# COMPUTATION APPROACH FOR REALISATION OF CONTEXT-AWARE ROBOTS

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***Abstract:*** *Humans are using memories, guesses and other implicit information stored or collected to reason about most appropriate solutions. Unlike humans, robots do not understand context by default. Compared to conventional approaches where robots are preprogramed to react to a finite number of environmental occurrences, contextual awareness can enable modeling of humanlike adaptation skills. Computational models presented in this work could be understood as context-to-data interpreters that transform contextual information into data, allowing machines to make context-driven decisions. The basic model contains three main parts. The first part is used to track and collect significant environmental information. The second part represents formal knowledge about the domain of interest. The model also contains a probabilistic component realized by a Bayesian Network. The overall methodology is presented through three separate examples illustrating reasoning based on: (i) phenomenon of social capital, (ii) human bodily awareness and (iii) human emotions.*

***Keywords:*** *Affective robotics; Context-awareness; probabilistic reasoning; knowledge representation.*

## 1. INTRODUCTION

Contemporary systems are usually programmed for a limited range of activities foreseen in advance by a system developer. Such systems cannot act in any unpredicted situation by default. Their reactions are based only on expected environmental stimuli. Such a reactive system can be very fragile if something unexpected occurs. This is why robots are so impressive in factories, but so incompetent in any human environment. In contrast, the system that is able to partially realize context can potentially do both: it can act reactively and it can comprehend the present and predict future results or actions. It seems that humans and animals are adapting to their natural environment in a similar way (Barrett, 2017). In most cases, contemporary machines are using explicit knowledge. In contrast, contextual perception presumes much more implicit understanding. Research into new methodologies and paradigms is therefore directed toward the development of adaptive, anthropomatic and cognitive agent capabilities. To achieve this kind of technology it is good to bear in mind a couple of things. It is not possible to predict all occurrences or changes that arbitrary environment could derive. Deterministic chaos as a phenomenon of the real world that inevitably obstructs absolute expectations, always producing slightly changed situations (Stipancic, 2008). Chaos is present in both, temporal and space continuum, resulting in inconsistencies and uncertainties in all dimensions. Every environment is naturally unstructured, which can be revealed if observed by using an appropriate scale. In other words, if a sub-molecular level is neglected from this analysis, it is not possible to completely determine any environment, no matter how tight the applied tolerance ranges may be. This is connected with issues of sensitivity and instability and may result in malfunctioning, even if small environmental changes occur. How to deal with such challenges? One way is to accept deterministic chaos as a natural phenomenon just as it is accepted by nature.
This paper emphasises the direction in context modelling where insights taken from three separate use case scenarios are discussed. In Section 1context modelling is outlined. In Section 2 theoretical explanation of the model is given together with the structure of the proposed model. In this way, detailed insights into "rational" and "probabilistic" parts of the computation mechanism are provided. Three use cases where the methodology is tested are presented and discussed in Section 3 together with directions for future work together with conclusions.

## 2. Theoretical explanation of the model

To mathematically describe the model, a multi-agent approach is used. In the model of interaction (Fig. 1), all agents (artificial agents or humans form a part of the same environment) and are able to communicate mutually, interact and share information within the same time domain.

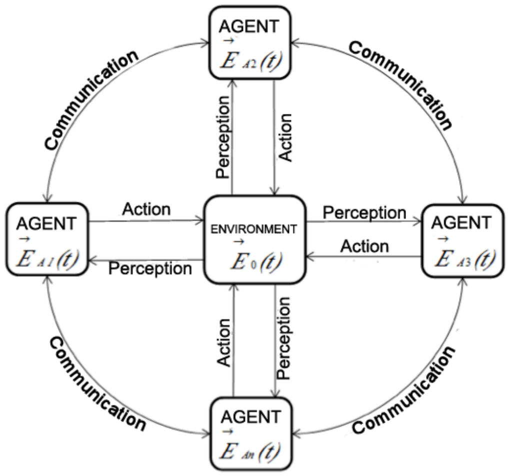


**Figure 1:** The model of interaction.

In this way, agent-to-agent and agent-to-environment interaction can be both mathematically described as:

$$\exists G\left(\vec{E}_{A1},\ldots,\vec{E}_{An}\right)\forall t_i \rightarrow G_{opt}\left|\vec{F}\right., \quad (1)$$

where the information collected by sensors and the model are mathematically defined as:

$$\vec{E}_A = \left[\vec{E}_{A1},\ldots,\vec{E}_{An}\right] = \left[f_{A1}\left(S_{11},\ldots S_{1m}\right),\ldots,f_{An}\left(S_{n1},\ldots S_{nm}\right)\right], \quad (2)$$

$$\vec{F} = \left(CO, BN\right). \quad (3)$$

In (2), vectors $\left[\vec{E}_{A1},\ldots,\vec{E}_{An}\right]$ representing sensors $S_{nm}$ are used to detect a targeted phenomenon. Information acquisition represents the first step in contextual perception of the environment. Therefore, these vectors contain information acquired by sensors that are placed ubiquitously into the environment in a meaningful way (4).

$$\vec{E}_A = f\left(S\right) \quad (4)$$

Based on (1), there is at least one function $G$ to describe context of an environment at a given moment $t_i$, using information from (2) altogether with a set of criteria $\vec{F}$ defined in (3) that generates a desired (optimal) robot behaviour, $G_{opt}$. As a part of the vector $\vec{F}$, the marks $CO$ and $BN$ defined in (3) are abbreviations for Case Ontology and Bayesian Network, respectively.
By following the presented mathematical formulation, a hypothesis of this paper is:
*By finding the function $G_{opt}$ defined in (1) and respecting the information stored in (3) along with other information collected by sensors (2), it is possible to alter a behaviour of an artificial agent based on targeted implicit or contextual information.*

### 2.1 The model as a computation mechanism

In essence, all human cognitive processes are seen here as context-driven. In (Dey, 2010), context is defined as any information that can be used to characterize the situation of an entity. A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on user's task. Context-aware applications look at who's, where's, when's, and what's of entities and use this information to determine why a situation is occurring.
To provide implicit or context driven decision-making capabilities to the artificial systems it is proposed a new computation mechanism that contains the following components: (i) data acquisition and transformation, (ii) semantically defined knowledge, and (iii) Bayesian Network (BN), as shown at (Fig. 2). The overall methodology is presented in this paper through three separated use case scenarios, which are explained in detail in (Stipancic, 2016, Jerbic, 2015, Stipancic 2017).

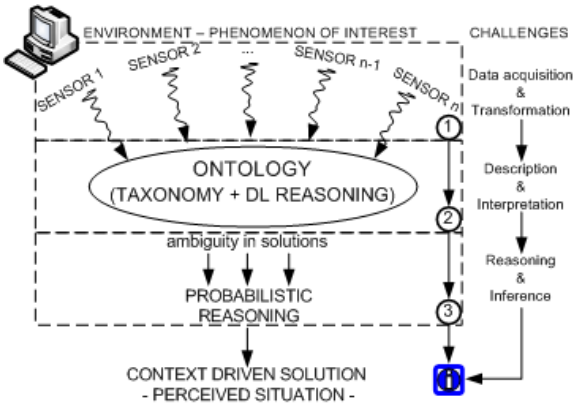


**Figure 2:** Computation mechanism for context to data transformation.

An environment in this vision becomes a space constantly analysed by smart sensors to detect significant changes. In relation to the real world, humans perceive only the information currently classified as significant and the majority of other occurrences remain hidden because the nature of such events is not relevant at the moment. This work adopted the conceptual framework from situation theory, a mathematical theory of information, where "…recognition is made of the partiality of information due to the finite, situated nature of the agent (human, animal or machine) with limited cognitive resources. Any agent must employ necessarily limited information extracted from the environment in order to reason and communicate effectively..." (Devlin, 2008).

The second part (ii) holds an expert's knowledge about the domain of activity. This part is used for logical or rational reasoning. It is called Case Ontology because it represents just a small part of the world in relation to the model application. The computation mechanism highly relies on predefined knowledge about the environment. In this case, knowledge is a subjective view of the system designer about targeted context or situation. Some authors consider certain types of context as important while characterizing a situation of a particular entity (Dey, 2010). Such contextual information can answer questions like: where, who, when and what. These represent the core of the knowledge implemented in Case Ontology. Ontology Web Language (OWL), used to define Case Ontology, follows the principles of Open World Assumptions (OWA) (Loyer, 2005). Such ontology can respond to a query by providing more than one right answer, thus allowing ambiguities in solutions. By combining inputs from sensors, ontology defines possible solutions in the form of robot responses.

The third part (iii) of the mechanism enables reasoning under uncertainties implemented in Bayesian Network and is used to ensure a single solution in relation to perceived context. Bayesian (Believes) Networks (BNs) reflect beliefs about the most appropriate solution in relation to perceived phenomenon. They allow the use of prior knowledge needed for capturing domain concepts, variables and probability values as well as building a graphical representation. BNs are convenient if evidence is not provided. While building BN in this work, a handcrafted approach is used (Daniel, 2003). This approach is usually time consuming and can be used to build small BNs. At the same time, this approach is very convenient when subjective experiences of a real human expert need to be coded in a computation model. The overall procedure of BN development is depicted in (Fig. 3). The first step in a BN development procedure is to define variables of interest, which are network nodes, and place them into a network topology. Arcs in BN connect the nodes with the direction indicating causal relationships. Condition Probability Tables (CPTs) quantify relationships between connected nodes. In the methodology used in this work, information about conditional probabilities has to be calculated in advance. By altering such information, the system designer gets the opportunity to define system priorities and/or to achieve certain goals. Each node in accompanied CPT contains probabilities emerged from influences of parent nodes. Given the specification of BN, it is possible to compute posterior probability distributions for each of the nodes, so-called "beliefs".

Determination of probability values within CPTs is the most important task in a design of BNs because those probabilities directly alter the network behaviour. Such values are often determined by using data mining techniques applied on some larger amount of data that describe a targeted phenomenon. In the approach used in this work, conditional probabilities are determined by analysing qualitative descriptions of relations between network nodes. A more comprehensive description of this procedure can be found in (Jerbic, 2015, Stipancic, 2017, Stipancic 2016).

The next phase in the development of BN is testing the network performance through three scenarios (or more than three, if needed). In that phase, the model designer fine-tunes the network behaviour. The first scenario represents an extremely positive situation. The second scenario represents a neutral situation and the third one represent an extremely bad situation. The main goal of this procedure is to ensure general network behaviour in all situations.

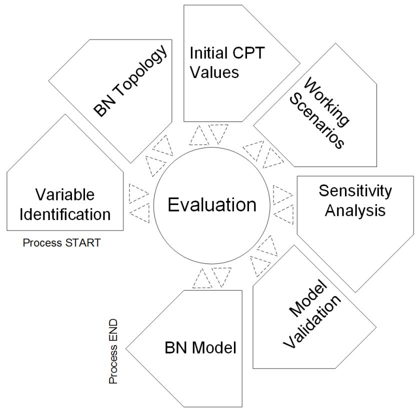


**Figure 3:** BN development procedure

To find out secret or inner influences that parent nodes have on child nodes and to test a quantitative part of BN the method called Sensitivity Analysis (Oakley, 2004) is used. The procedure can provide more insights into inner reasoning mechanisms of the network based on different node inputs and reduction in the system entropy. Shannon's Entropy is a measure for uncertainties of a particular event associated with a probability distribution of a possible event (5).

$$H(P) = -\sum_{s \in S} P(s) * \log_2 P(s) \tag{5}$$

This study employs the entropy reduction method to determine a decrease in query node's entropy before – H(Q), and after – H(Q/F) the evidence is provided to some particular node in the network. The method helped in determining those nodes to which query nodes (robot response variables) are significantly sensitive (6).

$$I = H(before) - H(after) = H(Q) - H(Q/F) \tag{6}$$

The aim is to provide proofs to all BN nodes one by one and to validate and measure how that affects query nodes. These nodes that cause the most significant reduction in entropy are the most influential ones for making decisions or changing the network reasoning output. Such insights can be used in the following two steps of the BN development procedure (Fig. 3) where the network reasoning could be additionally tested or refined. The last step in this procedure represents the integration of the model in accordance to the model application.

### 2.2 First Use Case Scenario – reasoning based on social capital phenomenon

In sociology, the concept of SC indicates the expected mutual benefit emerged from cooperation between individuals within a group. A value realized through social contacts can be measured by determining the increase in group productivity. In (Daniel, 2005), SC is defined as a common social resource that facilitates sharing of information and building knowledge through continuous interaction.
By implementing this concept into a group of industrial robots on assembly assignments some interesting system capabilities emerge, such as: system scalability, auto-recovery and partial contextual awareness. The system scalability resulted with increased overall group productivity because all the system components (robots and other system equipment) are classified and defined within the core ontology. By adding new Working Places, which are defined as a class along with all accompanying subclasses within the Case Ontology, it is easy to increase the overall production capacity. The second principle of auto-recovery can be recognized in such cases where some Working Place fails in performing its primary function, due to a defect or something similar. By using the Bayesian Reasoning part of the model, other working places can rearrange priorities and continue production. The third principle of partial context-awareness can be found in the way sensors are used while collecting information from the environment. Sensors are placed seamlessly to provide continuous flow of information. A final BN for this use case contains fourteen nodes in total where five of them represent query nodes used to control robot reactions. Detailed explanation of this work is available at (Stipancic, 2016).

### 2.2 Second Use Case Scenario – reasoning based on bodily awareness

Some authors emphasize the process of perception as the very first step in qualia development (Haikonen, 2012). Among various definitions, qualia is defined as: the ways things look, sound, and smell, the way it feels to have a pain, and more generally, what it is like to have experiential mental states (...) qualia are experiential properties of sensations, feelings, perceptions, and, more controversially, thoughts and desires as well (Guttenplan, 1994). It seems that qualia appear in the human mind as a mental picture (subjective interpretation) of perceived environmental occurrences. How perceived information appears in the form of subjective experiences today still remains a question. Bearing this in mind, qualia in this work are used with extreme caution.
To simulate bodily-awareness qualia, a new cognitive model is proposed. The developed model additionally combines the visual perception of the robot itself, enabling it to build a kind of ”mental” representation of its own body/existence within the environment. In the robot's workspace, the human operator as well as any other dynamic obstacle can appear as an object that can arbitrarily change its course and speed. By using the cognitive model, the robot is able to avoid, approach or escape from any kind of object while performing its spatial movements. If an obstacle is too near, the robot will decrease its speed to further ensure the safe operation and to plan its next movements while heading to the final movement point. Detailed explanation in (Jerbic, 2015).

### 2.3 Third Use Case Scenario – reasoning based on bodily awareness

The main hypothesis of this study is the idea that emotion may perform an adaptive function that requires a certain degree of processing complexity. Several studies reveal that cognitive processes in humans are highly intertwined with emotions. Emotions are considered to signal a person and motivate appropriate responses in relation to situations (Kim, 2005).
Emotions are necessary information for our wellbeing, our everyday experiences and even cognitive processes (Balduzzi, 2009). Ortony, Clore, and Collins defined emotions as valenced reactions (e.g., affective reactions based on the perceived goodness or badness of things) and asserted that emotions are determined by how the eliciting situation is understood by a person (Ortony, 1988).
A final BN for this use case contains 22 nodes in total, where six of them represent query nodes used to control the robot reactions. Detailed explanation of this work is available at (Stipancic, 2017).

## 3. DISCUSSION & CONCLUSION

The approach presented in this work builds on the notion that human cognition has the ability to handle uncertain information (Doya, 2007). It does 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 technical systems. In this way, the aim is to reflect subjective experiences of real human experts as they pick up information from the environment. This methodology is highly convenient when big data used to describe some phenomenon and build a model is not available.

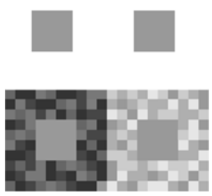

**Figure 5:** The simultaneous – contrast illusion

Desired robot reasoning can be explained by examining (Fig. 5) where two squares are having exactly the same gray color value. By adding different backgrounds to both squares, the square on the left is perceived as different from the square on the right. It seems that a change in context where objects are placed can change the way how people see them Adelson, 2000, Stipancic, 2010). This change in perception is triggered by mechanisms that are much more abstract than a simple true – false logic.
To validate a methodology, the third part of the computation mechanism is assessed in all use cases. BN is validated from the aspect of information entropy reduction. Some hidden and relative influences between the network variables are revealed. In this context, the method leads to better understanding of the overall system behaviour in relation to a particular application. Query nodes are sensitive to more then one variable whereby those nodes that are the closest to query nodes and those with the

strong positive connections are the most influential. In this way the methodology presented in this paper shows potential contribution to the design of context-aware robots.

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## 4. REFERENCES

(Adelson, 2000) Adelson E. H. Lightness Perception and Lightness Illusions. The New Cognitive Neurosciences, 2nd (ed.), MIT Press, Cambridge, pp. 339-351, 2000.
(Balduzzi, 2009) Balduzzi D., Tononi G. Qualia: The Geometry of Integrated Information. PLoS Computational Biology, 2009.
(Barrett, 2017) Feldman Barrett L. How Emotions are Made: The Secret Life of the Brain. Houghton Mifflin Harcourt. ISBN 9780544133310, 2017.
(Daniel, 2005) Daniel B.K., McCalla G., Schwier R.A. Data Mining and modeling social capital in virtual learning communities. In Proceedings of the 12th International Conference on Artificial Intelligence in Education 2005, Amsterdam; pp.2000-2008.
(Devlin, 2008) Devlin K., Rosenberg D. Information in the Study of Human Interaction, in Adriaans P & Van Benthem J (Eds): Philosophy of Information volume 8, Handbook of the Philosophy of Science, pp. 692-693. Elsevier, ISBN: 978-0-444-51726-5, 2008.
(Dey, 2010) Dey A.K. Context – Aware Computing," in: Krumm, J. (Ed.), Ubiquitous Computing Fundamentals, pp. 321-352, 2010.
(Doya, 2007) Doya K., Ishii S., Pouget A., Rao R.P.N. (Eds.), "Bayesian Brain – Probabil. Appr. to Neural Coding," MIT Press 4, 36, 2007.
(Guttenplan, 1994) Guttenplan S. D. Qualia: The Geometry of Integrated Information. Oxford, OX, UK; Cambridge, Mass., USA: Blackwell Reference, 1994.
(Haikonen, 2012) Haikonen P. O. "Consciousness and Robot Sentience," World Scientific Publishing Co. Pte. Ltd. Singapure, 2012.
(Jerbic, 2015) Jerbic, B., Stipancic, T., Tomasic, T. Robotic Bodily Aware Interaction within Human Environments. Proceedings of 2015 SAI Intelligent Systems Conference, London, 305-314, 2015.
(Loyer, 2005) Loyer Y., Straccia U. Any-world assumptions in logic programming. Theoretical Computer Science, 342 (2), pp. 351-381, 2005.
(Oakley, 2004) Oakley J.E., O'Hagan A. Probabilistic sensitivity analysis of complex models: a Bayesian approach. J. of the Royal Statistical Society: Series B 2004; 66(3), 751-769.
(Ortony, 1988) Ortony A., Clore G. L., Collind A. The cognitive structure of emotions. Cambridge University Press, UK, 1988.
(Stipancic, 2010) Stipancic T., Jerbic B. Self-adaptive Vision System. Emerging Trends in Technological Innovation. Camarinha-Matos LM, Pereira P, Ribeiro L (ur.). Heidelberg : Springer Verlag, pp. 195-202, 2010.
(Stipancic, 2016) Stipancic T., Jerbic B., Curkovic P. A context-aware approach in realization of socially intelligent industrial robots. Rob. and comp. integrated manuf. Elsevier, 37, pp. 79-89, 2016.
(Stipancic, 2017) Stipancic T., Ohmoto Y., Badssi S. A., Nishida T. Computation Mechanism for Situated Sentient Robot. Proc. of the 2017 SAI Computing Conf., London: IEEE, pp. 64-73, 2017.

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