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Semantic Valence Modeling

Emotion Recognition and Affective States in Context-Aware Systems

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***Abstract*—Defining and describing a context requires knowledge (contextual information); while research is addressing a wider range of potential contextual information in a diverse range of domains the diversity of potential contextual information has not been effectively addressed. This paper considers the implementation of context and identifies emotion (more accurately emotional response) as a factor in the personalization of services as under-represented in the literature. We propose semantic valence modeling implemented in fuzzy rule-based systems as a potential solution to the implementation of emotional responses in context-aware systems. It is concluded that the effective implementation of emotional responses based on the posited approach will improve the accuracy of personalized service provision and additionally offers the potential to improve the levels of computational intelligence in context-aware domains and systems.**

Keywords—emotional response, context, affective states, valence modeling, computational intelligence

I. Introduction

Context and context-aware systems have their genesis in pervasive and ubiquitous research dating back to the early 1990's [1]. Context is related directly to personalization and the targeting of service provision based on a defined profile (*context*) which identifies and describes an individual's current prevailing state. Defining a context requires knowledge (contextual information) and this may include both *tacit* and *explicit* knowledge. Historically, the diversity of potential contextual information has not been effectively addressed, the contextual information being (generally) restricted to spatial and temporal data with proximity information (the social situation). While research is addressing a wider range of potential contextual information in a diverse range of domains and systems this work has been largely restricted to the laboratory.

Context is characterized by uncertainty; context-aware systems are essentially decision-support systems and are by their very nature *fuzzy*. In operation, context-aware decision-support systems must ultimately arrive at a Boolean decision relating to the suitability of an individual for service provision. To meet these conflicting demands and realize the implementation of emotional response we propose semantic valence modeling implemented in a fuzzy rule-based system as a potential solution. This paper considers the contextual information applied to implement context and identifies emotion (more accurately emotional response) as a factor in personalization and the targeting of services which is under-represented in the literature. We conclude that the effective implementation of emotional response will improve personalization and offers the potential to improve the levels of computational intelligence in intelligent context-aware systems.

This paper is structured as follows: following consideration of the nature of knowledge, contextual information, *Kansei* engineering, cognitive conceptual models and semiotics are considered with emotion and emotional response is addressed. Valence, affective states, and semantic valence modeling is discussed. Ontology based context modeling (OBCM) is introduced followed by a discussion around implementation in fuzzy rule-based systems with an overview of the *Context Processing Algorithm* (CPA). A scenario-based evaluation is presented. The paper closes with a concluding remarks and observations relate to challenges implicit in realizing the implementation of emotional response.

II. Knowledge

Knowledge (in general and computational terms) falls into two general types: *explicit* and *tacit* knowledge. Conceptually, it is possible to distinguish between explicit and tacit knowledge however in actuality they are not independent but are interdependent where the creation of knowledge readable by individuals and usable in computer systems is the aim. The knowledge model (see Figure 1) graphically models the components which make up the descriptors of knowledge including *Cognitive Conceptual Models* and the related concept of *Semiotics* [2].

Explicit knowledge is: knowledge that can be clearly articulated and codified; as such it is easily gathered and used in computer systems. Tacit knowledge however represents a difficult challenge as it knowledge generated based on experience and observation in "real-world" situations (generally) in practicing a discipline or profession such as medicine. Tacit knowledge is generally sub-conscious in nature and individuals may not be aware of the tacit knowledge they possess; as such an expert operates, makes judgments, and reaches conclusions without reference to explicit rules or principles [3].

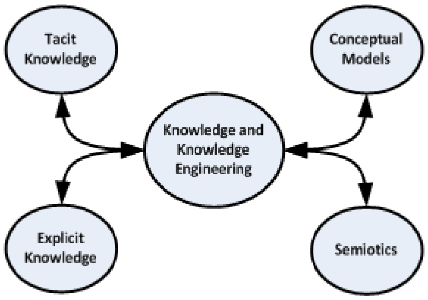

Fig. 1. Knowledge Concepts and the Knowledge Engineering Model

Knowledge in the form of contextual information is the foundation upon which intelligent context-aware systems function. Knowledge Engineering (KE) [4] is the process which identifies and codifies the explicit and tacit knowledge (contextual information) which characterises a domain of interest. KE is a function in software engineering and has been applied to the building, maintaining and development of applications and systems including: knowledge-based systems, expert systems, and decision support systems [4]. Additionally, KE has addressed cognitive science and socio-cognitive engineering where knowledge is structured according to the understanding of how human reasoning and logic functions [5][6]. KE describes the process of eliciting, and gathering knowledge from experts in a specific domain of interest. KE is a discipline that involves codifying and integrating knowledge into computer systems in order to solve complex problems normally requiring a high level of human expertise [4][7].

Identifying the contextual information however fails to address codification of tacit knowledge and its implementation in a context-aware system. An overview of the implementation of intelligent context is discussed in subsequent sections of this article where conceptual models and semiotics are introduced. For a detailed exposition on the implementation of intelligent context-aware systems with an evaluation and proof-of-concept see [7].

A. *Context and Contextual Information*

A context may include a broad and diverse range of contextual information. Therefore, contextual information such as: location, time, activity, physiological signals, a person's individual characteristics, and a user's affective state(s) are important metrics in intelligent context-aware systems. A context relates to an individual's current dynamic and prevailing *state* (context); as such it is inherently complex and domain specific [7]. A context is created using data which is processed into contextual information (context properties) useful in describing and defining an individuals context for the purpose of collaborative interactions and resource distribution based on context.

In actuality, almost any information available at the time of an individual's interaction with a context-aware system can be viewed as contextual information including:

- The variable tasks demanded by users with their beliefs, desires, interests, preferences, and constraints.
- The diverse range of mobile devices and the associated service infrastructure(s) along with resource availability. This relates to connectivity, battery condition, display, network, and bandwidth etc. This contextual information may also relate to nearby resources (accessible devices and hosts including I/O devices).
- The physical (environmental) situation (temperature, air quality, light, and noise level etc).
- The physical (orientation) situation. This relates to the location of an individual with the temporal data and their current physical position – e.g., in a health monitoring scenario if a patient with dementia is upright (standing) or horizontal (lying).
- The social situation (who you are with, people nearby - proximate information).
- Spatial and temporal information (location, speed and acceleration, time of the day, date, and season of the year, etc).
- Physiological measurements including: blood pressure, heart function – Electrocardiography (ECG), or EKG from the German *Elektrokardiogramm*, cognitive functions related to brain activity (EEG from *Electroencephalography*), respiration, galvanic skin response, and motor functions including muscle activity).
- Cognitive and abstract contextual information such as an individual's emotional responses, intuition, feelings, and sensibilities. This may include *Electromyography* (EMG) which records the electrical activity produced by skeletal muscles [8].

The potential contextual information identified demonstrates the diverse nature and inherent complexity of context and context-aware systems. While the list includes cognitive properties, research is generally restricted to EEG and *Cognitive Behavioural Therapies* (CBT). Extending context to include the diverse range of available data along with data identifying and defining emotional factors (as discussed in this article) forms a significant factor improving personalization (which includes emotional reactions to a range of stimuli) in intelligent context-aware systems.

B. *Kansei Engineering*

In context-aware systems, contexts may be dynamically influenced by user intuition, preferences, and emotions. An appropriate method termed Kansei Engineering has been developed as a methodology to deal with human feelings, demands, and impressions in context-aware applications.

Kansei is a Japanese term meaning sensibility, impression, and emotion [9]. *Kansei* words are given by adjectives describing human emotion, sensibility and impression; there is no equivalent term in English, the nearest applicable word is possibly intuition. Kansei evaluation is commonly used for evaluation methods to quantify impressions. For Kansei Evaluation, we have determined adjective pairs called Kansei words in pairs: (Synonym - Antonym) and (Synonym - Not Synonym). For instance, the pairs of adjectives (good - bad) and (successful - unsuccessful) are *Kansei* words.

C. *Cognitive Conceptual Models and Semiotics*

A model is (generally): (1) a Physical Conceptual Model (PCM) which is a representation of a process, state, or interaction with a physical object, device, or [for the purpose of this paper] a computerized system, or (2) a Cognitive Conceptual Model (CCM) which is a cognitive conceptualization of a process or entity (as discussed later in this section such a model may for example conceptualize color). The conceptualization process for a CCM manifests itself based on observation and experience and can arguably form the basis upon which humans view the world through an individual's perception filter which develops and changes over time based on observation and experience to a broad and diverse range of stimuli.

A PCM represents concepts (entities) and relationships that exist between them; an ontology and Ontology Based Context Modelling (OBCM) may be viewed in these terms. In computer science a PCM, (also termed a domain model), should not be confused with other approaches to the conceptual modelling addressing for example: data and logical modelling. Such models may be created using for example the Unified Modelling Language (UML) [10]. While these models are useful in the design and implementation process for computer systems the focus of this article is on CCM's.

A CCM arguably has synergy with the concept of Semiotics. Semiotics (the science of signs) has its genesis in the work the Swiss linguist Ferdinand de Saussure (1857-1913) and the American Philosopher Charles Sanders Pierce (1839-1914) [2]. Semiotics is defined as the study of signs and sign processes (Semiosis). Semiosis is a process in which currently experienced phenomena are interpreted as referring to other, experientially absent, phenomena, thereby becoming meaningful entities, or signs. The reference of a sign is made possible by memories of past interactions with the components of the environment.

Generally applied to the media (film and text) semiotics is often divided into three branches [2]: (1) *Semantics*: Relation between signs and the things to which they refer (their meaning which may differ between individuals based on experience and observation), (2) *Syntactics*: Relations among signs in formal structures, and (3) *Pragmatics*: Relation between signs and the effects they have on the people who use them (again this may reflect individuals experience and observation). Computational semiotics has addressed a diverse range of topics including: (1) logic, (2) mathematics, (3) theory and practice of computation, (4) formal and natural language studies, (5) cognitive sciences generally, and (6) semiotics in a formal sense with regard to cognition and signs. A common theme of this research is the adoption of a "sign-theoretic" approach on issues related to artificial intelligence and knowledge representation [11].

Many applications of computational semiotics lie in research addressing Human-Computer-Interaction (HCI) and the fundamental processes of recognition [6]. For example, research in this field, termed 'algebraic semiotics', combines aspects of algebraic specification and social semiotics [12]; this has been applied to the design of user interfaces and to the representation of mathematical proofs.

Emotional response to stimuli and events are influenced by CCM's and semiotic responses generated over time; additionally, tacit knowledge is also (generally) generated based on observation and experience over time. In considering CCM's, semiotics, and tacit knowledge as they apply to context (the focus of this research); intuitively there is a synergy between these concepts and an individual's perceptual filter which as observed has a relationship with an individual's emotional response (emotion) to any given situation.

In considering CCM's, semiotic responses, and tacit knowledge: (1) they are generated over time based on experience and observation, and (2) effective description, documentation, and articulation of these concepts to another individual represents a challenging problem. For example, in computational terms, the color 'red' can be described in the RGB (the additive primary colors 'red' 'green' 'blue') scale as: 255-0-0 (or in Hexadecimal ff0000). This however fails to describe the color 'red' (or more accurately the specific shade of 'red' in the spectrum) to another person to enable the color to be recognized; additionally, every person will interpret a specific shade of 'red' differently.

D. *Affective States*

Affect refers to the experience of feeling or emotion and it is a key part of the process of an individuals instinctive reaction to, and interaction with, stimulation and stimuli. The affective domain represents a number of divisions in modern psychology including: cognitive and affective domains which whilst expressed as independent domains are in fact interdependent as cognitive factors are arguably fundamental in affective behaviors. Automatic recognition of users' affective states has gained traction and implicit recognition of affective states has many applications including: personalization in service provision, recommender systems, and pedagogic systems. Intelligent context-aware systems adapt their behavior according to context [13]. It is therefore clear that modeling affective states forms a component in the identification and implementation of emotional response.

III. VALENCE

In considering Semiosis and emotion an interesting phenomenon is Valence [14][15][16] (see Figure 2 which relates to an agitated / calm state). In everyday life, humans interact with and react to a range of stimuli; in such conditions (contexts) discrimination and categorization of "significant" stimuli forms a pivotal cognitive function [14].

According to the widely accepted dimensional view of emotions [17]: "actions or action dispositions" are enabled using a valence categorization process (along the unpleasant/pleasant spectrum) in relation to the intensity (arousal) state that characterizes a situation. A simple yet effective theory employs a bidirectional emotional model defined by two basic parameters/variables as shown in Figure 2.

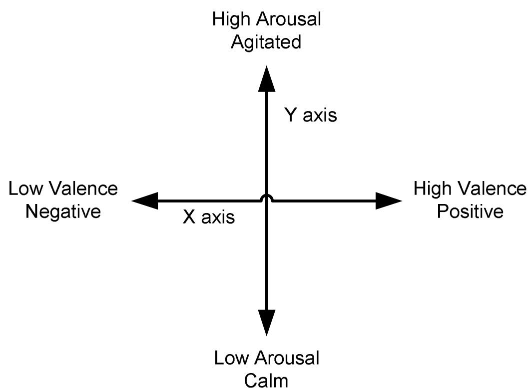

Fig. 2. A two dimensional (bi) valence model

Based on this view, experimental data has pointed to the valence of the on-going stimulus being accounted for at a number of points in the information processing stream as indexed by the temporal aspects and the topography of event-related potentials (ERP) [12][18][19]. On the basis that humans react to emotional stimuli, the reactions being individual, valence may have a relevance and significance in context and the related issue of computational intelligence.

A. Semantic Valence Modeling

The *Context Processing Algorithm* (CPA) (see section V and [7]) results in a numerical resultant value (***rv***) which identifies the degree to which an input context is a match for an output context (i.e., a representation of the suitability of an individual for personalization and targeted service provision). The (***rv***) value, while interesting, is not useful in context-aware decision-support systems. To realize effective decision-support the CPA performs a semantic conversion which is measured against the membership function; also termed a distribution function in the literature [20]. As discussed in this paper these semantic conversions are measured against a membership function (see [7]. As introduced in this paper the semantic modelling may be based on three approaches: (1) single: {X} axis (single axis), (2) double: {X, Y} axes (bi-directional), and (3) triple: {X, Y, Z} axes (tri-directional). The semantic classifications are{x_1, x_2, xy_1, xy_2, xyz_1, xyz_2, xyz_3, and xyz_4 where x, y, and z reflect the axis on the solution space and the numbers identify the 'zones' within the solution space as discussed in section III(*B*).

IV. Implementation

The Prior to addressing the implementation it is necessary to briefly introduce the data structure which forms a fundamental component in the proposed approach. A detailed discussion on the topic can be found in [21] however in summary, the data structure is based on the *Semantic Context Modelling Ontology* (SCMO) as discussed in [7]. In summary, the SCMO provides a generic, non-hierarchical, and readily extensible structure capable of adaptation to suit the domain specific nature of context with the capability to define the metadata, the context properties, and the literal values used in the context-matching process (Moore, 2013). While the approach presented in this paper does not currently use inference and reasoning which generally applies subsumption and entailment. Semantic terminology is used in valence modelling to identify the range of responses; this employs *Kansei* words [7] to designate emotive responses to stimuli; the semantic terms being defined in the SCMO.

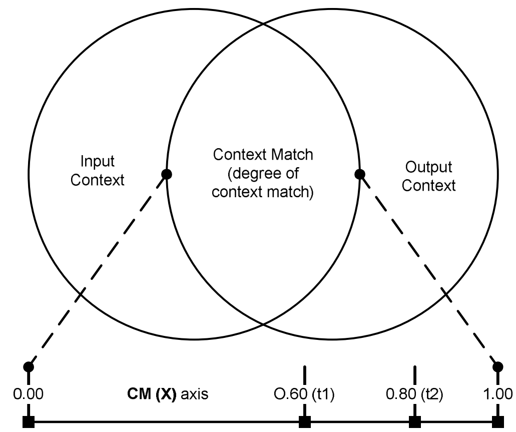

Fig. 3. Mapping the (***rv***) to to solution space and decision boundaries (thresholds). Shown is a simple single directional mapping model

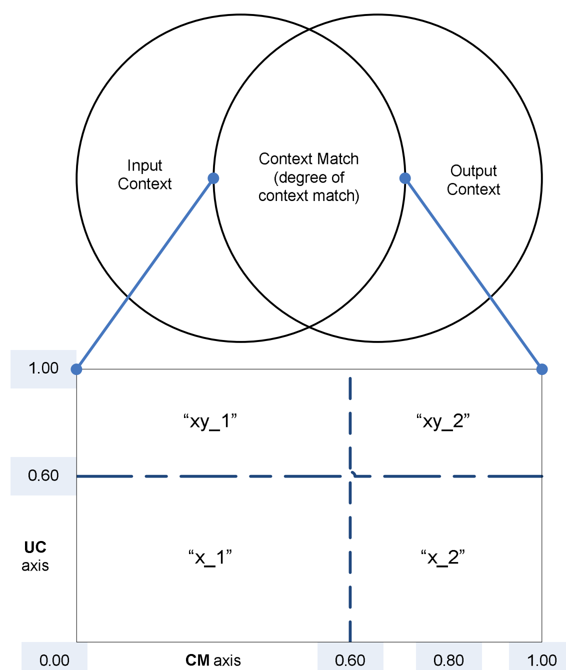

Fig. 4. The *extended* context match showing bthe CM(X) axis and the UC(Y) axis.

A. *Context processing*

Central in the proposed approach to CP is the *Context Processing Algorithm* (CPA) as discussed in [7] which employs *Context Matching* (CM) and provides a basis upon which contextual information can be processed in an intelligent context-aware system that enables CS with predictable decision support. The CPA approach is predicated on the processing of contextual information using the CM process [7] which is designed to create the input context and access the output context(s) definitions to determine if the output (solution) context is an acceptable match with the input (problem) context. Essentially, the context-matching process is one of reaching a Boolean decision as to the suitability of a specific individual based on context [7]. Given that a perfect match is highly unlikely the CM algorithm must accommodate the PM issue along with a number of related issues as discussed in [7].

In CM the probability of a perfect match is remote therefore *Partial Matching* (PM) must be accommodated. To address PM the CPA applies the principles identified in fuzzy logic and fuzzy sets with a defined membership function which is predicated of the use of decision boundary(s) [20] (thresholds) as discussed in [7]. The membership function provides an effective basis upon which predictable decision support can be realized using both single and multiple thresholds to increase the granularity of the autonomous decision making process.

The CPA is predicated on the *Event:Condition:Action* (ECA) rules concept, the <*condition*> component employing the IF-THEN logic structure [7] which relates to the notion of <*action*> where the IF component evaluates the rule <*condition*> resulting in an <*action*>. The <*action*> in the proposed approach can be either: (1) a Boolean decision, or (2) the firing of another rule.

Conventional logic is generally characterized using notions based on a clear numerical bound (the crisp case); i.e., an element is (or alternatively is not) defined as a member of a set in binary terms according to a bivalent condition expressed as numerical parameters {1, 0} [22]. Fuzzy set theory enables a continuous measure of membership of a set based on normalized values in the range [0, 1]. These mapping assumptions are central to the CPA [7].

CM places the *resultant value* (***rv***)and its *semantic* representation (step 7 in the CPA) on the CM(X) axis of the solution space, see Figure 4 and for a detailed discussion on the mapping of the CM and (***rv***) see [7]). The emotional response component is applied in step 8 of the CPA; in this step the classification of the emotional response (see Figure 2) is computed. Figure 4 models on a conceptual level the approach to the implementation of emotional response in CP using the CPA in its *extended* structure. The solution space for a single representation is shown in Figure 3 with a bi-directional representation modeled in Figure 4. The implementation of the emotional response component is achieved in step 8 of the CPA where result of CM is located in relation to the CM(X) axis and also on the UC(Y) axis.

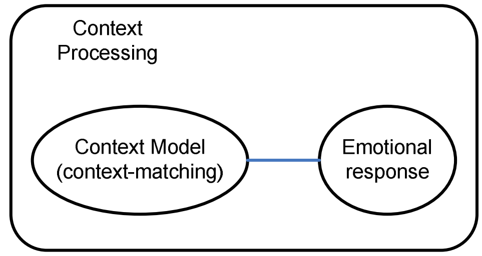

Fig. 5. A framework for emotion (more accurately emotional response) augmented context processing.

There remains the overlaying of the emotional component onto the semantic representation of the (***rv***) on the solution space in relation to the CM(X) and UC(Y) axes. The *extended* solution space is shown in Figure 5; the naming of the zones in the solution space is generic and in practice will be domain specific. This may be achieved in an step 8 in the CPA where complex rules are applied to map the emotive component onto the context match realized in step 7 of the CPA. Context is inherently domain specific [7] therefore the rule-set must reflect the domain of interest; this applies to all stages of the context processing.

B. *A Scenario-Based Evaluation*

This scenario-based illustrative generic example considers a simple bi- directional model with the complex tri-directional model discussed in section VI. Consider a sales scenario in which the promotion of a cosmetic product is the requirement. In such a scenario the potential customer, while being in the correct socio-economic category based on h/her context may be averse to the testing of animals and therefore not amenable to the sales 'pitch'. This would be reflected in an emotional response to the stimuli generated by the sale of cosmetic products. At best the sales pitch is unwanted; at worst the potential customer may be violently opposed to the product. The emotive reaction postulated in the scenario may be modeled in the bi-directional valence model (see Figure 2). The emotive response may be classified using numerical approach using a *Likert* scale [23] (e.g., 1 to 5) with 1 being 'negative' / 'low arousal' and 5 being 'positive' / 'high arousal'. Implementing such an approach potentially avoids: (a) wasted effort on the part of the sales agent, and (b) potential confrontation by agitated potential customers.

A critique of the posited approach using valence modeling may include the potential for errors in the evaluation of the emotional response. This represents a valid criticism and requires research to assess the accuracy of the classification. However, further consider points to the fact that while human intuition may detect emotive response based on sparse data (observations, body language, etc) errors are frequently made; e.g., a potential customer may have other issues or possibly it is just a 'bad day' which results in an agitated or aggressive response totally unconnected to the sales 'pitch'. In such cases the computational result may be exactly the same or similar to that of a human sales person.

The application of valence modeling clearly requires data (contextual information) captured non-invasively. This is discussed in e.g., Thomas *et al* [24]; the issues lie less in the hardware and sensor technologies than in creating the non-invasive approaches with the related data processing. However the major challenge lies in identifying the data points (the contextual information) to use on the valence modeling.

V. CONCLUSION

This paper has considered the nature of knowledge and the implementation of context and identifies emotion (more accurately emotional response) as a factor in the personalization of services as under-represented in the literature. We propose semantic valence modeling implemented in fuzzy rule-based systems as a potential solution to the implementation of emotional responses in context-aware systems. The discussion has identified 3 approaches to semantic valence modeling: (1) simple single and bi-directional models, and (2) complex tri-directional models. The focus in this paper has been on simple bi-directional valence modeling mapped onto the solution space shown in Figure 4. The posited rule-based approach to context processing implemented in the CPA however incorporates the capability to achieve complex tri-directional valence modeling with mapping being realized on the X, Y, and Z axes of the *extended* solution space.

The implementation of the approach proposed in this paper requires research to address challenges in: (1) the identification of the data for use in valence modeling, and (2) the optimal approach to overlay the emotional response component (in step 8 of the CPA) onto the semantic result of context processing derived from steps 7 and 8 of the CPA. Addressing these challenges represents ongoing research and future work. This paper concludes that the effective implementation of emotional responses based on the posited approach will improve the accuracy of personalized service provision and additionally offers the potential to improve the levels of computational intelligence in context-aware domains and systems.

REFERENCES

[1] P. Moore (IGI) Moore, P., Hu, B. & Wan, J. (2010a). 'Intelligent Context' for Personalized Mobile Learning. In Architectures for Distributed and Complex M-Learning Systems: Applying Intelligent Technologies. (Eds) S. Caballe; F. Xhafa; T. Daradoumis; A. A. Juan, Hershey, IGI Global, USA.

[2] D. Chandler,"Semiotics The Basics. Routledge", NY, USA, 2002.

[3] Schmidt & Hunter, (1993) Schmidt, F.L., and Hunter, J.E. (1993). "Tacit knowledge, practical intelligence, general mental ability, and job knowledge". Current Directions in Psychological Science, 2, 8-9.

[4] Gonzalez & Dankel, 1993 Gonzalez, A.J., and Dankel, D.D. (1993). "The engineering of knowledge-based systems theory and practice". Prentice-Hall, New Jersey, NJ, USA.

[5] Klir & Yuan, 1995; Klir G.K., and Yuan, Bo. (1995)."Fuzzy sets and fuzzy logic: theory and applications". Prentice Hall, NJ, USA, 1995.

[6] Negnevitsky, 2005). Negnevitsky, M. (2005). "Artificial Intelligence: A Guide to Intelligent Systems". Addison Wesley, ISBN 0-321-20466-2.

[7] P. Moore, "Intelligent Context: the realization of decision support under uncertainty", In Inter-Cooperative Collective Intelligence: Techniques and Applications, Eds: Fatos Xhafa, Nik Bessis, *Studies in Computational Intelligence*, Springer, 2013. (accepted – to appear).

[8] H. J. Hermens, B. Freriks, R. Merletti, G. Ha¨gg, D. Stegeman, J. Blok et al, editors. "SENIAM 8: European recommendations for surface electromyography", ISBN: 90-75452-15-2: Roessingh Research and Development, 1999.

[9] Salem et al, 2009 Salem. B., Nakatsu. R., and Rauterberg. M. (2009). "Kansei experience: aesthetic, emotions and inner balance". *Int. J. of Cognitive Informatics and Natural Intelligence*, 3, 54-64.

[10] UML, Object Management Group, [online], Available from: http://www.uml.org/, Accessed 2013.

[11] (10)Andersen, 1991 Andersen. P.B. (1991). "A Theory of Computer Semiotics". Cambridge University Press.

[12] (11)K. Tanaka-Ishii, "Semiotics of Programmin", Cambridge University Press, 2010.

[13] (12)M. Baldauf, s. Dustdar, and F. Rosenberg, "A Survey on Context-Aware systems", *International Journal of Ad Hoc and Ubiquitous*

[14] (13)H. Peng, B. Hu, Q. Liu, Q. Dong, Q. Zhao, and P. Moore, "User-centered Depression Prevention: An EEG Approach to pervasive healthcare". In Proc of the 5th International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health), 2011. 23-26 May 2011, Dublin, Ireland, 325-330, 2011.

[15] (14)S. Delplanque, M. E. Lavoie, P. Hot, L. Silvert, and H. Sequeira, "Modulation of cognitive processing by emotional valence studied through event-related potentials in humans". Neurosci. Lett. 356, 1-4, 2004

[16] (15)S. Delplanque, L. Silvert, P. Hot, S. Rigoulot, and H. Sequeira, "Arousal and valence effects on event-related P3a and P3b during emotional categorization", International Journal of Psychophysiology, 60, 315-322, 2006.

[17] (16)Lang et al, 1993 Lang, P.J., Greenwald, M.K., Bradley, M.M., Hamm, A.O. (1993). "Looking at pictures: affective, facial, visceral, and behavioral reactions". *Psychophysiology* 30, 261– 273.

[18] (17)Schupp *et al*, 2003 Schupp, H.T., Jungho fer, M., Weike, A.I., Hamm, A.O. (2003). "Attention and emotion: an ERP analysis of facilitated emotional stimulus processing". *NeuroReport* 14, 1-5.

[19] (18)Smith *et al*, 2003 Smith, N.K., Cacioppo, J.T., Larsen, J.T., Chartrand, T.L. (2003). "May I have your attention, please: electrocortical responses to positive and negative stimuli". *Neuropsychological* 41, 171– 183.

[20] (19)C. Berkan, and S. L. Trubatch. "Fuzzy Systems Design principles: Building Fuzzy IF-THEN Rule Bases". IEEE Press, Piscataway, NJ, USA, 1997.

[21] (20)Moore 2007 Moore, P., Hu, B., Zhu, X., Campbell, W. & Ratcliffe, M. (2007). A Survey of Context Modelling for Pervasive Cooperative Learning. *In the IEEE Proceedings of the First International Symposium on Information Technologies and Applications in Education* (ISITAE '07). Kunming, Yuan, P.R, China, November 23-25, 2007, pp K5-1-K5-6, IEEE, USA.

[22] (21)G. K. Klir, and Yuan. Bo. "Fuzzy sets and fuzzy logic: theory and applications". Prentice Hall, NJ, USA, 1995.

[23] (22)Likert Scale, "SimplyPsychology", [online], available from: http://www.simplypsychology.org/likert-scale.html, 2013.

[24] (23)A. M. Thomas, P.Moore, H. Shah, C. Evans, M. Sharma, F. Xhafa, S. Mount, Hai. V. Pham, A. J. Wilcox, A. Patel, C. Chapman, and P. Chima, P. (2013) 'Smart care spaces: Needs for intelligent at-home care", International Journal of Space-Based and Situated Computing, Vol. 3(1), 35-44, 2013.