Towards Integrating Emotion into Intelligent Context

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Abstract. Context-aware systems have traditionally employed a limited range of contextual data. While research is addressing an increasingly broad range of contextual data, the level of intelligence generated in context-aware systems is restricted by the failure to effectively implement emotional response. This paper considers emotion as it relates to context and the application of computational intelligence in context-aware systems. Following an introduction, personalization and the computational landscape is considered and context is introduced. Computational intelligence and the relationship to the Semantic Web is discussed with consideration of the nature of knowledge and a brief overview of knowledge engineering. Cognitive conceptual models and semiotics are introduced with a comparative analysis and approaches to implementation. Ongoing research with illustrative 'next generation' intelligent context-aware systems incorporating emotional responses are briefly considered. The paper concludes with a discussion where the challenges and opportunities are addressed; there are closing observations, consideration of future directions for research, and identification of open research questions.

Keywords: Intelligent Context, Emotion, Knowledge, Conceptual Models, Semiotics, *Kansei* Engineering, Computational Intelligence.

1 Background

Emotion represents an important element in an individual's response mechanism to a range of stimuli as emotional responses are fundamental to an individual's reaction to changing environments and social situations. Over time people develop an individual view of the world viewed through their personal dynamic perceptual filter created based on observation and experience; emotional response is the result of this individual view of the world. The factors that relate to emotional response form an important component in an individual's context which forms the basis upon which personalization and targeted service provision is achieved.

This paper presents a discussion around emotion and emotional response as it relates to the definition of context and its application in intelligent context-aware systems. Intelligence is a complex topic and can be viewed from two perspectives: (1) Human intelligence; in computational terms this relates to the Open World

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Assumption (OWA), and (2) Computational intelligence (in computational terms this relates to the Closed World Assumption (CWA). While in an ideal world the OWA may be applied, in practice the CWA is the only currently realistic approach to achieve [albeit limited] intelligence in context-aware systems. The challenge lies in effective use of contextual information which includes emotional responses based on the OWA; the opportunities lie in the results that may be achieved if the OWA can be effectively implemented and computational intelligence which more closely approximates to human intelligence realized.

The paper is structured as follows: section 2 sets out an overview of personalization and the computational landscape with context and the nature of contextual information considered in section 3. Computational intelligence and the relationship to the Semantic Web is discussed in section 4. Section 5 presents a discussion on the nature of knowledge with consideration of explicit and tacit knowledge with a brief overview of knowledge engineering. In section 5 there is a discussion around conceptual models and Semiotics with a comparative analysis of the relationship between knowledge, conceptual models, and Semiotics. Implementation is addressed in section 6. Current research projects which represent our view of the 'next generation' of intelligent context-aware systems incorporating emotional responses are briefly considered in section 7. The paper concludes with a discussion where the challenges and opportunities are addressed; there are closing observations, consideration of future directions for research, and identification of open research questions.

2 Personalization and the Computational Landscape

Personalization on demand has gained traction driven by the demands of computer mediated P2P and B2B interactions. Concomitant with these developments is the revolution in the capability and ubiquity of mobile technologies (generally implemented in large scale distributed systems and ad-hoc wireless networks) and the growing use of Web 2.0 technologies in data intensive systems [20].

The traditional paradigm of centralized 'internet' (also termed an Intranet) based networks has been largely replaced by a new distributed 'Internet' based communications paradigm characterized by distributed ad-hoc wireless networks which are increasingly accessing geospatial, temporal, and cloud-based systems [13][23]. These developments have resulted in systems in which a user's context may be static or, in mobile systems highly dynamic. Mobile systems incorporate a diverse range of geographically diverse infrastructures with a potentially large user base and a broad range of fixed and wearable mobile devices [20].

The 'Internet' systems paradigm is frequently characterized by Large Scale Distributed Systems (LSDS) [13][14][23] in which interactions between infrastructure components and individual users (more accurately the users devices) are inherently complex; the complexity increasing exponentially as nodes are added to and removed from in the system dynamically. This complexity places great strain on communication systems with issues in the management of the interactions and the ability to enable personalization on demand which requires both user and network infrastructure knowledge to effectively target service provision.

LSDS are inherently context-aware, context performing an increasingly important role. The rule-based approach presented in this article is posited as an effective approach to enable: (1) targeted service provision in complex data intensive systems, (2) the processing of data from a diverse range of geographically and technologically divers sources in Wide Area Networks (WAN), Local Area Networks (LAN), and Personal Area Networks (PAN, (3) the capability to handle the inherent complexity of context, (4) the ability to manage CS, and (5) the capability to realize predictable decision- support under uncertainty [18][20][21].

As discussed in this paper emotion (more accurately emotional response) can be viewed in terms of contextual information if it can be codified, digitized, and implemented in an intelligent context-aware system. Emotion is characterized by cognitive response to changing states (contexts); such responses are characterized by an increasingly large range of contextual information in data intensive systems which may be both large and highly dynamic incorporating temporal, spatial, infrastructure, environmental, social, and personal data. There is a requirement for CS [20][21]; this, along with the volume and dynamic nature of the data calls for an approach capable of effectively handling both in geospatially diverse LSDS increasingly implemented in cloud-based solutions. The approach as discussed in the following sections and in [21] is designed to realize these aims.

3 Context

Context is central in realizing *Personalization*, context describing h/her prevailing dynamic *state*, as such it is inherently complex and domain specific [17][18][20][21]. A context is created using contextual information (context properties) that combine to describe an individual or entity, therefore a broad and diverse range of contextual information combines to form a context definition [20]. 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 [20] 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 (connectivity, battery condition, display, network, and bandwidth etc), and nearby resources (accessible devices and hosts including I/O devices.
- The physical (environmental) situation (temperature, air quality, light, and noise level etc).
- The social situation (who you are with, people nearby - proximate information)
- Spatio-Temporal information (location, orientation, speed and acceleration, time of the day, date, and season of the year, etc).
- Physiological measurements (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.

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 Behavioral Therapies* (CBT) [11][24]. Extending context to include the emotional factors is addressed in subsequent sections of this paper.

4 Computational Intelligence and the Semantic Web

Intelligence is an extremely complex topic and can be viewed from two perspectives: (1) Human intelligence (in computational terms this is analogous to the OWA), and (2) Computational intelligence (in computational terms this analogous to the CWA). The OWA is generally used where inference and reasoning is utilized; a function that is generally easy (albeit with frequent errors) for humans but is difficult for computer systems where sparse, brittle, and incomplete data results in the failure to reach a decision or conclusion - an essential function in context-aware systems where decision-support forms a central function [20].

In formal logic, the OWA functions on the basis that facts not explicitly defined and are not included in (or inferred from) knowledge recorded in a system are deemed to be unknown (rather than incorrect or false). The CWA is however predicated on the principle of *negation as failure*; i.e., *if it is not provably true, then conclude that it is false* [20]. For example, a database functions on the basis of the *unique names assumption* [7], this also holds true for ontologies [20][21]. The unique names assumption operates on the basis that a name is unique with no duplicate; this allows efficient and predictable searches of the database to be achieved. For ontology searching, merging, and matching synonyms have been used to identify similar concepts [20]; this however arguably reinforces the unique names assumption upon which ontologies function.

There is an ongoing debate in Semantic Web circles surrounding the OWA versus the CWA [25][32]. As observed, the CWA is predicated on negation-as-failure. While the Semantic Web and Semantic Web languages such as OWL are based on the OWA the CWA is also useful in certain applications [10]; a detailed exposition on the topic is beyond the scope of this paper however a discussion with extensive references can be found in [10][32]. In practical applications where context with predictable decision-support forms a central function and the Semantic Web technologies and OWL are employed, as is the case for OBCM [16], the CWA forms the basis for such applications.

5 The Nature of Knowledge

Having considered context and intelligence in computer systems we now turn to knowledge and its relationship context. 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 usable by individuals and computer systems is the aim.

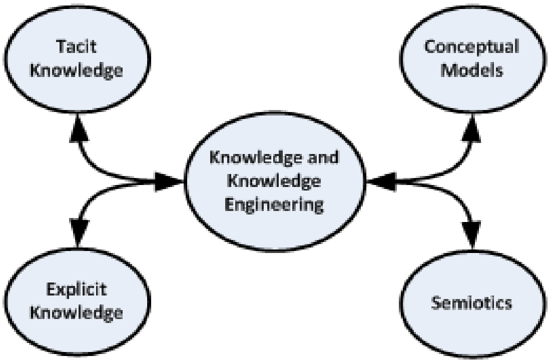

Fig. 1. Knowledge Concepts and the Knowledge Engineering Model

Explicit knowledge is: knowledge that can be clearly articulated and codified; as such it may be easily gathered and used in computer systems and applications. *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. 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 [29].

Knowledge in the form of contextual information is the foundation upon which intelligent context-aware systems function; Knowledge Engineering (KE) [9] is the process which identifies and codifies the explicit and tacit knowledge (contextual information) which characterizes 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 [9]. 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 [12][22]. 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 [9][20].

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 paper. For a detailed exposition on the implementation of intelligent context-aware systems with an evaluation and proof-of-concept see [20][21].

5.1 Conceptual Models and Semiotics

A model is (generally): (1) Physical Conceptual Models (PCM) which are representations of a process, state, or interaction with a physical object, device, or [for the purpose of this paper] a computerized system (Figure 1 is a simple example of such models), or (2) Cognitive Conceptual Models (CCM) which are cognitive conceptualizations 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. As we discuss later in this paper, such a perception filter may be an important component in inducing intelligence in context-aware systems.

A PCM represents concepts (entities) and relationships that exist between them; an ontology and 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 modeling addressing for example: data and logical modeling. Such models may be created using for example the Unified Modeling Language (UML). While these models are useful in the design and implementation process for computer systems the focus of this paper 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) [3]. A discussion of their work is beyond the scope of this paper however a detailed exposition with extensive references can be found in [3]. In summary 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) [3] Semiotics is often divided into three branches: (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 [1]. Many applications of computational semiotics lie in research addressing Human-Computer-Interaction (HCI) and the fundamental processes of recognition [4]. For example, research in this field, termed 'algebraic semiotics', combines aspects of algebraic specification and social semiotics [34]; 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 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 paper); 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.

In considering Semiosis and emotion an interesting phenomenon is Valence [6]. 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. [6]. According to the widely accepted dimensional view of emotions [15], these "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. 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) [5][30][33]. 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.

6 Implementation

The previous sections have considered Explicit and Tacit knowledge, knowledge engineering, Semiotics, and Conceptual Models; a synergistic relationship between tacit knowledge, semiotics, and CCM's has been drawn. This section addresses the implementation of these concepts in intelligent context-aware systems where CP with constraint satisfaction and preference compliance (CS) with decision-support form pivotal design goals. Following an overview of *Kansei* Engineering [20][28] intelligent context processing is addressed with an overview of the proposed approach to the implementation based on the context processing algorithm (CPA) [20][21].

6.1 *Kansei* Engineering

In semantic intelligent context-aware systems, contexts are 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 [20]. *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.

6.2 Intelligent Context Processing

Central in the proposed approach to CP is the Context Processing Algorithm (CPA) [20] and the extended CPA [21] 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.

Prior to addressing the context-matching process 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 [18][20] however in summary, the data structure is based on the *Semantic Context Modeling Ontology* (SCMO) created using the Web Ontology language (OWL) as discussed in [20].

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 [18][20]. Additionally, while the approach presented in this paper does not currently use inference and reasoning (which generally applies subsumption and entailment) the CPA, as discussed in [21], is designed to accommodate this approach where required.

6.3 The Context-Matching Algorithm

The CPA approach is predicated on the processing of contextual information using the CM process [20][21]; CM (an extension of the data fusion concept) 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 [20][21]. 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 [20][21]. In CM the probability of a perfect match is remote therefore partial matching (PM) must be accommodated.

The CPA is predicated on the Event:Condition:Action (ECA) rules concept, the <condition> component employing the IF-THEN logic structure [20][21] 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.

To address the PM issue 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) [2] (thresholds) as discussed in [21]. 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.

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} [11]. 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 [20][21].

A system becomes a fuzzy system when its operations are: “entirely or partly governed by fuzzy logic or are based on fuzzy sets” and “once fuzziness is characterized at reasonable level, fuzzy systems can perform well within an expected precision range” [2]. Consider a use-case where a matched context mapped to a normalized value of, for example [0:80], has a defined degree of membership. This measure, while interesting, is not in itself useful when used in a decision-support system; in the CPA this is addressed using a distribution function (more generally referred to in the literature as a membership function) to implement the essential process of defuzzification as discussed in [2][21].

CM with PM imposes issues similar to those encountered in decision support under uncertainty, which is possibly the most important category of decision problem [31] and represents a fundamental issue for decision-support. For a detailed exploration of fuzzy sets and fuzzy logic see [12], a discussion around decision theory can be found in [31]. A comprehensive discussion on fuzzy system design principles can be found in [2] where a number of classes of decision problem are identified and discussed. In summary, Fuzzy Rule Based Systems have been shown to provide the ability to arrive at decisions under uncertainty with high levels of predictability [2][15][16]. A discussion on the CPA and rule strategies with the related conditional relationships for intelligent context-aware systems with example implementations and a dataset evaluation see [18][20][21].

7 Next Generation Intelligent Context-Aware Systems

It has been shown in [17][18][20][21] that context-aware systems are capable of realizing [albeit limited] intelligence in the processing of contextual information. This paper has considered the issues and challenges implicit in providing for improved levels of computational intelligence predicated on the integration of emotion (more accurately stated as emotional response) in the provision of personalized services. Our research into personalization, intelligent context processing, and the nature of computational intelligence has addressed the topic from a conceptual perspective and also as it relates to implementation in 'real-world' scenarios. This work has considered use-cases in a range of domains including: the provision of tertiary education, the delivery of intelligent mobile marketing services, and importantly e-health monitoring.

In the case of tertiary education [35][19] the development of pedagogic systems using a range of sensors to capture data (contextual information) relating to students' which is then intelligently processed to target resources and services has been investigated. Whilst many issues and challenges have been addressed the issue of measuring engagement in pedagogic systems, while partially solved (using principally attendance records and similar data), remains a significant challenge and an open research question. Emotional responses, if correctly measured and codified, may be used to more accurately assess levels of engagement to the benefit of both students in the learning experience and also to the university in improved outcomes.

We have identified in investigations around intelligent marketing solutions the potential benefits to be gained for business and individuals in the targeting of promotional advertisements in a mobile context predicated on a user's context. This research [8] has created and tested an intelligent mobile advertising system (iMAS). There is a large body of research which has considered the use of semiotics and cognitive conceptual models as they relate to the media (film and print); this work has included advertising and marketing. In considering targeted marketing empirical investigations have identified that, notwithstanding expressed preferences, individuals have differing responses to specific adverts based on life experiences which are unknown to the system. As with pedagogic systems, if emotional responses could be captured and utilized the benefits are potentially great for: (1) business with improved targeting of advertisements with an improved financial returns from the marketing and advertising budgets, and (2) for individuals where increased relevance in terms of *precision* and *recall* may result in reductions in irrelevant and therefore potentially annoying, demotivating, and poorly targeted messages.

Possibly the most important potential use of emotional response in the domain of e-health monitoring [36] in, for example, cognitive degenerative conditions on the Alzheimer spectrum where emotional response has important implications for both 'real-time' monitoring of patients and interventions which may be graduated as measured against a patients current 'state'. Such 'states' currently include a broad range of contextual data [20] however there is a failure to capture emotional responses. Consider the potentially huge benefits for patients and carers in terms of quality of life and independent living for patients. Additionally, there are efficiency benefits to be derived from implementing intelligent context-aware assisted living solutions for healthcare professionals and the wider society where reductions in premature institutionalization offer the potential for huge financial savings on a global scale.

The challenges in realizing the integration of emotional response to a range of stimuli is diverse domains are huge and are not underestimated. However, if the effective use of emotion can be achieved the returns in both financial and personalization terms are very exciting.

8 Discussion

This paper has considered personalization to enable targeted service provision. Context has been addressed with a discussion around computational intelligence and the nature of knowledge including consideration of tacit and explicit knowledge, conceptual models, and semiotics. An overview of the approach to implementation of context in intelligent systems has been presented with examples of research where the integration of emotion offers the potential for the 'next generation' of intelligent context-aware systems. The focus of this paper is to consider how an increased range of contextual information utilizing tacit and explicit knowledge with conceptual models and semiotics can be used to improve computational intelligence in context-aware decision-support systems.

In considering emotion and emotional response, as it relates to context implemented in data intensive intelligent context-aware systems, we argue that: if the creation of computational intelligence which more closely approximates to human intelligence (which is characterized by sparse, brittle, and incomplete data) is to be realized, then the application of emotion using codified CCM, and semiotics in combination with tacit and explicit knowledge may provide a basis upon which this can be achieved. It is argued that in an ideal world the OWA is used however in practice the CWA is the only currently realistic approach to the realization of intelligence in context-aware systems where CS with predictable decision support is a central design requirement.

If computational intelligence which more closely resembles human intelligence can be realized there are exciting opportunities to exploit this capability in a range of domains including: e-Learning and e-Business applications. Perhaps the most interesting opportunity lies in increasing sophistication in levels of e-Health monitoring which is gaining traction in the field of assisted living in 'Smart Spaces". The challenges lie in effective use of knowledge in a context-aware system based on the OWA concept. We argue that addressing this challenge (at least in part) demands the codification of emotional response using CCM and semiotics. From an implementation perspective we postulate that the approach proposed in this paper using semantics and Kansei Engineering implemented using the CPA with OBCM provides a basis upon the codification of emotional response can be achieved.

In addressing pervasive computing [27] it has been observed that: all the basic component technologies exist today and in hardware, we have mobile systems and the related infrastructures, sensors, and smart appliances. Thomas *et al* [35][36] concur observing: components such as sensors, wireless mesh architectures, cloud services, and data brokerage/processing are all currently available and widely researched. It is argued in [20] that the challenges lie in the development of intelligent context middleware capable of processing the contextual information; this paper postulates that emotion and emotional responses form a part of an individual's response mechanism and as such can be viewed as contextual information. While the posited approach incorporates the ability to implement CP in LSDS the issues and challenges lie in the identification of the data points (contextual data), data capture and representation, addressing these questions represents the basis for future ongoing research.

While the research discussed in this paper has begun to resolve a number of issues relating to the processing of contextual information, including potentially the data that relates to emotional response, a number of challenges identified remain as open research questions. Such questions relate to: (1) the identification of the data (knowledge) that identifies emotional responses, (2) the development of a [non-invasive] approach to data capture of such information, (3) the development of a suitable Semiotic grammar and valence measurement system for emotion, and (4) representing the knowledge (data) in a suitable data structure; the OBCM currently utilized is recognized as an effective but sub-optimal solution. For a detailed discussion on the issues and challenges identified in the research with consideration of potential solutions including issues with alternative approaches to context processing see [11][18][20][21][24][37].

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