CONTEXT DRIVEN MODEL FOR SIMULATING HUMAN PERCEPTION – A DESIGN PERSPECTIVE

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1. Introduction

Somehow inside and outside the body humans can experience different mental states, such as presence of other people or objects, taste of wine, happiness or sadness, etc. As a hard cognitive problem, perception is often comprehended as something deterministic and certain. However, recent insights into biological perception systems, such as the perceptual pathways in the human brain, are beginning to question this view (Ferreira and Dias 2011). The approach presented here builds on the notion that human reasoning involves the ability to handle uncertain information. Authors do not, however, attempt to explain how the brain interprets perceived phenomena. This work is more focused on human representations, meanings and manipulation of uncertain information in order to examine the effect of uncertainty on the design of artificial systems. The proposed model reflects the perception of humans as they pick up information from the environment, of a robot's capability to successfully complete a task alone or in cooperation with other robots (Nishida 2010). A mechanism that works in a real environment relying on the same methodology focusing on perception has not yet been proposed, although similar approach has been proposed by authors (Stipancic, Jerbic, Curkovic 2016).

2. Methodology

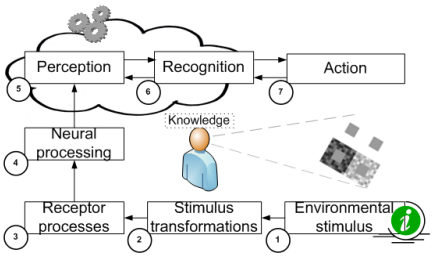

Fig. 1 The simplified process of perception

Nature is unpredictable and undefined. How an artifact like robot could survive in such environment? One way is by accepting changes in a surrounding as something natural just as they are accepted by living beings. This research analyzes psychological questions such as how people can perceive their environment and how this could be applied on technical systems. The seven steps process (Goldstein 2014) leads to behavioral responses, which are perception, recognition and action (Fig 1). The process of perception starts here by acquiring information and ends with action as a response to perceived stimuli. Although the perceptual process can be described as a series of steps, the overall process is dynamic and continually changing allowing an adaptation instead of pure reaction.

The new perceptive model contains the following components: (i) data acquisition and transformation part, (ii) semantically defined knowledge, and (iii) Bayesian Network that holds expert's beliefs (Fig. 2). In most cases, contemporary machines are using explicit information. Context-based reasoning as a feature of people presumes much more implicit understanding. The

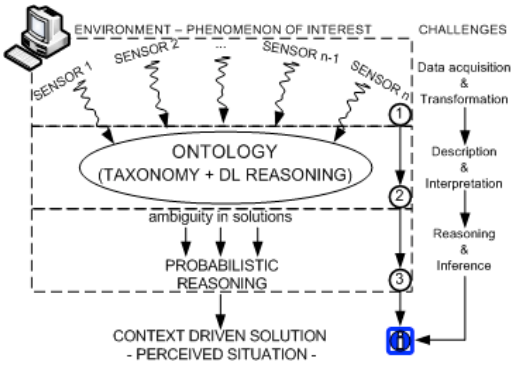

Fig. 2 The perceptive model.

model could be then understood as context-to-data interpreter, used to transform (high-level) context to (low-level) data allowing machines to make context-based decisions.

It is also an aim to build a perceptive network where the model could become a building block of mutually connected processing units used to shape contextual information. Humans use their knowledge that can vary from person to person because each person has its own subjective view about the world. Humans can also become unsure and then they can guess. The adaptation skills of the model are placed in (iii) where the system can guess about the most appropriate answer proposed by ontology (ii) as a response to changes or challenges within the environment (i).

A targeted result of this simulated perception is showed at (Fig. 1). A part of the figure shows two squares having exactly the same gray color value. By adding different backgrounds to both squares, the square on the left will be perceived as different from the square on the right. It seems that a change in surroundings of the objects can change the way of perception regardless the fact that the color of the original square remains the same (Adelson 2000). This phenomenon, as some other known optical illusion images, will be used in proof-of-concept activities showing that the perception generated by the model dependent on the situation.

3. Validation and conclusion

The Bayesian Network part of the model will be validated from the aspect of an information entropy reduction leading to analysis of the model behavior. To measure the perception level, the absolute threshold method will be used to determine the minimum value of background disturbance that changes the reasoning output. (Goldstein 2014).

Inspired by the multi-disciplinary insights from cognitive science, artificial intelligence and situation theory, this work addresses the challenges and possible solutions for the agent control. The new model provides reasoning under uncertainties where some information could remains hidden at the moment. Such a model is to underpin the design of intelligent and adaptive robots capable of functioning in unpredictable environments where nothing is ideal or accurate.

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