Applications of ontologies in knowledge representation of human perception

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ABSTRACT

Information overload is becoming bigger as Internet grows. This entails several problems such as difficulty in finding information and redundancy of knowledge. In this paper, a solution of these problems is presented as a global representation of knowledge based on human perception, and modelled by means of ontologies. This approach has several advantages shown in the study, but also some drawbacks related to state of the art technologies.

Keywords: human perception, knowledge representation, ontologies

INTRODUCTION

Human learning (knowledge acquisition) is a very complex and lifelong process (Jarvis, 2012), and perception process plays a fundamental role in it receiving stimulus from the environment, up to the point that "*without perception there is no knowledge*" (Neisser, 1993). Here comes into play the term cognition, defined as the *ability to process information from perception, the acquired knowledge (experience) and subjective characteristics that allow us to evaluate the information*, which can be seen as a link between human learning and human perception.

Oxford Dictionary defines perception as *the ability to see, hear, or become aware of something through the senses*. Relating to Psychology and Zoology: *the neurophysiological process, including memory by which an organism becomes aware of and interprets external stimuli*. As stated in the previous definition, memory plays an important role in perception. The way stimuli is processed and stored in the human being could be the key to enrich the non-supervised machine learning processes.

Since Aristotle (Slakey, 1961), several philosophers, psychologists and researchers have studied about perception and the interactions among senses. Irvin Rock, focusing in visual perception, considers that knowledge in the form of stored representation affect perception, enabling capabilities in the human beings such as recognition and interpretation, perceptual discrimination among similar members of a category, access to previously learn solutions to apply in cases where perceptual problem solving occurs, among others (Rock, 1985). Most authors centred their research in vision arguing it is the one that provides the richest and most detailed information about the environment, but perceptual system is very complex and it is based in different and combined systems. As example, Harry McGurk and John MacDonald published a study in 1976 analysing the influence of vision upon speech perception (McGurk & MacDonald, 1976). Also, there are well known interactions, such as odour/taste and studies in how this relationship affects the perception of flavour (Small & Prescott, 2005).

According to classical Aristotelian perceptual classification (Osborne, 1983), there are five main human senses (*sight*, *hearing*, *smell*, *taste* and *touch*). Each sense is associated with one sensory system (eyes, ears, nose, tongue and skin). These senses allows people to perceive the environment around them. However, several other senses have been defined and included in this list. Senses that add information about the environment or the being itself. *Proprioception* (kinaesthetic sense) provides humans awareness of the position of the parts of the body, and awareness of movement of the body and how much force is required to move each part. This sense is based in dedicated receptors in the muscles, tendons and joints (Macpherson, 2011). *Equilibrioception* (vestibular sense, or sense of balance) allows detect body movement, direction and acceleration by sensing the gravitational field by means of the fluid-filled semicircular canals and the otolithic organs in the ears (Macpherson, 2011). *Chronoception* (sense of time) is responsible of perceive and experience the passage of time. (Le Poidevin, 2011)(Phillips, 2010). *Thermoception* (Pogorzala, Mishra, & Hoon, 2013) and *Nociception* (Suzuki & Dickenson, 2003) determine perception of temperature and pain respectively, and they have a close relationship due both use transient receptor potential (TRP) channels in the process of sensing. As can be seen, some of these senses detect objects and properties in the world external to the body (such as sight and hearing). These senses are called *exteroceptive*. On the other hand, some other senses detect changes to the body. These ones are called *interoceptive*. Both exteroceptive and interoceptive combination of senses provide the brain multiple sources of information that compose the perception of the environment. It is intuitive to think the more sensory information is received, the most complex and precise definition of the environment is perceived. For example, some animals have special senses adapted to the environment where they live, such as the cases of dolphins, fitted with *Echolocation*, or the ability to emit ultrasounds in order to determine obstacles or fishes which compose their food; the homing pigeons, which use *Magnetoception* (ability to sense magnetic field) to return home; or some sharks which use *Electroception* to detect any muscular movement or twitches in living animals and fish (similar to electrocardiogram machines tracking the heart beating).

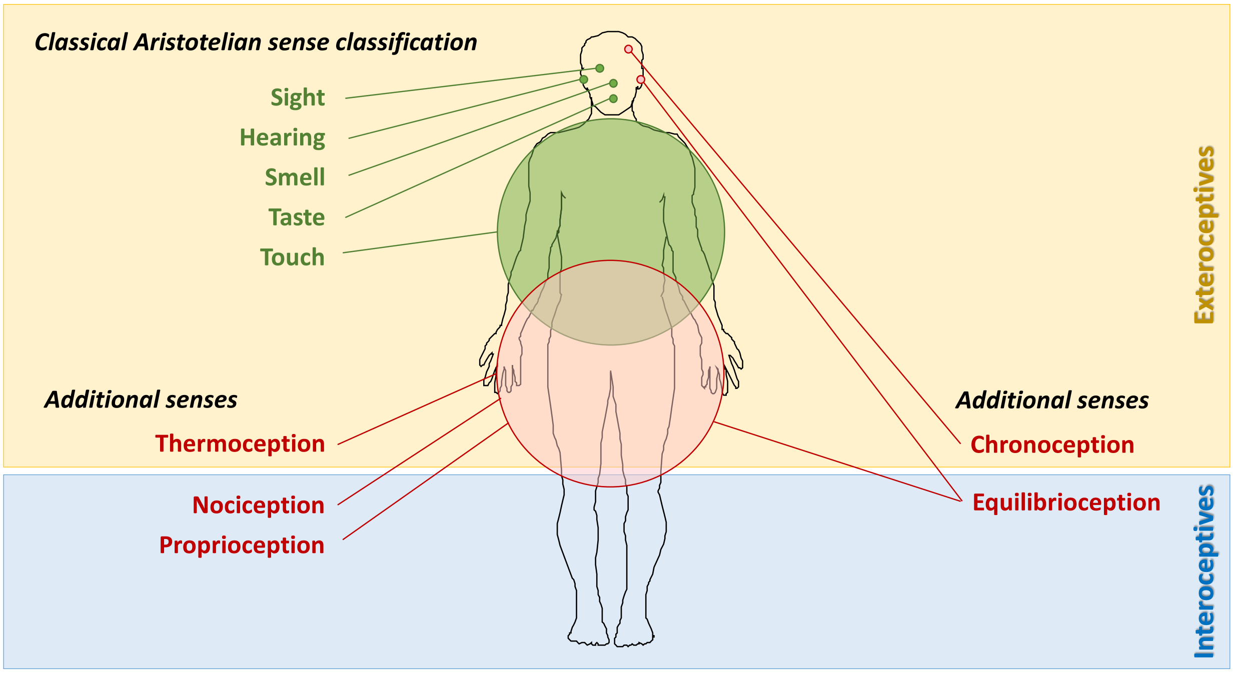


Figure 1 - Human senses

Adding new senses to human being may result quite complicated despite important advances in science (mainly bioengineering and medicine), but it is a trivial task in computer environments (basically add a specific new peripheral, such an infrared camera and configure it), so it is possible having a sense-overloaded system with improved (or more precise and numerous) stimuli receptors than human have. Processing and combining all these received stimuli and storing the resulting inferred knowledge (extended semantic information) about the environment accordingly to a representation model could help process and link the information in a way similar as humans do. This fact would represent a breakthrough towards automated reasoning and unsupervised learning processes, providing capabilities and benefits such as reduction of redundancy according to prototype theory (Rosch, 1973), which is a very important theory related to human perception and memory fundamentals. This reduction in redundancy is of utmost importance in the information overloaded world we live in.

Nowadays, ontologies and some other models are used to achieve knowledge representation. These models are very powerful, allowing the conceptualization of entities within a domain and the characterization of relationships between them. However, these models present some drawbacks, such as heterogeneity between ontology languages (Shvaiko & Euzenat, 2008) and difficulties with combining existing knowledge (Gao & Xu, 2013), although over the last decade different approaches to match, merge and integrate ontologies have emerged. Approaches based in human interaction (Simperl, Wölger, Thaler, Norton, & Bürger, 2012) as well as in unsupervised techniques (Djeddi & Khadir, 2013). Anyway, the common usage of ontologies is to represent specific and individual areas of knowledge, such as biomedical or e-commerce business ones, but not a global combined knowledge domain. This can be a problem when representing a combination of different heterogeneous domains related to different sensory devices. In order to perceive the environment and categorize it as humans do, the solution should be able to unify these domains to interrelate their concepts and create a global representation of knowledge unifying each domain information to have a complete conceptualization of entities from different qualitative aspects, such as measure, colour, sound, aroma, shape, etc.

The remaining of this paper is structured as follows. In the following section, “Literature Review”, authors present different approaches for knowledge representation and modelling. In the next section, ontologies as a means to represent human perception-based knowledge are considered, analysing benefits, limitations and caveats of this solution. Finally, the paper ends with a discussion of research findings, concluding remarks and future research plans.

LITERATURE REVIEW

Knowledge Representation (KR) has undergone a major evolution from its origins. In this section some different models of KR developed over time and their characteristics are presented.

a. SGML as key-value and markup model

The Standard Generalized Markup Language (SGML) is a standard for document description (ISO8879:1986) proposed by the International Organization for Standardization (ISO). It is designed to enable text interchange and is intended for use as well in publishing field as in the office and engineering areas. SGMLS documents have a rigorously described structure which allows being easily analysable by computers and easily understood by humans (Van Herwijnen, 1994).

SGML is considered a meta-language, which has led to several well-known and extensively used languages (SGML subsets), such as Hyper Text Mark-up Language (HTML) and Extensible Mark-up Language (XML). The latter one designed initially to ease the implementation of a parser compared to SGML whole specification. This characteristic among other additional restrictions (such force closing each opened tag) has made XML to be more widely used than full SGML.

Application of this language and some subset variants are present even in the definition of certain ontology languages, such as Web Ontology Language (OWL), (W3C, 2009).

b. Semantic networks as knowledge visualization and presentation model

Semantic networks are knowledge representation schemes based in directed graphs. The nodes represent objects or concepts and the links represent relations between nodes. The nodes and the links are usually labelled. An example can be seen in the following figure:

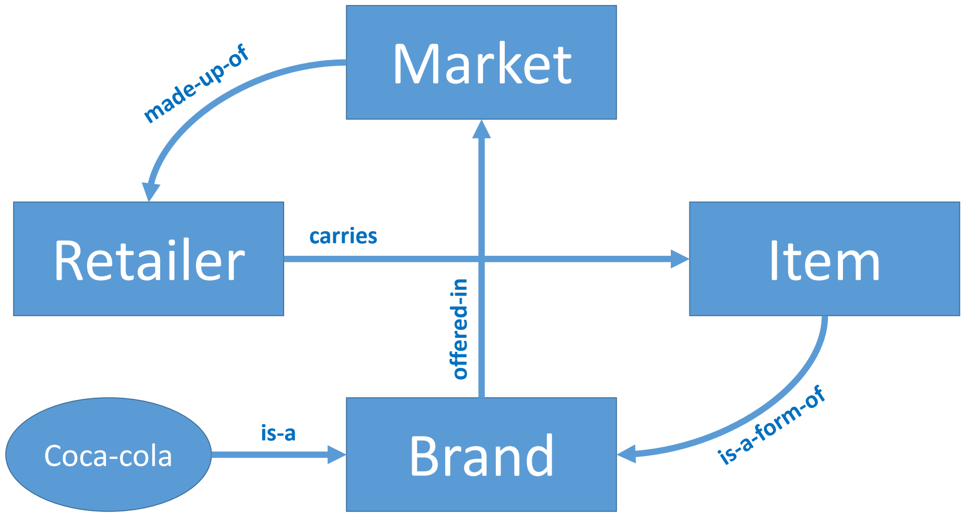
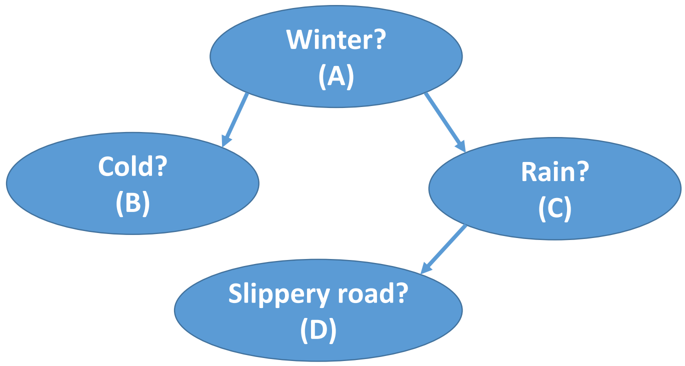


Figure 2 - Semantic Network example

Some of the first uses of the nodes-and-links formulation were on how natural language is understood and how the meanings of words can be captured in a machine (Quillian, 1967), but over time this model has been used for various uses such as complex system relationship modelling (Motlagh, Tang, & Homayouni, 2013) using semantic networks.
Semantic Networks present some specific difficult problems in knowledge representation related to expressivity. For example, concerning to negation and disjunction, they are not easily represented relationships. As well as quantification (Woods, 1975).

c. Bayesian networks as stochastic model

A Bayesian network is a tool for modelling and reasoning with uncertain beliefs. A Bayesian network consists of two parts: a qualitative component in the form of a *directed acyclic graph* (DAG), and a *quantitative component* in the form *conditional probabilities*. The nodes in the graph represent the variables of interest and the graph edges represent direct influences among these variables. The conditional probabilities of a Bayesian network quantify the dependencies between variables and their parents in the DAG. Formally though, a Bayesian network is interpreted as specifying a unique probability distribution over its variables.



A	Θ(A)
True	0,5
False	0,5

A	B	Θ(B|A)
True	True	0,8
True	False	0,2
False	True	0,4
False	False	0,8

A	C	Θ(B|A)
True	True	0,6
True	False	0,4
False	True	0,2
False	False	0,8

C	D	Θ(B|A)
True	True	0,8
True	False	0,2
False	True	0,05
False	False	0,95

Figure 3-Bayesian Network example

Just in Computer Science, Bayesian networks are used in a large way of applications, such as information retrieval (Sebastiani, 2002), reasoning services for semantic web (Costa, 2005) and decision support (Weidl, Madsen, & Israelson, 2005).

d. Ontologies as representation models

According to Gruber, *an ontology is a formal, explicit specification of a shared conceptualization* (Gruber & others, 1993). Along time, this definition has been refined, including ideas such as *hierarchically structured set of terms* (Swartout, Patil, Knight, & Russ, 1996), *explicit representation of concepts in a domain* (Noy & McGuinness, 2001) and *theory which uses a specific vocabulary* (Fonseca, Egenhofer, Agouris, & Câmara, 2002).

From these definitions and ideas proposed by cited authors, it is possible to identify some aspects of ontologies:

- Ontologies are used to describe a specific domain.
- The meaning of the terms used in a specific ontology must be consistent among its users.
- Relations and terms used by an ontology must be clearly defined.
- Terms are organized following a mechanism (such as a hierarchical structure).

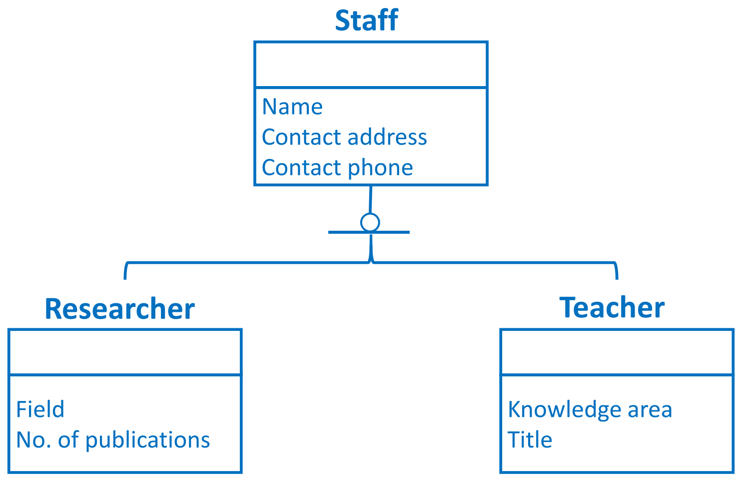


Figure 4- Basic ontology example

A wide variety of tasks in diverse research areas are supported by ontologies. Apart from knowledge representation, some relevant tasks are knowledge sharing in multi agent systems, knowledge management, knowledge acquisition and information retrieval.

As knowledge sharing is concerned, ontologies allow intercommunication with information resources between human or software agents. Relationships in ontologies (which describes data semantics) are machine readable, enabling abilities such as making statements and asking queries under a specific domain due to the conceptualization which describes entities and their relationships. The usefulness of ontologies in agent based systems can be seen as they enable knowledge-level interoperation. Similarly, ontologies support shared understanding, interoperability between tools, systems engineering, reusability and declarative specification (Farquhar, Fikes, & Rice, 1997).

Ontologies conform the basis of knowledge bases, which are composed by an ontology and a set of individual instances of its classes (Noy & McGuinness, 2001). This kind of knowledge storage can be used by intelligent agents in order to enrich, reuse and maintain them. According to (FIPA00006, 2001), knowledge bases are formed by state-dependent information, while ontologies concentrate state-independent information.

With regard to knowledge acquisition, ontologies can be used as a useful tool. For example, team works can use ontologies as a common support to classify the knowledge of an organization, as ontologies allow users to reuse knowledge in new systems, enhancing

Related to information retrieval applications, ontologies can be used to elaborate taxonomies of terms in order to enhance the precision of results and to disambiguate user queries (FIPA00006, 2001). Also, ontologies based on users' interactions can be extended via machine learning techniques.

ONTOLOGIES AS A MEAN TO REPRESENT HUMAN PERCEPTION-BASED KNOWLEDGE: CHALLENGES AND OPPORTUNITIES

According to previous sections, ontologies are a powerful method to represent and share knowledge, but as cited before, usually each defined ontology is focused to a specific domain. Moreover, human perception is composed of a complex series of interrelated synergistic systems including stimuli receptors and memory. From a simplistic point of view, each sense perceives (at least) one characteristic from the environment, processes and filters it having into account its significance level based on experience (memory). Irrelevant stimuli (filtered ones) are lost due to short-term memory (like a computer buffer). On the other hand, relevant stimuli are processed in a global way. This is, having into account the perceived information by other senses at this moment. In this processing, reasoning tasks are done, accessing to memory and refining existing information about stored concepts.

From a modular point of view, and considering the simplistic human perception way of working, an initial computer knowledge representation based on perceptual inputs approach could be constructed having into account the following requisites:

1. Different ontologies can be used, each one to represent particular stimuli domains (visual, auditory, thermal, etc.). There already exist ontologies and reasoning techniques to process different senses. For example, related to vision, (Maillot, Thonnat, & Boucher, 2004) propose to use a visual concept ontology to guide experts in the visual description of the objects of their domain enabling semantic image interpretation. Alike (Tongphu, Suntisrivaraporn, Uyyanonvara, & Dailey, 2012) propose a detection framework capable of detecting composite object instances, and test it using car sides. Nevertheless, each sense should be represented in a specific way that could not be related to the other domains.

2. Ontologies defined for each domain must have the ability to be expanded and modified according to new perceived and unclassified characteristics.

3. It is required a processing of each stimuli perceived by each sensory system, having into account the sense stored knowledge to determine if the significance degree of the stimuli. This allows to filter received stimuli with associated existing knowledge, and classify the new (unknown) stimuli, increasing the sense related knowledge base.

4. Apart from processing each sense in an individual way, the combination of knowledge perceived by other senses should be considered in order to define concepts or entities in a global knowledge base. As example, visually a plastic apple can be similar to a natural one, and both belong to “apple” category. To difference them and realize that they are not of the same kind, it would be necessary to touch / smell / taste them. Or maybe knocking them and hear the sound produced by each one. This global stimuli combination can help differentiate and perceive characteristics of a wide range of elements from the environment.

5. Enrichment of global knowledge base should be done in a similar but more complex way than stimuli processing and filtering (point 3).

A diagram combining the different required elements can be seen in Figure 5.

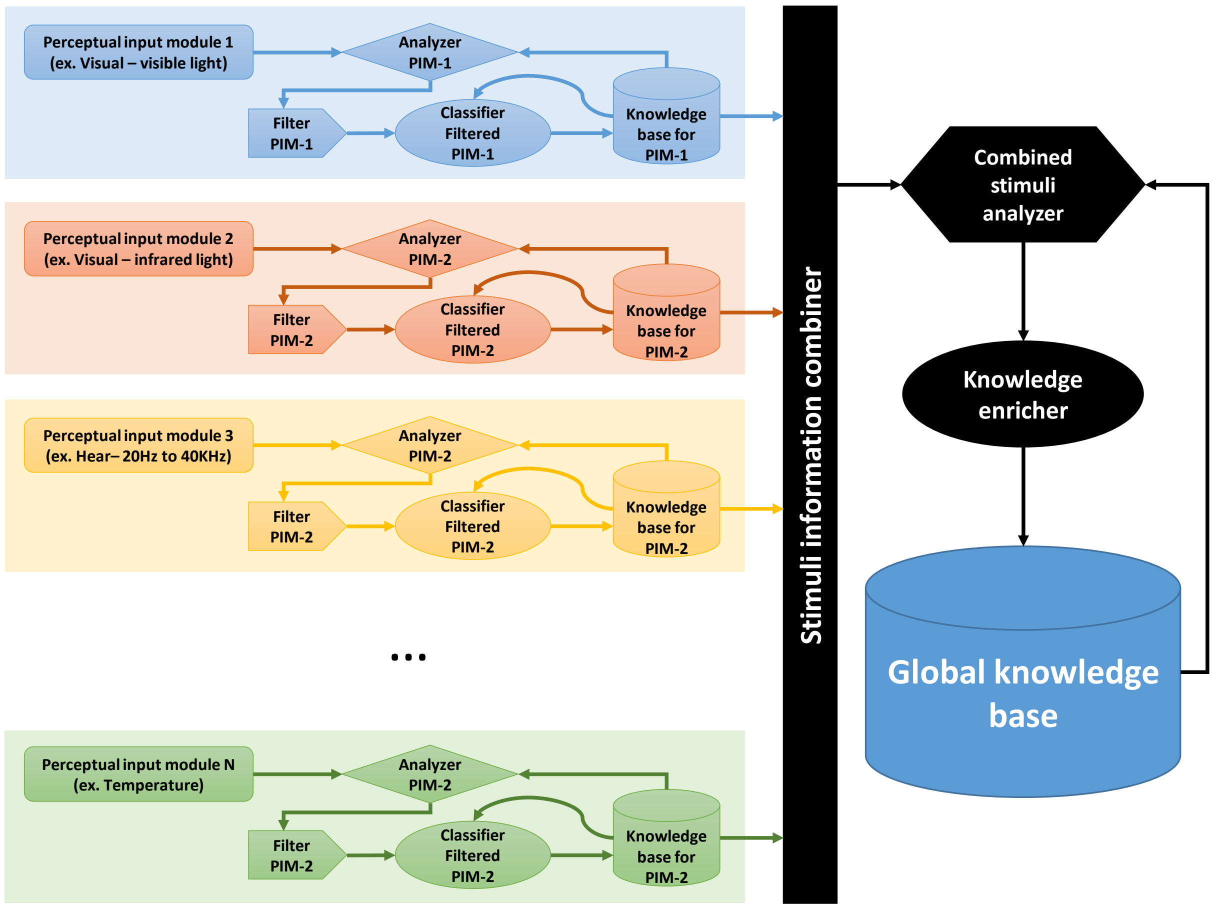


Figure 5-Combined perceptual knowledge base

Is not obvious to define several parts of this architecture, such the *stimuli information combiner*, which should analyse each sensory input together having into account the previously stored knowledge, combine it and check if the generated piece of information is suitable to enrich the global knowledge base through the *knowledge enricher* module.

Creating such system provides the ability to learn automatically from the environment, doing an extensive classification of elements by each sense feature characterization and reduce redundancy by a filtering process. Also, by being based on ontologies it is possible to develop and implement reasoners which can use this global knowledge information as well to enrich existing applications such web search engines, or decision support systems, as develop a wide range of new intelligent applications.

CONCLUSIONS AND FUTURE WORK

The development of this new model is aimed to provide a global knowledge representation in an abstract non-conventional way. These models must take into account the perception of the concepts as an important factor that will help to classify and recognize them. This new mechanism will be able to refine these concepts, to eliminate redundancies and to discover relations and new inferences among them. The motivation behind this system is to emulate the way humans store and learn information in order to develop a new wide range of applications based in an intelligent system capable of autonomous learning from the environment, assimilating existing knowledge in all its forms and combine them into a global knowledge base in order to develop new concepts, ideas and theorems in an efficient way.

Also this model pretend to expand ontologies capabilities by representing multiple different but related domains in an efficient way, combining externally each one under a common abstract global knowledge base.

As future work it is intended to delve into the literature to determine existing ontologies or frameworks oriented to model perceptual information related to senses and analyse their applicability in the proposed model. In the same way, it is intended to perform a deep analysis of cutting edge ontology combination techniques to develop the “stimuli information combiner”.

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BIOGRAPHICAL NOTES:

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