Proceedings

2015 10th International Conference on P2P, Parallel, Grid, Cloud and Internet Computing

3PGCIC 2015

4-6 November 2015
Krakow, Poland

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ISBN-13: 978-1-4673-9473-4
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Cover art production by Mark Bartosik
Printed in the United States of America by Applied Digital Imaging

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Machine Cognition and the Integration of Emotional Response in the Monitoring of Mental Disorders

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***Abstract*—Computer science relies heavily on computational modeling and while the value of such an approach is generally recognized the methodological account of computational explanation is not up-to-date. In this paper we explore machine cognition with the creation of effective cognitive modeling and consider the elemental components that combine to create an effective cognitive model. The creation of such a model will enable the processing of information in intelligent context-aware systems while integrating emotion (more accurately stated as emotivel response). We present a brief review of related research addressing cognitive science and machine cognition in which we identify the concept of self. Modeling is introduced with an overview of conceptual models and semiotics followed by consideration of implementation using a proposed approach based on fuzzy sets. We introduce depression as a use-case to illustrate the proposed approach and a general discussion where future directions for research and open research questions are considered. The paper closes with concluding observations. We posit that creating an effective cognitive model offers the potential to integrate emotive response and thereby improve context-aware systems in a broad and diverse range of domains and systems along with improvements in the levels of computational intelligence.**

Keywords*—*Cognitive Science, Machine Cognition, Cognitive Modeling, Emotive Response, Context-Awareness, Health Monitoring, Mental Disorders, Computational Intelligence

I. BACKGROUND

Marcin Miłkowski in [1] noted that: "Explanations in cognitive science rely predominantly on computational modeling" and observed that while: "scientific practice is systematic there is little doubt about the empirical value of numerous models [however] the methodological account of computational explanation is not up-to-date". Cognitive science has been investigated over many decades, see for example: [2] [3] [4] [5] [6] [7]. However the research addressing machine cognition and conciousness is arguably at an embryonic stage [1] as is the integration of emotive response in intelligent context-aware systems [8] [9].

Emotion is a complex topic and there is no a generally agreed definition of the term [10]. Dating from the 1960s and 1970s cognitive psychology was motivated by computer-related concepts, e.g., information processing and pattern recognition; these concepts however failed to address emotion or affect [11]. Research around the 1980s and 1990s into psychology and cognitive neuroscience identified that an understanding of cognitive processes in 'real-world' settings (including attention, memory, categorization, and decision making) required the emotional component [11].

In this paper we explore the challenges inherent in the creation of effective cognitive modeling and consider the elemental components that combine to create a cognitive model. Computational modeling is identified by Miłkowski as a predominant feature of cognitive science and the ability to create such models will enable the processing of information in intelligent context-aware systems with the integration of emotion (more accurately stated as *emotive response*).

In considering context-awareness a number of observations are relevant:

- The range and scope of the contextual information currently used in context-aware systems is very limited. Viewed from an historical perspective the predominant data used has been spatio-temporal, environmental, and proximity information as discussed in [12].
- While the range and scope of contextual information investigated in research projects has improved in the recent times [13] to include physiological and cognitive factors the glaring omission in the research is the ability to objectively measure and integrate emotional response in context-aware systems.

We consider that emotional response forms an elemental component in realizing truly intelligent context-awareness. To illustrate the concept we consider an important use-case where emotional response forms an important consideration, namely e-health monitoring with a focus on the monitoring of patients with mental disorders including depression. We conclude that realizing the aims of this research presents a significant challenge however given the centrality of emotive response in the arena of cognitive modeling achievements in realizing (even to a limited degree) our aims represents a significant advance over current intelligent context-aware systems. The challenges inherent in the problems introduced above are clearly non-trivial and represent long term research goals however to realize truly effective context-awareness with related levels of computational intelligence we must consider how such aims may be achieved.

We propose that realizing the creation of effective cognitive modeling offers the potential to improve context-aware systems in a broad and diverse range of domains and systems with improvements in the levels of computational intelligence in respect of context-awareness.

The remainder of this paper is structured as follows: Section II presents an overview of related research addressing cognitive science and machine cognition including the introduction of the concept of self. modeling is introduced in Section III where an overview of physical and cognitive conceptual models is presented with an introduction to semiotics. Section IV introduces implementation using an approach based on fuzzy sets. We consider depression as a use-case to illustrate the proposed approach in Section V. Section VI presents a general discussion where future directions for research and open research questions are considered. The paper closes with concluding observations in Section VII.

II. Related Research

Cognitive science can be traced over many decades. Kenneth Craik in 1943 [2] considered models and noted that the "idea that an organism may make use of an internal model of the world is not new". Prior to the development of digital computers Craik observed that if a "small-scale model" of external reality and of its possible actions is carried in an organism's head alternative courses of action may be evaluated and the optimal reactions to present and future situations may be identified before they arise by utilizing knowledge (or experience) of past events. The ability to utilize learned experience provides a basis upon which individuals may react better to both *external* and *internal* stimuli [9]. There is an interesting synergy between the '*internal model*' as espoused by Craik and an individual's *context* in intelligent context-aware systems in terms of the individual's cognitive processes developed over time and the related reactions to *stimuli*.

Gallagher in [5] provides an interesting perspective on internal cognitive models. In discussing the philosophy of the mind and cognitive science two concepts of *self* are introduced: the *minimal* self ("a self devoid of temporal extension") and the *narrative* self (which "involves personal identity and continuity across time"). The twin concepts of *self* illustrates how the philosophical approach can inform cognitive science and suggests that a two-way collaboration (between neuroscience and computer science) may lead to a more fully developed account of self and awareness in computer systems with potential application in machine cognition.

Human physiology has certain facets that define an individual including: *biological*, *physical*, and *intellectual* (or cognitive) components [3]. The basic conceptualization can be considered as follows: (1) intellectual processes are the result of the operation of several separable systems, (2) sensory-perceptual systems, (3) central processing(or *thought*), (4) memory, and (5) response output (motor control). Sensory transducers feed a constant stream of environmental data and information to central processing structures for processing, analysis, and interpretation in cognitive systems which control

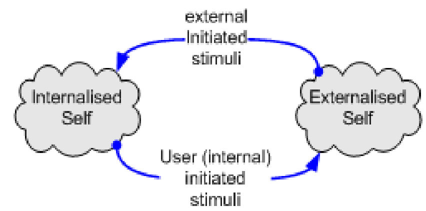

Fig. 1. A conceptual view of the continuous information processing *internalized-externalized feedback loop* where *externalized* learned experience feeds into the *internalized* view of the world

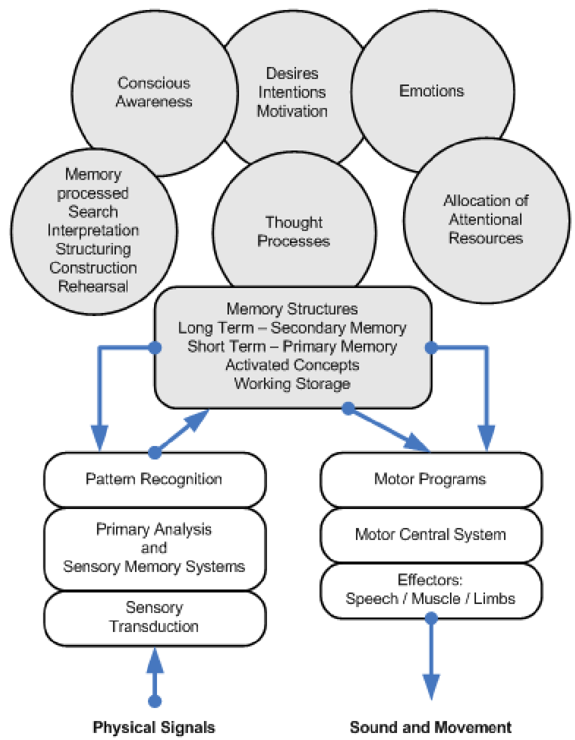

Fig. 2. The conventional flow chart of the human information processing system. Shown is a summary of the *pure cognitive system* which is a system built around pure cognitive functioning, with a physical symbol system as its central component. The basic components are processing systems that use environmental information to perform general central processing operations, and control motor output. (adapted from Norman [3])

physical and auditory functions. Such processes represent a highly dynamic system in which constant interaction between an individual and their external environment. This may be viewed in terms of a *feedback loop* as modeled in Figure 1.

This well accepted view of cognitive functions [3] has resulted in the modeling of cognitive functions as separable information processing subsystems which include: *information processing*, *perceptual* (including pattern recognition), *motor* or *output*, and *memory* systems. Additionally, there are systems to implement: *internal reasoning and deduction* (which includes thought processes), *problem solving*, and *language* [3]. A summary of the components as proposed by Norman is shown in Figure 2 which may be viewed in terms of a modem updating of the conventional flow chart of the human information processing systems.

In considering machine cognition Mondal in [14] poses the question: "*Does Computation Reveal Machine Cognition?*". Mondal argues that the: "*nature of machine cognition has been shrouded in incomprehensibility*" and that the '*'human cognition is still faintly understood*". Going further it is argued that machine cognition is far less understood than human cognition despite the current knowledge relating to computer architectures and computational operations. Moreover, Mondal argues that human interpretation [of computation] is required whereupon it becomes a type of "semiotic causation" which gives meaning to computation; for an introduction to semiotics see Section III.

Machine cognition and the integration of emotive response demands *intelligent systems*. We may consider such systems with reference to their temporal characteristics, i.e., their relative time scales. In considering cognitive science, Simon in [4] argues that we may view intelligent systems over *short*, *medium*, and *long* time scales. In the case of the shortest time scale, intelligent systems dynamically adapt to changing environments while for longer (medium) time scales, such systems preserve the adaptations which are stored and remain available for interpreting new phenomena.

Over the longest time scale, Simon argues that intelligent systems evolve and going further considers that their evolution may be Darwinian using mutation and natural selection in the "organismic case". He further argues that it may equally well be social, through discovery of new knowledge and strategies and their transmission from one system to another. This transmitted inheritance, whether biological or social or both, will also cause a progressive change in system behavior, and will consequently narrow the domain of "invariance".

Emotion and its relationship to machine cognition has been a fertile field of research over many decades with research investigating human responses as they relate to the cognitive and psychological aspects of the subject, for example see: [15] [16] [17] [18] [19]. In considering machine cognition and emotive response we wish to implement strategies which enable the processing of contextual information representing external stimuli (problems / threats / opportunities etc) and individuals (humans') where the response is predicated on the degree to which a specific individual derives "happiness", "pleasure", or "fear" etc as a response to stimuli (either *external* or *internal* stimuli) [11] [18]. Additionally, behavioural biologists have identified additional specific adaptive functions for particular emotions including emotive responses such as: *happiness*, *sadness*, *anger*, *fear*, *likes*, *dislikes*, *welcomes* , and *surprise* (e.g., see [20]).

The emotional component is central to understanding the emotive functions and emotional response forms an important element in behavioral choices. Peters in [11] identifies roles that emotions can play in behavioral choices (on occasion prompting multiple roles). The roles are: a guide to information, (2) a selective "attentional" spotlight, (3) a motivator of behavior, and (4) a common currency for comparing alternatives.

A detailed discussion on the nature of the roles is beyond the scope of this paper however in summary, The proposed roles (as they relate to emotion) are consistent with generally accepted clinical and pathological data related to decisions that arise from a disconnection between emotion and cognitive processes. Specifically, such disconnection results from damage to the orbitofrontal cortex which is a key region of the brain for linkage between emotion (as it relates to brain activity) and information processing regions of the brain [21]. It is interesting to note that in role 4 the intrinsic emotional responses such as "happiness" or "pleasure" may form a cognitive component in a comparison of alternative decisions [11].

Going further we may observe that, notwithstanding the emotional influence on cognition, the inverse is also true with cognitive processing generating emotions [11]. A prototypical example may be where cognitive dissonance generates discomfort [15], moreover discomfort [from cognitive dissonance] has been shown to occur not only at the "feeling level" but also at the physiological level in the form of skin conductance responses (galvanic skin response) [22].

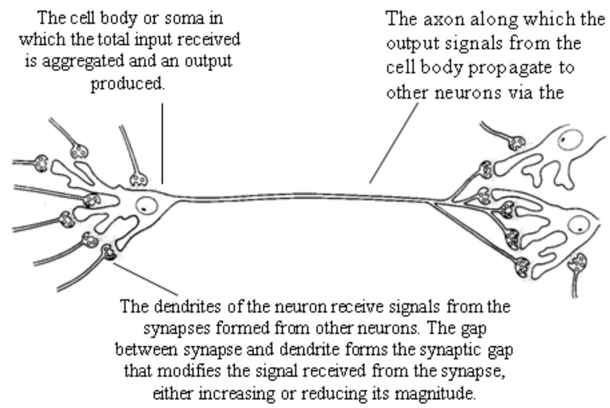

Fig. 3. A model of a neuron in the human brain

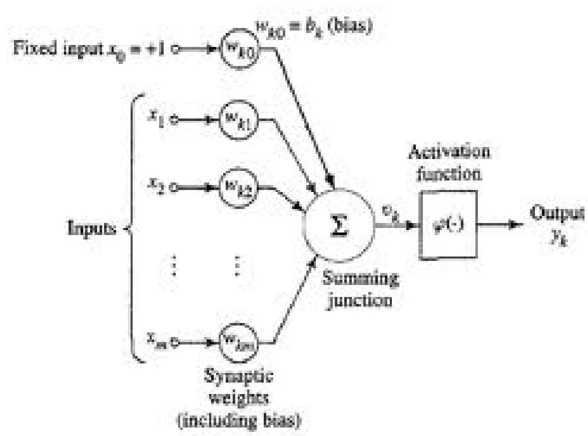

Fig. 4. A computational model of a neuron in the brain. Shown is a model of an application in an Artificial Neural Network.

In considering the human brain and cognition we may conclude that while models of the human brain have been created, for examples see Figures 3 and 4. Figure 3 shows a conceptual model of a physical neuron in the brain while Figure 4 is a computational representation of the processing of information in a neuron in the human brain implemented in an artificial neural network (ANN) as originally envisaged by McCulloch and Pitts in 1943 in a paper entitled “a logical calculus of the ideas immanent in nervous activity” [23]. The models demonstrate the fact that the knowledge of the brain and its function remains largely rudimentary and is the subject of much (albeit carefully researched and considered) conjecture. We may also conclude that along with the cognitive functions that characterize a sentient being such as a human, intelligent systems must be capable of dynamic change in response to uncertainty and dynamic environments characterized by sparse and incomplete data [8][9].

Humans are animate beings which must function in a highly dynamic environment, this observation has significance for the incorporation of emotive response in intelligent context-aware systems which are highly dynamic and such systems must be capable of managing the dynamic ‘state(s)’ (or *context* driven by dynamically changing environments. In considering the [human] capacity for adaptation to their environment and the relationship to cognitive science there is a synergy between the *inner* and *outer* environments and the *internalized* and *externalized* environment(s). Additionally, as discussed by Simon, we must consider if there are any basic characteristics we should expect to be held in common among diverse forms of intelligent computational systems [including both *hardware* and *software* systems] and if there are any shared characteristics in complex problem environments.

The concept of *self* forms an important component in an context definition; this may be viewed in terms of an individual’s *internalized* view of the world developed over time based on interactive experience of their *externalized* world. Going further, we must consider the *stimuli* that prompts an emotional response. There are two types of stimuli: (1) *external* stimuli that affects individuals (this relates to situations that confront an individual in their interaction with their environment), and (2) **internal** stimuli (this relates to actions the individual initiates).

In practice, individuals interact with their ’world’ and learned experience gained from their external environment ’feeds’ into the *internalized* self which in turn influences the way humans interact with their world. This process can be viewed as a continuous cognitive information processing *feedback loop* between the *externalized* and *internalized* self, Figure 1 shows a high level conceptual view of the process and thus a cognitive model of an individual which may be implemented (at a very basic level) in a computer system which incorporates machine cognition.

This brief overview of related research identifies what may be viewed as the genesis of cognitive science and therefore the challenges faced if effective modeling and implementation of machine cognition in intelligent systems is to be realized. In subsequent sections we consider modeling and implementation strategies.

III. MODELING

A model is (generally) either: (1) a physical conceptual model (PCM), or (2) a cognitive conceptual model (CCM) [8]. In this section we consider these models, the relationship between CCM and Semiotics, and present concluding observations. Figure 5 shows a conceptual high-level view of an intelligent systems development model.

A PCM is a representation of a process, state, or interaction with a physical object, device, or [for the purpose of this paper] a computerized system, Figure 4 is an example of such a model. A PCM represents concepts (entities) and relationships that exist between them; an ontology and OBCM [24] 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 which typically include data and logical modeling. Such models may be an *Entity Relationship* (ER) model) or 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 is a cognitive conceptualization of a process, entity, or phenomenon. To illustrate the concept consider for example the description of a color. Such a description is simple in computational terms where 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). However, this 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. Moreover, every individual will interpret a specific shade of ’red’ differently. It is clear that without reference to analogies or similes it is impossible to describe color which is learned based on observation and experience. We would argue that cognitive conceptual modeling forms the basis upon which humans view the world through an individual’s unique perception filter. Such a filter forms an important component in inducing intelligence in context-aware systems.

In this paper the focus is on the implementation of emotional response in intelligent systems. In considering the relationship between Semiotics and emotional response, in everyday life, humans interact with and react to a range of stimuli with reactions influenced by observation and experience. Under such situations discrimination and categorization of “significant” stimuli forms a pivotal cognitive function as discussed by Delplanque in [25].

Semiotics (the science of signs) which has its genesis in the work the Swiss linguist Ferdinand de Saussure (1857-1913) and the American Philosopher Charles Sanders Pierce (1839-1914). Semiotics may be defined as the study of signs and sign processes 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 environmental phenomena.

Frequently applied to the media (film and text) [26], Semiotics is often divided into three branches (1) *semantics*, (2) *syntactics*, and (3) *pragmatics*.

1) *Semantics* refers to the relation between signs and the things to which they refer, their meaning which may differ between individuals based on experience and observation as is exemplified by color recognition as we have discussed.
2) *Syntactics* relates to relations among signs in formal structures. For example, classical methods of systems analysis and design [in computer systems] recognize only the existence of signs (messages and records) in

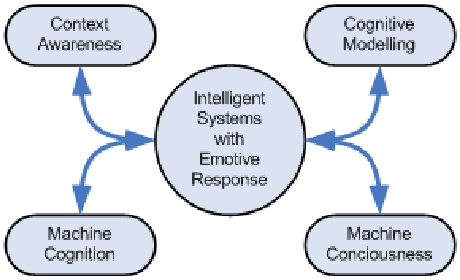

Fig. 5. A conceptual high-level view of intelligent systems development model for systems designed to incorporate emotional response. Shown is the relationship between emotional response and cognitive modeling, machine cognition, machine consciousness, and intelligent systems with context-awareness

their formal structures and have little interest in their implication beyond these signs [27]. Semiotics [in computing] has raised a number of questions and answers viewed from a philosophical and organisational perspective,which are "regarded as in information systems development [27].

3) *Pragmatics* is a sub-field of linguistics and semiotics that studies the ways in which context contributes to meaning. Applied to linguistic behaviors, pragmatics relates to philosophy, sociology, linguistics and anthropology [28]. Semantics considers meaning that is conventional or "coded" in a particular language, however pragmatics addresses how the transmission of meaning relies on: (1) structural and linguistic knowledge of both speaker and listener, and (2) context of the statement, pre-existing knowledge, and the inferred intent of the speaker, and other factors [29]. Thus pragmatics offers an explanation to how in conversation users may overcome apparent ambiguity given that meaning relies on the manner, place, time etc. of an utterance [28].

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. Semiotics are discussed by Anderson in [30] where it it is postulated that: "Semiotics is the science of sign systems just as linguistics is the science of language". In terms of sign systems we can conclude that Semiotics incorporates linguistics along with all other sign systems which include:

1) sign systems used in parallel with linguistics. Examples are: the tone of voice and body posture (including pointing)
2) signs that operate on a longer time scale such as the externalized projected image [to others] of self' (e.g., choice of clothing or car)
3) a broader conception of 'self' (e.g., where applicable, the image of 'self' as presented by civic architecture)

We can observe that there is a synergy between items 2 and 3 and the concept of *self* as discussed in Section II.

Semiotics represent a comprehensive sign system that incorporates linguistics along with images and artefacts; this identifies Semiotics as an integral component in an individuals view of the world and as such a central component in a context definition. A common theme of this research is the adoption of a "sign-theoretic" approach on issues related to artificial intelligence and knowledge representation [30]. There is a synergy between a CCM and the concept of Semiotics. Moreover, 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 or phenomenon either known of not previously experienced.

IV. Implementation

Thus far we have considered cognitive science and modeling, in this section implementation is considered. Our proposed method to provide a basis for the processing of data (contextual information) uses *Context Matching* (CM), Figure 6 shows a high level conceptual view of the CM. This method provides an effective basis upon which *Partial Matching* (PM) [based on fuzzy set theories with degrees of set membership] while accommodating CS. In a medical domain the intention is the monitor a patient's current prevailing *state* (or *context*) to:

1) Compare changes in a patient's context at time (t_0) and (t_1) (the period between (t_0) and (t_1) will be determined by a clinician). The evaluation is designed to identify relative change (positive or negative) in a patient's context and implement appropriate intervention(s) as required.
2) Compare a patient's presenting symptoms (the *input* context) against the symptoms that classify specific diseases (the *output* context) in the diagnostic process. This demands that multiple symptoms and test results are evaluated and a recommendation made (decision-support)

These processes can be viewed in terms of iterative context processing modelled in Figure 7.

A. The proposed Approach

The approach considered in this paper is, in summary, an event driven fuzzy rule-based system with ontology based context modeling [12]. This approach can be viewed in terms of a system designed to provide an effective basis upon which targeted service provision can be achieved under uncertainty while accommodating user preferences and constraint satisfaction (or at least mitigating violations of constraints). For a detailed discussion on CP, CM, and CS see [12].

The approach is in effect a deterministic search where (u) is a member of a set (U), this process is essentially a linear 'brute-force' search of the hypothesis space (U) with the objective of achieving CM. In thinking about medical diagnostics, we aim to match patients observed symptoms and test results to specific conditions. In this case the information will be the tacit and explicit knowledge derived from clinicians in collaborative systems development.

There are a number of diseases with their related symptoms which must be accommodated in matching a patients presented symptoms with a specific disease or mental disorder. The

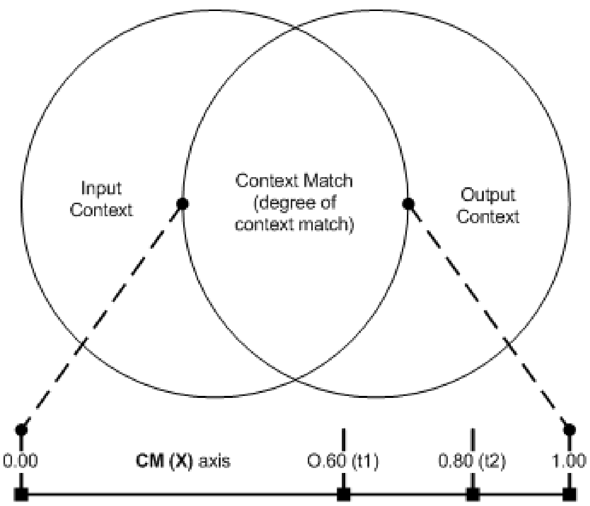

Fig. 6. A conceptual high-level view of CM. The model shows the relationship between the *input* and *output* contexts where PM is implemented with *defuzzification* using defined thresholds (decision boundaries)

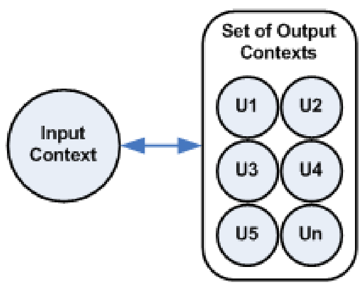

Fig. 7. Context processing for iterative context matching is shown where the *input* context is matched to the *output* context(s) shown as $(U_1...U_n)$ where the *input* context is a set of symptoms plus medical test results (metrics) and $(U_1...U_n)$ represents potential diseases to be matched to the reported metrics

delineation in respect of the measurement of symptoms is characterized by uncertainty and is essentially fuzzy. Therefore we must accommodate PM with the capability to express the results in quantitative and qualitative formats. This requires the use of semantics and linguistics as discussed in [31] where the efficacy of the proposed approach has been demonstrated. To achieve this aim we propose the use of fuzzy sets which enable PM (degrees of membership of a set). For a comprehensive exposition on fuzzy sets and fuzzy logic see [32]; fuzzy rule-based systems with decision support are discussed in detail in [33]. A central feature of fuzzy sets is defuzzification and the design on membership functions, for an extensive discussion on the topic see [32] [33]

Fuzzy sets are a generalization of *Crisp* sets. In crisp sets the *characteristic function* assigns a value of 0, 1 to identify *members* and *non-members* respectively. Fuzzy sets provide the functionality to provide gradual transitions from membership to non-membership (and vice versa). This capability has a broad utility as, while it provides a basis for graduated membership transition, it also enables the representation and measurement of uncertainties / vague concepts expressed in natural language.

When (A) is a fuzzy set and (x) is a relevant object, the proposition: (x) is a member of (A) may not be either *true* or *false* as is required by two-valued logic. It may be the case that (x) is a member of (A) is *true* only to some degree where the degree to which (x) is actually a member of (A).

It is most common (but not required) to express degrees of membership in fuzzy sets (also as degrees of truth of the associated propositions) quantitatively in the closed unit interval [0,1], The extreme values in this interval, 0 and 1, then represent, respectively, the total denial (no membership) and affirmation (full membership) of the membership in a given fuzzy set as well as the falsity and truth of the associated proposition. A fuzzy set can be defined mathematically by assigning to each possible individual in the universe of discourse a value representing its grade of membership in the fuzzy set. This grade corresponds to the degree to which that individual is similar or compatible with the concept represented by the fuzzy set. Thus, individuals may belong in the fuzzy set to a greater or lesser degree as indicated by a larger or smaller membership grade.

Membership of set is often represented by 'real-number' ($\Re$) values ranging in the closed interval between [0, 1]. Membership grades (degrees of full membership and full non-membership in the fuzzy set) can still be indicated by the values of [0, 1] respectively. We may consider the concept of a crisp set to be a restricted case of the more general concept of a fuzzy set for which only these two grades of membership are allowed.

V. Depression

In this paper we are addressing emotive response to events (stimuli). Depression is a prototypical mental disorder and we argue that cognitive factors (along with possible physical symptoms) forms a pivotal feature is the diagnosis and treatment of the condition. Depression is a feature of a number of mental disorders [34] we may however view depression on a spectrum as, while it may be clinical depression, it may also be a normal reaction to life events or side effects as a result of drugs and medical treatments. Recent evidence has suggested that recurrent episodes of severe depression are associated with changes in brain function that further heighten vulnerability and functional impairment. It is argued in [35] that an: "integrated approach to diagnosis and management imbues profound beneficial effects for all stakeholders in the treatment of depression.

There is a very large (and growing) body of of documented research in the literature addressing depression and depressive states. Depression is a highly variable condition that impacts individuals across demographics and gender [35] [36]; Greenberg in [37] introduces the emotional component into the treatment of depression. We have considered the concept of *self self* in both *internalized* and *externalized* forms and this forms an important element in such mental disorders in terms of the diagnosis and management (both short and long term) of the conditions and we argue that emotive responses are central to this process.

Depression and depressive states reflect an individuals low mood and aversion to activity such that there can be significant affects in terms of an individuals thoughts, behavior, feelings and sense of well-being [38] [39] [34]. Depression may trigger mood swings including feeling: *sad*, *anxious*, *empty*, *hopeless*, *helpless*, *worthless*, *guilty*, *irritable*, *ashamed* or *restless*. There is a clear synergy between these observations and the emotive responses identified by behavioral biologists such as Plutchik in [20] (see Section II) where similar negative and positive reactions are discussed. Other symptoms may include *excessive sleeping*, *fatigue*, aches, pains, digestive problems or reduced energy and in serious cases, patients may contemplate (or even commit) suicide [40].

In this paper we are interested in the cognitive aspects of depression and it's treatment. While an "integrated approach" [35] may include: (1) cognitive behavioral therapies (CBT) [41] using both face-to-face and remote (possibly on-line) consultations, and (2) drug treatments, our aim is to provide an effective basis upon which the cognitive and physiological factors that relate to depressive states are captured and processed to improve the diagnosis and treatment of depression.

Moreover, our aim is to include emotional response (based on objective data (much of the cognitive response data is subjective) using cognitive modeling) to stimuli in the diagnosis and treatment of patients in the depressive spectrum as this aspect of the condition is, we argue, central to understanding depression and other serious mental disorders such as psychosis and schizophrenia. Such systems must be designed to implement the concept of *self* in both internalized and externalized forms.

VI. General Discussion

In this paper we have explored machine cognition and cognitive modeling with consideration of the elemental components that combine to create an effective cognitive model. In considering implementation we have introduced an approach predicated on fuzzy sets to address the fuzzy nature of cognitive processes and context-awareness.

In research the optimal approach to the processing of contextual information investigations have included alternative approaches such as: Bayesian methods, inference and reasoning with ontology-based context modeling, decision-trees, artificial neural networks, and nature inspired systems including genetic algorithms and particle swarm optimization. For a discussion on a number of these methods see [12] however in summary, given the fuzzy nature of cognitive functions and the approach introduced in this paper [an event driven rule-based system with ontology-based context modeling] currently represents the optimal approach. Alternative methods continue to be investigated and the optimal approach remains domain specific and as such is an open research question.

Our review of research has concluded that in cognitive science explanations [of the human brain] rely largely on conceptual modeling however, while the empirical value of numerous models is generally accepted the methodological account of computational explanation remains an open research question. Additionally, we conclude that while models of the human brain have been created (see Figures 3 and 4) the knowledge of the brain remains largely the subject of much conjecture. We may also conclude that along with the cognitive functions that characterize a human, intelligent systems must be capable of dynamic change in response to uncertainty and dynamic environments characterized by sparse and incomplete data.

In Section II we have identified the concept of *self* in its *internalized* and *externalized* forms, this has synergy with context-awareness in intelligent context-aware systems. This is expressed in terms of a context definition which models an individual' state (or entity) in terms of both the individual's cognitive and physical state (analogous to the *internalized* self) plus the environmental factors (analogous to the *externalized* self).

Traditionally, the range and scope of the contextual information currently used in context-aware systems is very limited. Viewed from an historical perspective the predominant data used has been spatio-temporal, environmental, and proximity information. We propose that to improve the intelligence in context-aware systems emotive response is required to mirror human cognitive processes. We posit that creating an effective cognitive model offers the potential to integrate emotional response and thereby improve context-aware systems in a broad and diverse range of domains and systems along with improvements in the levels of computational intelligence.

We have illustrated the concept of cognitive modeling using e-health monitoring with a focus on the monitoring of patients with mental disorders with a focus on depression. Realizing the aims of this research represents significant non-trivial challenges which are manifested in the desire to model the human brain and cognitive processing which remain largely the subject of conjecture. Given the centrality of emotive response in the arena of cognitive modeling achievements in realizing (even to a limited degree) our aims represents a significant advance over current intelligent context-aware systems.

The challenges inherent in the problems considered in this paper are clearly non-trivial and represent long term research goals however to realize truly effective context-awareness with improved levels of computational intelligence we must consider how such aims may be achieved. We have introduced a potential solution which, we argue, provides a basis upon which we may approximate cognitive models based on data in semantic ontologies with data processing using fuzzy sets. This approach presents opportunities and is a potentially interesting direction for research and future work however achieving the research goals and creating truly intelligent context-middleware remains an open research question. Additionally, there are issues which also represent open research questions, namely the ability to capture cognitive data using non-invasive sensors. It is accepted that the majority of hardware issues are in principal resolved [42] the development of non-invasive sensors remains an ongoing challenge.

Notwithstanding the current technological and modeling limitations we posit that creating an effective cognitive model offers the potential to integrate emotional response and thereby improve context-aware systems in a broad and diverse range of domains and systems along with improvements in the levels of computational intelligence.

VII. Conclusion

This paper has presented a discussion on the demands related to machine cognition and the integration of emotional

Response in context-aware systems with the monitoring of mental disorders as a prototypical use-case where emotive response and the concept of *self* in its *internalized* and *externalized* forms are a central components in context processing and the related context middleware.

An important consideration in the development of any computer software is the ability to generalize to a range of domains and systems. We would propose that the posited approach will, indeed, generalize to other domains than the healthcare domain. For example it has been shown to be effective in the domain of tertiary education where the distribution of resources or collaboration interactions based on context is the aim. We do not underestimate the challenges but if they can be overcome the results will be very exciting.

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