

A Cognitive Approach to Modelling Semantic Sensor Web Solutions

Agnes Korotij and Judit Kiss-Gulyas

University of Debrecen, Debrecen, Hungary

Abstract. Semantic sensor solutions are characterized by a lack of consensus on what features make sensor networks semantic, and what services a semantic layer should provide. Although authors emphasize the fact that humans outperform software in managing inconsistent knowledge and unreliable sensor data, no attempt has been made so far to construct a model of semantic sensor networks inspired by human cognition. The aim of the present paper is to investigate whether the structure and organisation of concepts and meaning in the human mind (as proposed by cognitive linguists and psycholinguists) can serve as a model for constructing ontologies and knowledge representations for the semantic sensor web (hereafter SSW). We also aim to show how multimodal sensory data can be integrated with these representations based on contemporary findings in human perception. We suggest that SSW solutions based on cognitive mechanisms and psychologically plausible knowledge representations overcome the challenges that handling of fuzzy data and inconsistent information generates at present.

1 Introduction

The Semantic Sensor Web (SSW) initiative targets the integration of unstructured sensor data (e.g. GPS, timestamps, temperature, visual and auditory data) with artificial knowledge repositories. Despite the growing interest in SSW solutions, there seems to be no consensus on what features make a sensor network or web solution *semantic*; such confusion has measurable effects on the performance of the system and make interoperability of these networks difficult. For the most part, semantics boils down to the use of semantic web representation techniques, specifically RDF¹ and OWL² (e.g. [18]). On other occasions, semantics is abused as a synonym for the tagging or annotation of raw data. A. Seth, for example, talks about the SSW in the context of annotating sensor data with spatial (*where*), temporal (*when*) and thematic (*what*) metadata, which together constitute the semantic metadata [24]. In a later work, Seth's mention of semantics implies 'anticipating when to gather and apply relevant knowledge and intelligence', 'minimal explicit concern or effort on the human's part', and 'the meaningful representation and sharing of hypotheses and background knowledge' [26]. Although authors emphasize the fact that humans outperform software in managing inconsistent knowledge and unreliable sensor data

¹ Resource Description Framework (RDF). Available from: <http://www.w3.org/RDF/>

² Web Ontology Language (OWL). Available from: <http://www.w3.org/2004/OWL/>

[25], no attempt has been made so far to construct a cognitively inspired model of semantic sensor networks. (For one notable exception see [7].)

The aim of the present paper is to investigate whether the structure and organisation of concepts and meaning in the human mind can serve as a model for constructing knowledge representations (KRs) for the SSW, which at the same time support the processing of sensor data. The paper explores the following questions:

- i. What constitutes knowledge in the human mind? What are the basic cognitive processes that underlie the organization of concepts?
- ii. Do semantic web technologies (e.g. RDF and OWL) provide a plausible model of human knowledge organization?
- iii. How does the human mind integrate sensory data with conceptual knowledge? Can the same principles of organization hold in different modalities?
- iv. What are the implications of a cognitive approach to modelling sensor integration?

We suggest that SSW solutions built on cognitive mechanisms and psychologically plausible KRs overcome the challenges that fuzzy and inconsistent data present.

2 Concepts in the Mind

In the context of the semantic web, knowledge is organized in *ontologies*, formal representations of conceptualization. In this section, we examine the question of how the human conceptual structure is organized. By *conceptual structure* we mean the organization of concepts, and *conceptual space* refers to the representation level where concepts are stored. We assume that knowledge constitutes conceptual structure and information stored in the declarative memory.

2.1 The Representation of Concepts in the Mind

Understanding how language processing works sheds light on the mechanisms that interact with conceptual structure. Processing language is supposed to take place at different stages and involve three levels of representation [11]:

1. *Subsymbolic level*: information is directly related to sensor data;
2. *Linguistic level*: information is expressed by a symbolic language;
3. *Conceptual level*: prelinguistic, information is represented in a metric space defined by a number of cognitive dimensions.

The linguistic level appears to be too specific given the assumption that mental representations are not necessarily propositional in nature (see [21]). In order to cover the representation of non-linguistic constructs, we propose that the linguistic layer should be complemented with a more general, symbolic rule-based level, whose role is to capture regularities of any form, linguistic or non-linguistic. Psycholinguistic evidence has shown that an ad hoc, primary analysis of form measurably precedes semantic interpretation [22], which supports Gärdenfors' three-layer model: the

linguistic input discerned while reading (visual stimuli) or listening (auditory stimuli) is processed by the rule-based system (syntax), and then mapped onto the conceptual dimension. The order of the phases is not strongly sequential, non-sensible semantic interpretations may feed back to the rule-based module for an alternative syntactic analysis [10].

Semantic and conceptual information is stored in the mental lexicon [3]. Concepts corresponding to word meanings are represented in the brain by cell assemblies distributed over different areas depending on the semantic properties of the word. These properties include sensory and motor attributes, which determine whether a word represents an easily visualizable object, or stands for a performable action [6]. While motor regions are important in processing and naming movement related words [27] and imagining movement [12], other areas seem to be specialized for categories in which visual form is primary [27]. The representation of abstract words has only recently gained attention in psycholinguistic circles [29]. Research results imply that knowledge of abstract concepts is secondary to knowledge of concepts directly rooted in perception (see [17]).

2.2 General Cognitive Processes in the Organization of Conceptual Space

Cognitive scientists assume that human cognition is composed of basic mechanisms which underlie the various aspects of intelligent behaviour, including language processing, spatial orientation, or the organization of concepts. Croft and Cruse (2004) identify four cognitive abilities as primary in conceptualization: (1) attention, (2) comparison, (3) perspective, and (4) constitution.

Attention is the focus of consciousness; it comprises the selection of relevant parts, the granularity of the observed phenomena, and scanning. Attention is sensitive to the statistical properties of the input irrelevant of its modality [13].

Comparing entities is basic to establishing relationships like hyponymy, synonymy and antonymy. Categorization, metaphor and the figure-ground alignment are special cases of comparison. Although both cognitive scientists and semantic web activists make considerable efforts to uncover how *categorization* works, there is a major discrepancy between the two approaches in the treatment of category membership. For cognitive scientists, humans manage fuzzy categories which exhibit graded membership [23]; for example, CHAIR is a more prototypical instance of FURNITURE than LAMP. For the semantic web activist, category membership is strictly defined, and members have equal status within the category (see Section 2).

Perspective captures the individual's spatial and temporal location. As Table 1 shows, perspective is not central in the organization of content words; this process is more salient in visual perception and the organization of function words.

Constitution unravels the composition of the entities perceived and thus plays a role in identifying parts and wholes. It helps determine whether a group of perceivably different entities form a coherent whole, and is also responsible for breaking up large objects into smaller chunks.

Redundancy of cognitive mechanisms is crucial in human cognition, i.e. multiple processes may be involved in a task at the same time [27]. An example of redundant cognitive mechanisms at work has been observed in adult foreign language learning

[30]. When adults learn a second language, initial weaknesses in the grammatical system can lead to compensatory storage of long phrases in the memory.

General cognitive processes organize space along various types of relationships (see Table 1). *Association* is the primary means of organizing concepts. Association is a weighted relationship between any two items, irrelevant of the modality the items belong to (associations may exist between pictures and words, for instance). The strength of associative links is heavily influenced by previous experience: for example, co-occurrence of words, words and visual stimuli, visual stimuli and other sensory input establish new or strengthen existing associations.

In an overview of lexical relationships, Cruse outlines the relationships that may possibly exist between word meanings, including hyponymy, meronymy, synonymy and antonymy [5]. These relationships may all be considered as special cases of association. In *hyponymy*, one item is superordinate over another. *Meronymy* corresponds to part-whole relations; however, meronymy is constrained to words whose representation involves visual modality. *Synonymy* is the phenomenon when words map onto similar concepts in the mind. *Antonymy*, i.e. oppositeness of meaning is not fundamental to the structuring of the mental lexicon.

Table 1. An overview of semantic relations and their cognitive basis.

Name	Description	Example	Cognitive basis
Association	Arbitrary relationship between two items of any modality.	“news” – “coffee”, smell of cinnamon – “winter”	Attention
Hyponymy	One item is superordinate over another; graded membership	“vehicle” – “car”	Comparison (categorization)
Meronymy	Part-whole relation.	“hand” – “finger”	Constitution
Synonymy	Words map onto similar concepts.	“nice” – “handsome”	Comparison
Antonymy	Words map onto concepts with opposite attributes.	“nice” – “ugly”	Comparison

3 On Psychologically Plausible Knowledge Representations

Based on the structure and organization of human conceptualization presented in Section 1, we suggest that a psychologically plausible KR should:

- (a) be able to represent weighted associations;
- (b) be able to represent fuzzy categories;
- (c) be able to represent part-whole relationships in the case of concepts that correspond to visually perceivable objects;
- (d) support direct links to items from other modalities, i.e. allow for associating concepts directly with sensor data representations (e.g. images);
- (e) be sensitive to co-occurrence of items in its environment and support the update of association weights;
- (f) be context-dependent, in the sense that information stored in knowledge representations may vary in different applications.

As to the representation of semantic sensor data in SSW solutions, the two prevailing trends are (1) OGC syntactic standards defined for the management of

sensory data [20], and (2) W3C semantic web standards [1]. Since OGC standards lack semantic description, we limit our discussion to semantic web standards as the only candidates for a cognitively inspired model of KR.

Ontology languages provide a means for representing terms and establishing relationships among the entries. Compared against our criteria, none of the current semantic web technologies (e.g. RDF, OWL) prove to be psychologically plausible. Although these languages are able to represent categorization-based (“is-a”, “generalization” or “inheritance”) relationships, they cannot model prototype effects, and as a consequence, have problems in dealing with fuzzy categories. These technologies do not make use of probability information in modelling relationships, and do not allow for the distributed or overlapping representation of concepts either. As to the representation of comparison-based relations, it is possible to define structures (e.g. predicates) for the modelling of such special-purpose relationships. Semantic web representation techniques also provide a means for attaching various sensory data to concepts in the form of resources, which is a definite advantage.

Conceptual structure at the lowest level is best represented by vector space models (VSM) or neural networks. Both representations provide a natural way for modelling comparison (as the extent to which activated neurons overlap in a neural network, or the distance of vectors corresponding to the concept feature combinations in VSMs). These representations have the further advantage of providing a solution to the symbol grounding problem [14].

Should semantic web technologies be discarded then, and be replaced by distributed representations? In our view, formal ontologies are not incompatible with low-level distributed representations. Despite their lack of psychological plausibility, ontologies are nevertheless valid symbolic systems in the intermediate layer of Gärdenfors’ model. Formal ontologies could exploit the advantages of neural networks or VSMs with indices that point to these lower level structures.

4 Integrating Human Perception with Conceptual Knowledge

Semantic sensor networks need to make intelligent use of their knowledge stores when processing sensor data. While human interaction with the environment involves the processing of sensor data from five different modalities, artificial sensors capture only a small proportion of all the possible environmental data, specifically spatial location, time and physical details like humidity and temperature. Semantic sensor networks should also provide a means for extracting information from pictures, videos or voice recordings. In this section, we examine the way in which human cognition integrates sensor data from multiple modalities with conceptual knowledge.

4.1 Cognitive Processes Involved in Human Perception

It has been assumed that ‘the cognitive abilities that we apply to speaking and understanding language are not significantly different from those applied to other cognitive tasks, such as visual perception, reasoning or motor activity’ [4]. In Marr’s model of visual perception [19], the processing of visual stimuli is considered to be a

mechanism in which information and knowledge are represented and processed at different levels of abstraction, ranging from sensory stimuli to symbolic encoding. Although Marr intended his model to describe visual modality exclusively, it appears to be compatible with Gärdenfors' three levels of representation.

Attention as a cognitive mechanism plays an important role in processing sensory data. Visual perception, for instance, has a pre-attentive and an attentive phase. At the pre-attentive level, no distinctions are made between important and irrelevant parts [8]. The focus of attention can be guided by the inherent characteristics of the visual stimulus (e.g. a lonely building on the horizon), or free association (e.g. seeing a flower may send the perceiver looking for a butterfly). Evidence from early cognitive literature on vision suggest that *viewer centred* and *object centred* representations of images coexist in human memory (e.g. [9]), which proves that perspective is also fundamental in human vision.

4.2 Integrating Sensor Data with Conceptual Structure

The integration of sensor data with conceptual knowledge raises two fundamental questions. First, how does the brain integrate data received from different senses? And second, how are these data mapped onto conceptual space?

In the case of conflicting parallel inputs from different sensory domains, one modality will tend to dominate the final perception depending on the type of the task and the relative reliability of the source of the sensation [28]. Experiments show that integrating multimodal sensory data is so fundamental to cognition that separate brain regions are dedicated to this task [2]. Fig. 1 shows a cognitive architecture of sensory integration.

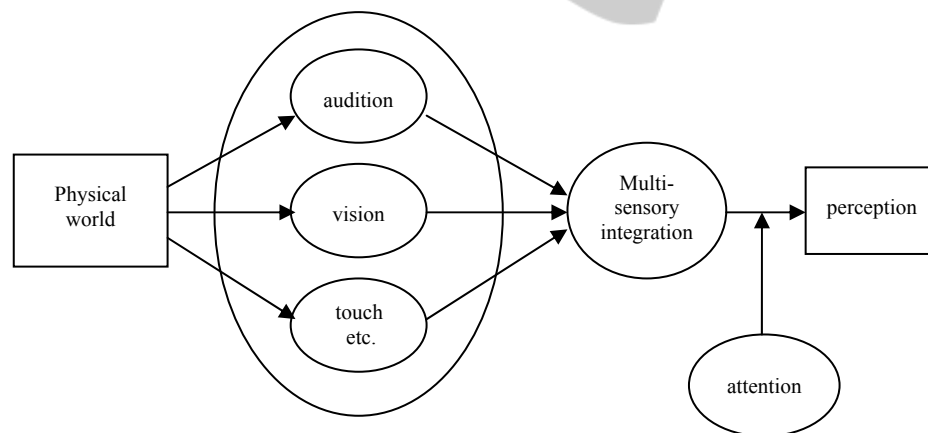


Fig. 1. The cognitive architecture of sensory integration based on Verhagen and Engelen (2006).

As we have shown in Section 1, the organization of concepts in the human mind is influenced by sensori-motor attributes. One account for this phenomenon is the *semantic hypothesis*, which claims that the dissociations reflect differences in the conceptual semantics of the words [27]. This implies that conceptualization is deeply

rooted in perception, and strong associations exist between the representations of words and mental footprints of sensory experience.

5 A Cognitive Architecture for Semantic Sensor Web Solutions

In this section, we wish to bring together into a coherent model the suggestions introduced in previous sections. The rationale of the layered approach to the system has been presented in Section 1, in Section 2 we have described the principles that make knowledge representations psychologically plausible, and Section 3 has focused on the interaction of sensory data and knowledge representations.

Architectures proposed by the SSW community are either limited in focus (see [16] on pattern recognition, and [24] on metadata extraction for the SSW), or fail to define the interconnections of the architectural components. Seth, for instance, proposes that among others, computing for human experience should provide solutions for pattern recognition, image analysis, casual text processing, sentiment and intent detection [26]. Seth, however, does not explain how these components should be related to each other or what their exact roles are.

Based on evidence from cognitive neuroscience and psycholinguistics presented in earlier parts of this paper, we propose that the following architectural components be included in a SSW solution (see Fig. 2.):

- At the sensory level, SSW solutions should support the integration of multiple sensor data with a separate *integration module* that helps decide which data are more relevant and of better quality in the given situation.
- SSW solutions should provide *redundant mechanisms* for the solution of various tasks, and use the best approach depending on the type of the task, the context and background knowledge. A separate *Selector* module should be responsible for deciding which mechanism should be preferred.
- SSW solutions should have *rule-based modules* to capture rules which may apply to the operation of the system, and a *declarative knowledge base* which subsumes the conceptual structure and caches solutions for frequently occurring problems. (Note that Fig. 2. does not aim to illustrate all the possible symbolic modules, it only shows examples of such components.) It is preferable that the Selector first checks the availability of cached solutions, and delegates the task to rule-based modules only in the case of a negative response from the knowledge stores. The division between online computation and the retrieval of complete solutions to recurring tasks is the cornerstone of an efficient SSW solution.
- *Knowledge representation* technologies should combine symbolic ontologies with low-level representations based on the principles outlined in Section 2.
- SSW solutions will benefit from *automated learning* based on the principles of human concept acquisition. Learning should be sensitive to *statistical information* inherent in the environment.

The architecture we propose is limited in its granularity: lower level implementation details are out of the scope of the present paper and are subject to future research. However, if future implementations were to be tested and validated

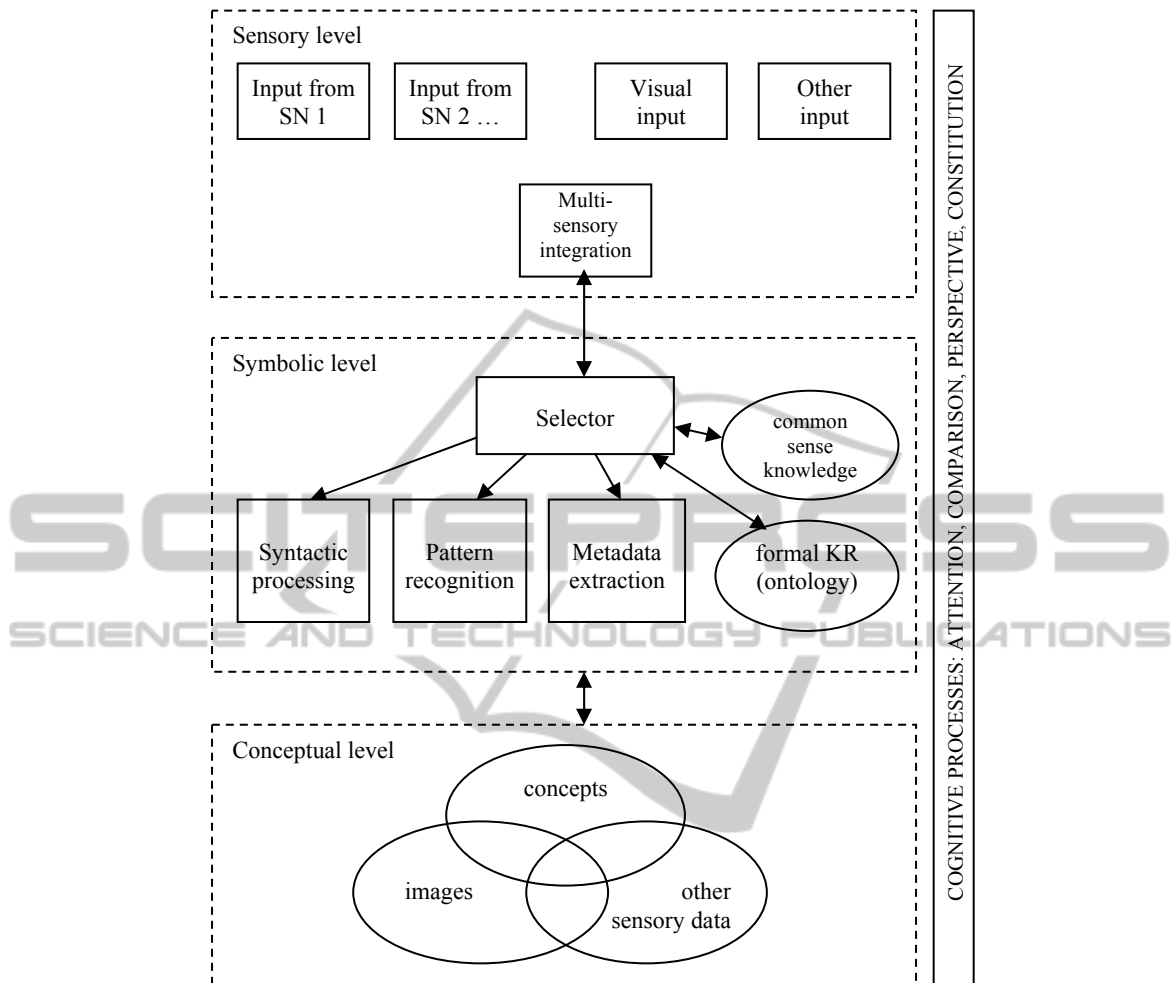


Fig. 2. A cognitive architecture for SSW solutions. The sensory level delegates the integrated cross-modal input to symbolic processing. The Selector decides which method suits best the given task, and chooses either a rule-based solution (represented as rectangles), or retrieves the answer from the knowledge store, which comprises common sense knowledge and domain-specific ontologies (represented as ellipses). Both rule-based methods and the knowledge store rely on the conceptual level, which integrates conceptual, visual and other representations. Cognitive processes underlie the workings of the system.

according to standard measures, we expect that systems built on the cognitive architecture presented in this paper will be as efficient as solutions based on other types of architectural patterns, and will perform better with fuzzy input than non-cognitive systems. For most tasks, the separation of layers and the redundancy of processes are not likely to cause significant performance overhead, since the system operates with cached or—in the case of novel tasks—best-fit procedures. We expect experimental findings to support our claim that a cognitively inspired SSW solution will outperform traditional sensor systems when faced with conflicting, fuzzy or

deficient environmental data, because it will include the necessary strategies that humans employ in their day-to-day interactions with the environment.

6 Conclusions

In this paper, we have explored the characteristics of the mechanisms that the human mind employs to organize and structure conceptual knowledge. We have shown that human knowledge representation subsumes three levels of abstraction, (1) the sensory (subsymbolic), (2) the rule-based symbolic and (3) the conceptual level. At the conceptual level, word meanings are distributed across several brain regions, which overlap with areas activated during the processing of sensori-motor stimuli. These evidence suggest that concepts are grounded in perception, and associations exist across the mental representations of input from different modalities.

While RDF, OWL and other semantic web technologies fail to live up to the criteria of a psychologically plausible knowledge representation, they are nevertheless valid components of the symbolic layer of SSW solutions. In order to approximate human conceptualization, KRs similar to neural networks or vector space models should be positioned at the lowest level of the knowledge base architecture.

The same cognitive processes (attention, comparison, perspective and constitution) underlie language processing, the organization of visual, auditory and other sensory stimuli, and the construal of concept relations. The integration of sensory data from multiple modalities involves the activation of dedicated brain regions and processes, which entails that any SSW solution inspired by human cognition should provide adequate sensor integration modules or processes.

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