \text{Hyponym} \\
\quad <HL_i: \Xi \mid HL_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (HL_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge C_i|\text{SM}.ID|S \in C_j|\text{SM}.O|\Xi, \; w_{ij}|\mathbb{I})\}> & // \text{Holonym} \\
\quad <MR_i: \Xi \mid MR_i|\Xi = \{ \mathop{\mathcal{R}}_{j=1}^{n} (MR_{ij}|\text{S} = C_j|\text{SM}.ID_j|\text{S} \wedge C_j|\text{SM}.ID|S \in C_i|\text{SM}.O|\Xi, \; w_{ij}|\mathbb{I})\}> & // \text{Meronym} \\
\quad)
\end{array} \tag{3}$$

where each field of C is associated to a quantitative semantic weight w_{ij}; A^*|SM denotes the collective attribute or hypernym of a formal concept; and |SM, |Ξ, |S, and |$\mathbb{I}$ denote type suffixes of structural model, set, string, and the unit interval, respectively.

In the semantic space of knowledge, each node of CKB and their weighted relations can be illustrated in Fig. 1. The CKB is represented at three levels known as the knowledge (concept), object (extension), and attribute (intension) levels. Once any formal concept is invoked, all details of its intention, extension, and semantic relations to other concepts can be accessed in the CKB.

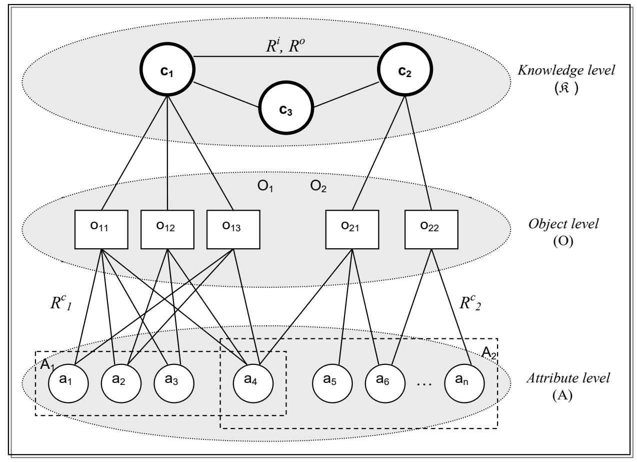


Fig. 1. The hierarchical semantic model of formal concepts

CKB serves as a kernel of cognitive knowledge manipulation and learning for cognitive robots and machine learning systems as well as brain-machine interfaces. The properties of the semantical CKB are hierarchical, relational, quantitative, weighted, and nonnegative. A set of calibrated formal concepts is elicited in Table 1 generated by machine learning. As shown in Fig. 1 and Table 1, any specific domain of knowledge can be quantitatively described by a CKB enabling brain-machine interfaces and interactions.

III. ALGORITHM FOR CKB GENERATION

On the basis of the theories and mathematical models of CKB and formal concepts as established in preceding section, a methodology for CKB acquisition and generation by cognitive robots is developed. It is underpinned by a set of deep machine knowledge learning technologies in cognitive linguistics and cognitive computing [5, 6, 10].

The CKB system is embodied by an Algorithm of CKB Generation (ACKBG) supported by autonomous machine learning technologies in order to enable a cognitive robot to acquire and comprehend complex human knowledge in a formal approach. The algorithm autonomously generates a formal and quantitative CKB on an arbitrary set of target concepts between human-machine communications.

Algorithm 1. The algorithm of CKB Generation (ACKBG) autonomously builds a formal and quantitative CKB|SM by machine learning as formally described in Fig. 2. The inputs of ACKBG are a set of informal concepts

(ConceptID|S), intension (CoAttributes|Ξ) and extension (CoObjects|Ξ) for brain-machine interfaces. Two selection thresholds for conceptual attributes and objects, θ_a and θ_o, are specified for eliciting significant sematic relations between arbitrary pair of concepts. The outputs of the ACKBG algorithm are a set of formal concepts in (O) and a relational semantic hierarchy of machine comprehensive knowledge generated in the general model (GM).

```
ACKBG|PM(<I:: ConceptID|S, CoAttributes|Ξ, CoObjects|Ξ, θ_a|𝕀, θ_o|𝕀, θ_s|𝕀>,
              <O:: C⁺|SM>, <GM:: CKB|SM = R_{i=1}^{n} C(i)|SM>) ≜
{ → n|N := CKB|SM.size|N
  → C⁺|SM.ID|S := ConceptID|S
  ↣ Intial|PM(<I:: C⁺|SM.ID|S>; <O:: C⁺|SM>; <GM:: CKB|SM>)
  → R_{i=1}^{n} ( � C⁺|SM.ID|S ∈ CKB|SM.C(i)|SM.HO|Ξ  // Learning hyper attribute
              → C⁺|SM.A*|S := CKB|SM.C(i)|SM.ID|S
          | �~
              → C⁺|SM.A*|S := ∅
        )
  → R_{j=1}^{|CoAttributes|Ξ|} (� CoAttributes(j)|Ξ.w|𝕀 ≥ θ_a|𝕀        // Learning collective attributes
              → C⁺|SM.A|Ξ := C⁺|SM.A|Ξ ∪ CoAttributes(j)|Ξ.ID|S
          )
  → R_{j=1}^{|CoObjects|Ξ|} (� CoObjects(j)|Ξ.w|𝕀 ≥ θ_o|𝕀          // Learning collective objects
              ∧ CoObjects(j)|Ξ.ID|S ∉ C⁺|SM.A|Ξ
              → C⁺|SM.O|Ξ := C⁺|SM.O|Ξ ∪ CoAttributes(j)|Ξ.ID|S
          )
  → R_{i=1}^{n} (�C⁺|SM.A|Ξ ~ CKB|SM.C(i)|SM.A|Ξ ≠ 0                     // Nonindependent
          → ( � C⁺|SM.A|S ~ CKB|SM.C(i)|SM.A|Ξ = 1              // Synonym
                → C⁺|SM.SN|Ξ := C⁺|SM.SN|Ξ ∪ CKB|SM.C(i)|SM.ID|S
                → CKB|SM.C(i)|SM.SN|Ξ := CKB|SM.C(i)|SM.SN|Ξ ∪ C⁺|SM.ID|S
            | � θ_s|𝕀 ≤ C⁺|SM.A|Ξ ~ CKB|SM.C(i)|SM.A|Ξ < 1     // Partial synonym
                → C⁺|SM.PS|Ξ := C⁺|SM.PS|Ξ ∪ CKB|SM.C(i)|SM.ID|S
                → CKB|SM.C(i)|SM.PS|Ξ := CKB|SM.C(i)|SM.PS|Ξ ∪ C⁺|SM.ID|S
            | � 0 < C⁺|SM.A|Ξ ~ CKB|SM.C(i)|SM.A|Ξ < θ_s|𝕀    // Hypernym
                ∧ C⁺|SM.A|Ξ ⊃ CKB|SM.C(i)|SM.A|Ξ
                → C⁺|SM.HE|Ξ := C⁺|SM.HP|Ξ ∪ CKB|SM.C(i)|SM.ID|S
                → CKB|SM.C(i)|SM.HE|Ξ := CKB|SM.C(i)|SM.HE|Ξ ∪ C⁺|SM.ID|S
            | � 0 < C⁺|SM.A|Ξ ~ CKB|SM.C(i)|SM.A|Ξ < θ_s|𝕀    // Hyponym
                ∧ C⁺|SM.A|Ξ ⊂ CKB|SM.C(i)|SM.A|Ξ
                → C⁺|SM.HO|Ξ := C⁺|SM.HO|Ξ ∪ CKB|SM.C(i)|SM.ID|S
                → CKB|SM.C(i)|SM.HO|Ξ := CKB|SM.C(i)|SM.HO|Ξ ∪ C⁺|SM.ID|S
            | � ~  → ∅
            )
        )
  → ↑ (n|N)        // Update learning result in CKB
  → CKB|SM.C(n)|SM := C⁺|SM
}
```

Fig. 2. The algorithm of CKB generation (ACKBG) by machine learning

Algorithm ACKBG|PM first initializes the target concept by the given identifier ConceptID|S according to Definition 3. It then learns and selects the hyper attributes, collective attributes, and collective objects for the target concepts in the existing knowledge base. Once the target concept is identified, its semantic equivalency with respect to all known concepts in the CKB will be analyzed by $C_i \sim C_j = |A_i \cap A_j| / |A_i \cup A_j|$ determined by relative sets of attributes. As a result, each formal concept is semantically classified and allocated in a proper position in the hierarchical semantic space of CKB quantitatively generated by machine learning. Each formal concept in CKB is characterized by a set of potential semantical relations to other concepts such as those of synonyms $(C_i \sim C_j = 1)$, partial synonyms $(\theta_s \le C_i \sim C_j < 1)$, hypernyms $(0 < \Omega|\mathrm{SM}.w_{ij}|\mathbb{I} < \theta_s|\mathbb{I} \wedge \Theta_i|\mathrm{SM.A}_i|\Xi \supset \Theta_j|\mathrm{SM.A}_j|\Xi)$, and hyponyms $(0 < \Omega|\mathrm{SM}.w_{ij}|\mathbb{I} < \theta_s|\mathbb{I} \wedge \Theta_i|\mathrm{SM.A}_i|\Xi \subset \Theta_j|\mathrm{SM.A}_j|\Xi)$.

In the machine generated CKB, semantical relations among concepts in a natural language interface between humans and machines are quantitatively analyzed. Rigorous communications between cognitive robots and humans are enabled by CKB in natural-language-centric cognitive computing and cognitive inference systems.

IV. Experiments and Case Studies

Machine knowledge learning and natural language comprehension are demonstrated by the experiments on CKB generation by the ACKBG algorithm implemented in MATLAB. ACKBG is fully autonomous and unsupervised for machine learning in order to build a relational hierarchy of formal concepts enabling brain-machine communications. ACKBG hierarchically visualizes a machine leant CKB as a semantic network where each node represents a formal concept and the edges denote a weighted semantic relation. Applying the ACKBG algorithm, any ontological and semantical CKB can be autonomously generated and quantitatively visualized as shown in the following experiments.

The first experiment on a set of 20 concepts G_1 generates CKB_1 as given in Table 1. CKB_1 represents a machine learning result of formal concepts in the clusters of realistic entities, abstract artifacts, and animals. The ACKBG algorithm rigorously analyzes semantical relations and determines their hierarchical levels among the target concepts. As a result, CKB_1 is rigorously generated on G_1 by machine learning as plotted in Fig. 3, which indicates a deep and quantitative machine comprehension of human concepts and complex semantics that outperform informal descriptions in typical dictionaries. In CKB_1 the blue links across semantic levels denote a hypernym or hyponym between a pair of formal concepts. The green links represent a synonym or partial synonym quantified by a corresponding semantic weight. The red links indicate a set of 1-to-*n* holonym/meronyms relations from the top down where a meronym is an object of the holonym.

The ACKBG algorithm quantitatively classifies arbitrary informal words into three coherent semantic clusters of formal concepts with rigorous measures of relational weights, semantic relations, and hierarchical allocations. The structured knowledge in CKB_1 models semantic connections among formal concepts in terms of synonyms and partial synonyms at the same semantic level, as well as hypernyms/hyponyms or holonyms/meronyms at a higher/lower level in the CKB.

The second experiment is carried out on a concept group G_2 = {office, drawing, text, pen, writing, nib, paper, tool, printing, expression, material, stationery, pencil, printer, device, instrument, data, word, ink, system, emotion, showing, computer} for generating CKB_2 for a brain-machine interface system. The learning results autonomously establishes CKB_2 as plotted in Fig. 4(a). As shown in the experiment, an arbitrary set of words has successfully classified into a coherent semantical framework among the semantic clusters of writing, instrument, ink, expression, and print sharable by humans and cognitive robots. Fig. 4(a) is partially elicited from a machine built CKB as illustrated in Fig. 4(b), which encompasses 600+ formal concepts generated by the ACKBG algorithm.

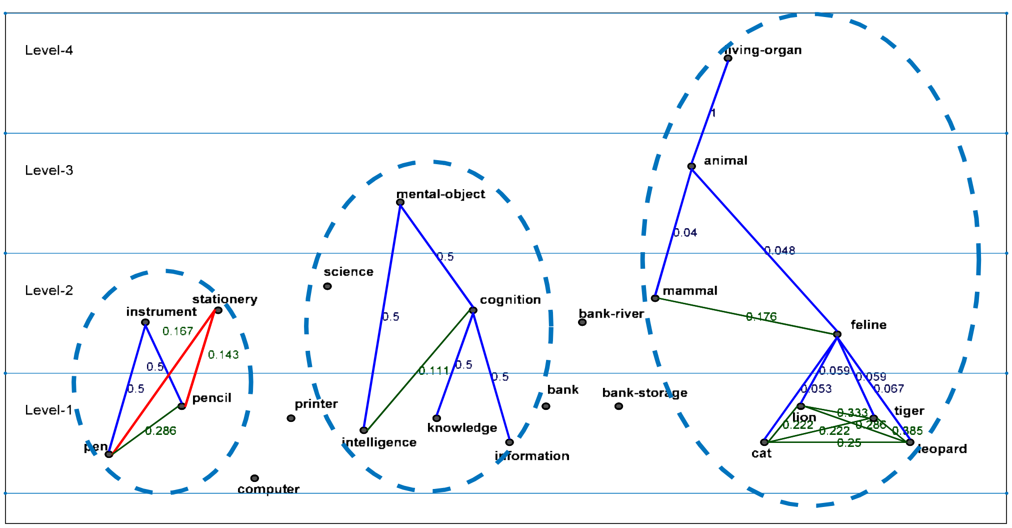
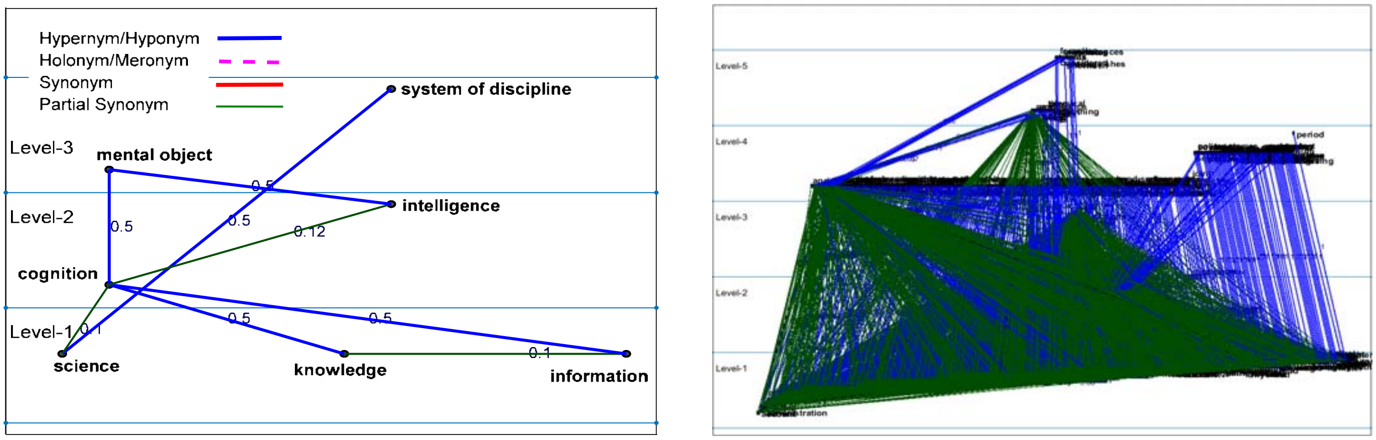


Fig. 3. The visual interface of a machine generated CKB (Experiment 1)

TABLE 1. A PARTIAL SAMPLE OF COGNITIVE KNOWLEDGE BASE (CKB) FOR A SEMANTIC BRAIN-MACHINE INTERFACE

No.	Formal concept	Weighted attributes ($A\|\Xi$)	Weighted objects ($O\|\Xi$)	SN	PS	HE	HO	HL	MR
1	C_1(*pen*)	A_1 = {(instrument*, 1.0), (writing, 1.0), (ink, 1.0), (nib, 0.5)}	O_1 = {(ballpoint, 1.0), (fountain, 0.9), (marker, 0.8), (quill, 0.7)}		2		3		3
2	C_2(*pencil*)	A_2 = {(instrument*, 0.8), (writing, 1.0), (lead, 0.9), (wood, 0.8)}	O_2 = {(automatic$_p$, 0.8), (normal$_p$, 0.7), (color$_p$, 0.4)}	1			3		3
3	C_3(*stationery*)	A_3 = {(office_material*, 1.0), (writing, 1.0), (office, 0.6)}	O_3 = {(paper, 1.0), (pen, 0.8), (envelope, 0.6), (pencil, 0.3)}			1, 2		1, 2	
4	C_4(*computer*)	A_4 = {(system*, 1.0), (electronic, 0.9), (data, 0.9), (memory, 0.7), (processor, 0.5), (program, 0.5)}	O_4 = {(desktop, 0.8), (mainframe, 0.6), (analog$_c$, 0.5), (digital$_c$, 0.5), (laptop, 0.5)}		5				
5	C_5(*printer*)	A_5 ={(device*, 1.0),(data, 0.8),(print, 0.7), (interface, 0.6), (images, 0.5), (output, 0.5), (paper, 0.5)}	O_4 ={(laser$_p$, 0.7), (matrix$_p$, 0.6), (line$_p$, 0.5), (inkjet$_p$_P, 0.5), (thermal$_p$, 0.3)}		4				
6	C_6(*bank$_{finance}$*)	A_6 = {(organization*, 0.9), (money, 1.0), (deposit, 0.9),(withdraw, 0.9),(finance, 0.7)}	O_6 ={(international$_{b_6}$, 0.8),(commercial$_{b_6}$, 0.5), (investment$_{b_6}$, 0.5), (reserve$_{b_6}$, 0.4)}						
7	C_7(*bank$_{river}$*)	A_7 ={(geostructure*, 0.5), (pile_of_earth, 0.7), (side_of_river, 0.6), (raised_ground, 0.5)}	O_7 ={(river$_b$, 0.8), (canal$_b$, 0.7), (lake$_b$, 0.5)}						
8	C_8(*bank$_{storage}$*)	A_8 = {(storage*, 0.7), (container, 0.6), (repository, 0.4)}	O_8 = {(blood$_b$, 0.8), (data$_b$, 0.5), (sperm$_b$, 0.5)}						
9	C_9(*animal*)	A_9 = {(living_organ*, 1.0), (movement, 0.9), (brain, 0.8), (organic_feed, 0.8), (multicellular, 0.6), (sensory, 0.6), (adaptive, 0.4)}	O_9 ={(mammal, 0.4), (bird, 0.2), (fish, 0.2), (repitile, 0.2), (insect, 0.4), (wild$_a$, 0.9), (domestic$_a$, 0.2)}			10		10	
10	C_{10}(*mammal*)	A_{10} = {(animal*, 0.6), (milk, 0.9), (organic_feed, 0.9), (hair, 0.7), (warm_blooded, 0.7), (vertebrate, 0.6)}	O_{10} = {(monotremes, 0.6), (placental, 0.5), (rodents, 0.4), (whales, 0.4), (humans, 0.4)}				9		9
11	C_{11}(*feline*)	A_{11} = {(animal*, 0.5), (cat_like, 0.9), (mammal, 0.4), (flesh_feed, 0.3)}	O_{11}={(persian_cat, 0.9), (jaguar, 0.6), (leopard, 0.6), (puma, 0.6),(tiger, 0.6),(cheetah, 0.5),(lion, 0.5), (felidae, 0.3),(bigcat, 0.3)}				9	12-15	
12	C_{12}(*cat*)	A_{12} = {(feline*, 0.6), (domestic, 0.7), (flesh_feed, 0.7), (pet, 0.6), (rat_hunter, 0.5), (soft_fur, 0.5)}	O_{12} = {(felis_catus, 0.6), (kitten, 0.6), (mouser, 0.5), (kitty, 0.4), (tomcat, 0.4), (pussycat, 0.3)}		15		11		11
13	C_{13}(*lion*)	A_{13} = {(feline*, 0.8), (large_body, 1.0), (brown_fur, 0.9), (long_hair, 0.9), (flesh_feed, 0.6)}	O_{13} = {(African$_l$, 0.9), (Panthera$_l$, 0.9), (Asian$_l$, 0.8)}				11		11
14	C_{14}(*tiger*)	A_{14} = {(feline*, 1.0), (yellow_fur, 1.0), (black_ stripes, 1.0),(large_body, 1.0), (flesh_feed, 0.4)}	O_{14} = {(Panthera$_t$, 0.5), (Asian$_t$, 0.3), (Bengal$_t$, 0.3)}				11		11
15	C_{15}(*leopard*)	A_{15} = {(feline*, 0.9), (black_spots, 1.0), (yellow_fur, 0.9), (flesh_feed, 0.5)}	O_{15} = {(African$_l$, 0.8), (Asian$_l$, 0.8), (panthera_pardus, 0.8)}		12		11		11
16	C_{16}(*knowledge*)	A_{16}={(cognitive_object*, 0.5),(awareness, 0.8), (abstract, 0.6), (to_have, 0.6), (to_be, 0.5), (to_do, 0.3)}	O_{16} = {(truth, 0.9), (abstract$_k$, 0.8), (experience, 0.7), (skill, 0.4)}		17				
17	C_{17}(*information*)	A_{17}={(cognitive_object*, .6), (code, .6), (context, .5), (representation, .5), (denotation, .4), (instruction, .4)}	O_{17} = {(relation$_i$, 0.9), (semantic$_i$, 0.7), (structure$_i$, 0.6), (characteristic$_i$, 0.3)}		16				
18	C_{18}(*cognition*)	A_{18}= {(mental_object*, 0.9),(behavior, 0.9), (awareness, 0.7), (comprehension, 0.6), (reasoning, 0.5)}	O_{18} = {(thinking, 0.7), (inference, 0.7), (perception, 0.6)}		19				
19	C_{19}(*intelligence*)	A_{19}={(mental_object*, 0.4), (able_to_do, 1.0), (transfer_infor_to_knowledge,0.6),(transfer_infor_to_behaviour, 0.4), (execution, 0.4)}	O_{19}={(autonomous$_{i_{19}}$, 1.0), (natural$_{i_{19}}$, 0.7), (AI, 0.5), (animal$_{i_{19}}$, 0.4), (reflexive$_{i_{19}}$, 0.4)}		18				
20	C_{20}(*science*)	A_{20}={(system_of_disciplines*, .5),(knowledge_creation, .8), (experiment, .7), (inference, .7), (meta_methodology, .7), (natural_phenomena, .7), (behavior, .4)}	O_{20} = {(natural$_s$, 0.6), (abstract$_s$, 0.6), (engineering$_s$, 0.6), (social$_s$, 0.5), (humanity$_s$, 0.5)}	Note: The terms of six types of semantical relations may refer to Definition 3.					



(a) A partial plot of the CKB (b) The entire CKB with 600+ formal concepts built by machines

Fig. 4. The visual interface of a machine generated CKB (Experiment 2)

The formal ontological CKB generated by ACKBG can be flexibly visualized by a threshold (θ_s) of semantical weights where $0 < \theta_s \le 1$. The value of θ_s determines the inclusion of a certain semantic relation in semantic analysis and CKB generation. The smaller the threshold, the more the potential relations as well as the higher the analytic complex, and vice versa, towards different needs of cognitive system applications.

As demonstrated in the experiments, the ACKBG algorithm powered by the deep machine learning engine enables autonomous CKB generation in knowledge engineering and semantic comprehension. ACKBG enables machines to create their own knowledge bases by formal concept generation and quantitative semantic clustering in order to precisely understand human commands and semantics, which was a fundamental demand and challenge in cognitive computing. The experimental results of ACKBG reveal a deep machine understanding not only on complex human semantics of knowledge, but also on quantitative semantic relations beyond human empirical perspectives on knowledge and natural language expressions. CKB plays a central role in explaining the mechanisms of human knowledge acquisition and learning, because it underpins almost all forms of multimedia brain-machine interfaces for machinable semantic comprehension in the development of cognitive robots, cognitive learning engines, and human-machine interaction systems.

V. CONCLUSION

It has been recognized that cognitive knowledge base (CKB) is a fundamental technology for all forms of multimedia brain-machine interfaces in order to enable machines' semantic comprehension in cognitive systems. This paper has formally presented the theory and methodology for a CKB as a common platform for brain-machine interfacing and interactions. A novel methodology for autonomous generation of CKB by cognitive machines has been formally described based on the mathematical models of concept algebra and cognitive machine learning. It has led to the development of the ACKBG algorithm for autonomous CKB generation by deep machine learning. The experimental results have demonstrated applications of the methodology and algorithm in cognitive computing and brain-machine interactions. This work has paved a way to large-scale CKB generation enabling a cognitive robot to acquire equivalent knowledge to the Grade-12 student level and beyond in the future work.

ACKNOWLEDGMENT

This work is supported in part by a discovery grant of the Natural Sciences and Engineering Research Council of Canada (NSERC). The authors would like to thank the anonymous reviewers for their valuable suggestions and comments on the paper.

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