Intelligent Context with Decision Support under Uncertainty

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***Abstract*—Context is inherently complex requiring intelligent context processing to address the broad and diverse range of available data that when processed can be viewed as contextual information useful in intelligent context-aware systems in a broad range of domains and systems. The function of context-aware systems is to target service provision based on an entities context; an entity has been defined as "a person, place, or physical or computational object". Given the diverse range of available data and entities a primary requirement for an intelligent context-aware system is decision support under uncertainty. This paper provides an overview of context and intelligent context processing. The novel 'extended' context matching algorithm is presented with an overview of fuzzy systems design as it relates to context processing and matching. The design of the membership function is discussed and it is shown that context matching using a membership function based on semantic representation provides a basis upon which the granularity of the context matching result can be improved. Anomalies where the context matching result lies close to a decision boundary are discussed with context processing under uncertainty. The paper concludes with a discussion conclusions, and open research questions.**

Keywords-intelligent context processing, decision support, context matching, uncertainty.

I. INTRODUCTION

Context-aware systems are inherently complex and dynamic resulting in the generality of contextual information being restricted to location, identity, and proximate data. There is however an increasing research focus on the use of a broad and diverse range of contextual information (in research projects and less so in commercial applications.

Addressing the range of available contextual information (if data can be captured, digitized, and codified it can be viewed as contextual information) requires the application of computational intelligence implemented in intelligent context-aware systems. A central function in context processing is *context matching* (CM) [1]; this function is implemented in the CM algorithm which along with the design of the fuzzy *distribution function* (often termed a *membership function* in the literature) [2] forms this paper's central contribution.

The CM algorithm presented in this paper extends the CM algorithm presented in [1]. The extended CM algorithm (hereafter termed the *CM algorithm*) implements additional functions to address uncertainty and the *decision boundary* (DB) proximity issue as discussed in this paper. This paper sets out an overview of context with consideration of intelligent context processing. The novel CM algorithm is presented with conclusions related to its operation. The results derived from the CM algorithm are semantic descriptions representing the degree to which a user is a suitably qualified recipient for service. These metrics while interesting are not particularly useful in decision support; to effectively implement the CM results the design of the membership function is discussed. The paper concludes with a brief consideration of the DB issue, context processing under uncertainty and a discussion with open research questions.

II. CONTEXT

Context describes a concept in which the profile of an entity is defined by its 'context', an in relationship to an entity context is defined as [3]: *"Any information that can be used to characterize an entity"*; and entity being: *"a person, place or a physical or computational object"* [3]. Context is highly domain and application specific [4]; a context is also potentially highly dynamic and must reflect a user's current dynamic state [4]. Location is central to context in mobile systems; context however includes more than just location [4][5]; a broad and diverse range of context factors combine to form a context definition, in fact, almost any information available at the time of an interaction can be viewed as contextual information.

An example of this diversity is the use of *Kansei* words [6] in quantifying trader sensibilities about trading decisions, market conditions with uncertain risks in a *Context-Aware Group Decision Making* [7]. By aggregating user preferences and selecting alternatives, a group of individuals enhances potentially optimal solutions based on contextual information. The use of *Kansei* evaluation shows that if data can be captured, measured, codified, and digitized it can be considered to be contextual information.

A challenge to the effective implementation of context is the accommodation of constraint satisfaction and preference compliance (CS) [8]. CS relates to the ability of a context-aware system to accommodate system defined and user-defined constraints, expressed user preferences, and security (generally) defined in the form of policy constraints defined as access rights and permissions. Examples of system constraints include restrictions based on specific locations or times and policy restrictions based on an individual's

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membership or role in a system or organization. Examples of user-defined constraints include restricting service provision to specified locations and times; user-defined preferences reflecting a user's predefined needs, beliefs, desires and interests.

A. *Intelligent Context Processing*

Central in the proposed approach to context processing is the CM algorithm which provides a basis upon which contextual information can be processed in an intelligent context-aware system that enables CS with predictable decision support under uncertainty while accommodating the inherent complexity of context.

The proposed approach is predicated on the processing of contextual information using CM [9]. The CM process is designed to create the *input* context and access the *output* context(s) definitions and using the CM algorithm to determine if the *output* (solution) context (properties) is an acceptable match with the ***input*** (problem) context (properties). Figure 1 graphically models the CM problem; shown is the *partial matching* (PM) issue with a DB membership function (a threshold) used in the CM algorithm as discussed in [1] and in subsequent sections of this paper. Figures 2 and 3 show the DB and *uncertainty boundary* (UB) in relation to the solution space. The proposed approach enables multiple thresholds (the CM membership function) in for example context-aware health monitoring systems where multiple decisions (prognoses) must be accommodated under uncertainty.

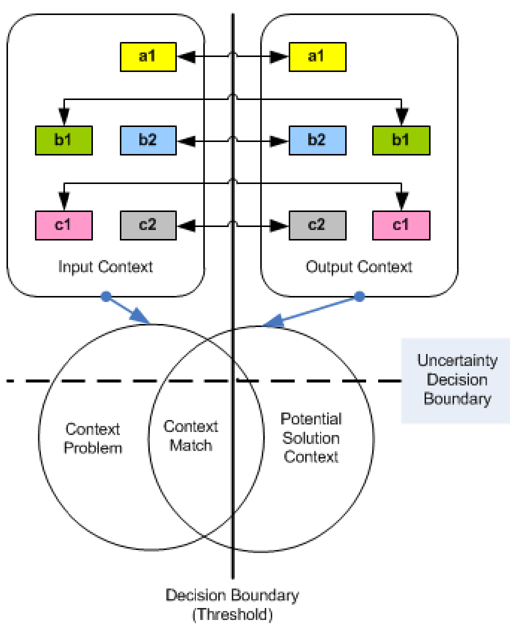

Figure 1. Personalization and the CM problem.

Central to context processing is the PM issue and the relationship between the *input* and *output* context properties. Essentially, the context-matching process is one of reaching a Boolean decision as to the suitability of a specific individual based on his or her context [1]. The CM algorithm is designed to address the PM issue as discussed in the following section.

As discussed in [1] accommodating CS represents a significant issue in intelligent context-aware systems. To mitigate CS violations the CM algorithm implements a prioritizing bias into the context processing and matching process.

III. The Context-Matching Agorithm

The CM algorithm is predicated on the *Event:Condition:Action* (ECA) rules concept [1]. The *Condition* component of an ECA rule (the *antecedent*) employs the IF-THEN rule strategy commonly found in *Reaction* rules [10] which relate 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 CM algorithm applies the principles identified in fuzzy logic and fuzzy sets with a defined membership function. 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}. 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 both the earlier CM algorithm [1] and the (extended) CM algorithm presented in this paper.

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 normalised 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 CM algorithm this is addressed using a membership function to implement the essential process of *defuzzification* as discussed in this paper and in [1].

CM with PM imposes issues similar to those encountered in decision support under uncertainty, which is possibly the most important category of decision problem and represents a fundamental issue for decision-support. A discussion on the topic is beyond the scope of this paper however a detailed exploration of fuzzy sets and fuzzy logic can be found in [11] with an exposition on "Decision, Order and Time" presented in [12]. 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]. A discussion on the CM algorithm, logic systems, and rule strategies with the related conditional relationships for intelligent context-aware systems can be found in [1]; the CM algorithm which implements uncertainty as modeled in

Figure 3 is set out below. For a discussion on earlier CM algorithm with an evaluation see [1].

A. *The CM Algorithm*

The CM algorithm is as follows where:

(**1**) **e** := {0, 1} – the numerical (Boolean) evaluation for each context property match {*true* = [1]} or {*false* = [0]}

(**2**) **w** := {0.10…1.00} – a weight applied to each context property to reflect its relative priority

(**3**) **av** := ∏(e ∗ w) – the *Actual Value* (av) for each context property match evaluation in the range [0.00…1.00] following the application of the weight (w)

(**4**) **sav** := ∑(av ($a_1…a_n$) – the *sum* of the *Actual Values* (av)

(**5**) **mpv** := ∑(av ($a_1…a_n$) – the *Maximum potential Value* (mpv). This represents a state in which all context property matches (av ($a_1…a_{n)}$ are *true* [1]. The mpv assumes that a perfect context match has been identified.

(**6**) **rv** := (sav / mpv) – the *resultant value* (rv) represents the degree to which the overall context match is true in the range [0.00…1.00]. The (rv) value is computed in step 6 and used in step 7 to test if (rv) is greater than (t1, t2). (note: in actuality the value for rv will be: ((rv + yc) for the ‘y’ axis)) and ((rv + xc) for the ‘x’ axis)).

(**7**) **yc** :- the Euclidean distance [0.01] (1% of the normalized context match) between two points {rv to t1, t2, t3}

(**8**) **xc** :- the Euclidean distance [0.01] (1% of the normalized context match) between two points { rv to t4 }

(**9**) **q** := the resultant semantic value representing the degree of the “qualifiedness” of the CM

(**10**) **uc** := the relationship of rv to the uncertainty boundary (t4); i.e., (positive) (+) or (negative) (-)

(**11**) **t1** := {0.60} the lower bound for a good quality “GQ” context-match on the CM axis

(**12**) **t2** := {0.80} the lower bound for a good quality “GQ” context-match on the CM axis

(**13**) **t3** := {1.00} the upper bound for the high quality “HQ” context-match-match on the CM axis

(**14**) **t4** := {0.70} the lower bound for the uncertainty boundary on the UC axis.

(**15**) Let **f** : = {f1,f2, …, fn} be a set of rules, represented by uncertain environmental conditions

Step 1: Evaluate the context match {1, 0} for each individual context property, for example:

IF (**a1**(*input*)) ***.equalTo*** (**a1**(*output*)) THEN **e** = {1}
IF (**a1**(*input*)) ***.notEqualTo*** (**a1**(*output*)) THEN **e** = {0}

Step 2: Obtain the pre-defined property weighting (**w**) for each context property in the range [0.1, 1.0]:

w = **a1** [0.1, 1.0]

Step 3: Apply the weighting (**w**) to the value as derived from step 2 (note: the **w** is applied irrespective of the value of **e**. Thus retaining the result for **e**):

IF **e**(**a1**) = {1, 0} THEN **av** = (**e** ∗ **w**)

Step 4: Sum the values derived from the CM process:

sav = ∑(**av**(a1) + **av**(b1) + **av**(b2) + **av**(c1) + av(c2))

Step 5: Compute the potential maximum value (**mpv**) for the context properties {a1, b1, b2, c1, c2}:

mpv = ∑(**w**(a1) + **w**(b1) + **w**(b2) + **w**(c1) + **w**(c2))

Step 6: Compute the resultant value (**rv**) for testing against threshold value (**t**):

rv = (**sav** / **mpv**)

Step 7: Using the heuristically defined threshold values (t1, t2, t3) determine if the output (potential solution) context definition is a suitably qualified match with the input (resource or collaboration request) context. Derive the semantic measures of the degrees of “qualifiedness”: {“LQ”, “GQ”, “HQ”}. Note: as shown the value of **rv** is (**rv** + **yc**) – see note 7 above.

IF ((**t1**) < (**rv** + **yc**)) THEN **q** = “LQ”
IF ((**t1**) >= (**rv** + **yc**) < (**t2**)) THEN **q** = “GQ”
IF ((**t2**) >= (**rv** + **yc**) **<=** (**t3**)) THEN **q** = “HQ”

Step 8: Adjust uncertain environmental conditions to adapt with context matching and compute the relationship to the uncertainty boundary where {$\mathbf{f_1}$,$\mathbf{f_2}$ … $\mathbf{f_n}$} is a be a set of *Event:Condition:Action* rules which represent domain specific uncertainty in environmental conditions. Note: **uc** := the relationship of **rv** to the *uncertainty boundary*; i.e., (*positive*) (**+**) or (*negative*) (-) is defined using (**rv** + **xc**) where ((**t4**) >= **uc**(+)) and ((**t4**) > **uc**(**-**)).

IF (**t4** >= **rv**) AND <***event***>):
Rule $\mathbf{f_1}$: {<*condition*$_1$> AND <*condition*$_2$> AND <*condition*$_n$> THEN <***action***> **uc**(+)}
ELSE IF (**t4** < **rv**) AND <***event***>):
Rule $\mathbf{f_2}$: {<condition$_1$> AND (<condition$_2$> OR <condition$_n$>) THEN <action> **uc**(-)}
ELSE (0.70 >= **rv**(t4) <***event***>):
Rule $\mathbf{f_n}$: {<condition$_1$> AND <condition$_2$> AND <condition$_n$> THEN <action> **uc**(+)}

B. *Analysis*

An analysis of the CM algorithm results in a number of conclusions:

Step 6 computes the resultant value (rv) for testing against DB values (t1, t2, t3).

The result of ***step 7*** is a semantic conversion of the rv CM metric to one of: {“LQ”, “GQ”, and “HQ”}. There is a direct relationship between this and an expressed user preference relating to the degree of membership derived from CM the user is happy with. The semantic measures {“GQ”, “HQ”} relate to the well understood precision and recall metrics. A user may opt for a lower level of CM (higher recall) and specify: “GP” (general precision) which relates to the “GQ” metric. Similarly, the “HP” (high precision) preference relates to the “HQ” level in the CM process. In the CM algorithm the results utilize the semantic metrics for the degrees of “qualifiedness”. Table 1 sets out the relationship between the CM result and the user expressed preference level. For example, where the actual result of the context processing is “GQ” and the user’s expressed preference is “HP” the result of the CM is [0] as the CM result is less than the expressed preference.

Step 8 identifies the context match as a positive (+) or negative (-) condition relative to the uncertainty boundary (***t4***). Note that the posited approach enables multiple uncertainty boundaries thus introducing increased granularity in the classification of uncertainty. Figure 3 expands on Figures 1 and 2 and shows the DB's and the UB with the semantic classifications ("U-LQ", "U-GQ", "U-HQ", "C-LQ", "CGQ", and "C-HQ") where "U" and "C" represent *uncertainty* and *certainty* respectively.

TABLE I. USER PREFERECE / CONTEXT MATCHING RELATIONSHIPS

	LQ	GQ	HQ
GP	[**0**]	[**1**]	[**1**]
HO	[**0**]	[**0**]	[**1**]

The result of the CM process while interesting, is not in itself useful when used in a decision-support system. This is addressed in the implementation where domain specific rules are applied to interpret the CM result in terms of a Boolean decision {1, 0}, true of false respectively.

IV. THE MEMBERSHIP FUNCTION

An essential process within fuzzy systems is *defuzzification* as discussed in [2]; the result derived from this process is a Boolean decision. This process requires the development of a *membership function*. In this research the membership function employs semantic descriptions to apply degrees of CM which are representations of the normalized value (**rv**) in the range [0.00, 1.00] and are used to classify the CM and where applicable apply stopping criteria within the context processing.

A. The Design of the Membership Function

The design of a membership function is domain specific requiring domain specific design to meet the design goals set for the system under consideration [2]. In considering *fuzzy variable design* there are essentially two approaches: *Linguistic* design and *Data-Driven* design [2]. Given the nature of the input contextual data utilized in the context processing and matching the Data-Driven approach with semantic representation has been adopted.

The DB concept forms an essential element of the design for both *fuzzy variable* development and *rule formation* (both of which are central to the CM algorithm); variable and rule design being closely interconnected thus one cannot be performed without consideration of the other. DB's can be viewed in terms of a mapping (in this case an *input* context to an *output* context) of the context match to the solution space in the context processing.

As observed, the membership function employs semantic descriptions to apply degrees of input context to output context matching. These terms must be classified in terms of the normalized values used in the CM process; this is achieved using a partitioning technique [2]. In its simplest form, partitioning is an attempt to find a decision boundary between (at least two) data points on a solution space. In this research the solution space (the normalized input range [0.00, 1.00]) is partitioned to into three partitions on the CM (**x**) axis each with defined lower and upper bounds, Figure 2 graphically models the partitioning of the CM axis with the notional (*crisp*) DB and the *heuristically* derived DB (***t1***, ***t2***, ***t3***); note: ***t3*** is a special case as no ***rv*** value can exceed [1.00]. These decision boundaries are also shown in Figure 3 with the UB (***t4***).

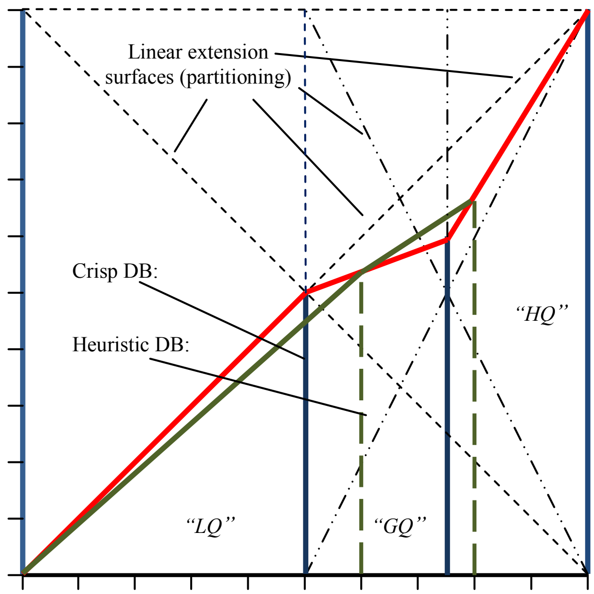

Figure 2. The Membership Function with Decision Boundaries.

The partitioning approach for the CM axis adopted applies *linear extension surfaces* [2] with an heuristic interpolation technique predicated on: (1) the results published in the literature relating to the success of recommender systems (generally information systems), and (2) the decision boundaries defined using the partitioning approach as discussed in this section. The heuristic interpolation employs a number of assumptions:

(1) The literature addressing recommender systems has identified success rates in the range 55% to 75% (0.55 to 0.75 normalized).

(2) There is no *a priori* knowledge relating to the identification of the crisp points [within the solution space] upon which to base the partitioning of the solution space.

(3) The contribution (as discussed below) of each context property in the set of context properties. For example, in a set of 9 context properties each property contributes 0.11 (to 2 decimal places for a recurring figure) resulting in the normalized value of 0.99, rounded up to 1.00 for a solution space in the range [0.00, 1.00].

Based on the 3 assumptions the partitioning of the solution space (as shown in Figure2 and 3) has identified 3 decision boundaries: the lower, intermediate, and upper bounds. The initial partitioning coincidentally falls within an experimental error range of the identified crisp points for recommender systems. Considering point 3 the following assumptions as set out in points 4, 5, and 6, have been applied:

(4) It is unlikely that a context match in which 5 or less true matches will be acceptable (5 x 0.11 = 0.55). An analysis of the contribution made for differing numbers of context properties [in an overall context] supports the

conclusion that that in general a context with less than 5 properties may result in ales reliable CM.

(5) A context match of less than 7 context properties is not a very good match (7 x 0.11 = 0.77)

(6) Based on these assumptions the heuristics applied to set the upper and lower bounds (DB's) are that 6 context properties (maximum 6 x 0.11 = 0.66 degree of membership) will be used for the lower bound for an acceptable match. Clearly 1.0 will be the upper bound, and for the intermediate bound 7 context properties (7 x 0.11 = 0.77 degree of membership) will identify a suitable demarcation point. The degrees of membership for the numbers of true context (property) matches are: 5 true matches:= 0.55, 6 true matches:= 0.66, 7 true matches:= 0.77, 8 true matches:= 0.88, and 9 true matches:= 0.99.

(7) Based on these degrees of membership the median (m) points are: (1) between 5 and 6 true context matches m = 0.605, and between 7 and 8 true context matches m = 0.825.

Thus the lower, and intermediate, and upper bounds (decision boundaries) set using the heuristics discussed above are: 0.60, 0.80, and 1.00 respectively. The solution space classifications defined by these decision boundaries relate to the semantic metrics "LQ", "GQ", and "HQ" as discussed in this section. Therefore, in the presence of fuzzy data between (at least two) crisp points on a solution space, equidistance partitioning (a result of the first approach) can be modified to accommodate the desired boundaries identified by asymmetric (as opposed to symmetric) functions.

From a design perspective an analysis has identified that the *prioritising bias* (<W>) has a significant effect on the performance of an intelligent context matching system and as such forms an important function in membership function design.

B. *The Decision Boundary Proximity issue*

Identifying the decision boundaries, while enabling defuzzification and providing a basis upon which predictable decision support can be realized raises a significant issue. Consider, for example, a normalized context match of 0.595; this degree of membership when tested against the lower bound for the semantic measure "GQ" (the 0.60 DB) fails. It is arguable that this is not logical given the very small difference (0.5% of the overall solution space, and as discussed below 0.834% of the "LQ" solution space).

To attempt to address this issue there is a need for an approach which at the very least attempts to mitigate such anomalies. To this end the concept of Euclidean distances (based on the triangle law) has been investigated in [13]; as it applies to a DB the degree of membership (**rv**) there are two data points: (1) the **rv** value and (2) the related DB.

Adopting this approach provides a basis upon which the use of distance can be extended to other relationships between a decision boundary and data points (**rv** values) with CM achieved using other methodologies such as machine learning techniques. Additionally, the use of Euclidean distance provides an effective basis upon which a relationship with the UB can be created and uncertainty addressed. Shown in Figure 3 is the relationship of the solution space to the degree of membership derived from CM and the DB (on the CM axis) and the uncertainty boundary (on the UC axis).

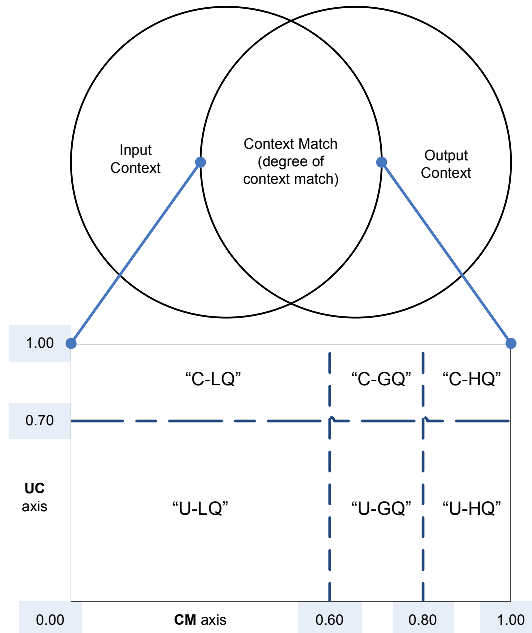

Figure 3. The solution space with the DB(s) and UB

The CM algorithm has been extended to incorporate a rule-based function which identifies IF a context match (in the CM algorithm) the rv value is within 1% (on the negative side), i.e., 0.01, of a DB. In such a case the following rule is applied where: t1 = the lower bound (the 0.60 decision boundary); rv = 0.595; and r = the result of context matching:

{IF (**t1** <= (**rv** + 0.01)) THEN (**r** = "GQ")}

It can be seen from the above that within restricted parameters this rule, when implemented in the CM algorithm, provides a basis for mitigating the potential anomaly identified. In the example shown above the initial result "LQ" is elevated to "GQ". Space restricts a detailed discussion however in summary the analysis demonstrates that the actual % adjustment reduces as the value for the rv metric increases; for the t1 DB it is 1.67% and for the **t2** DB it is 1.25%; thus with increasing degrees of confidence in the CM the adjustment reduces in direct proportion.

There are clearly issues in adopting this approach which are shared with the setting of decision support parameters in domain specific context-aware systems. Principal amongst the issues is how to set the distance metric; in practice this will be domain specific and will in probability be based on expert knowledge and the decision support the system is designed to address.

C. *Context Processing under Uncertainty*

The highly dynamic nature of context and its inherent complexity (refs) imposes issues related to decision support under uncertainty. To address this issue the use of an additional *uncertainty boundary* has been investigated. Figure 2 identifies 2 axes (the CM (CM) axis and the UC (uncertainty) axis). The initial investigations have used an additional uncertainty boundary located on the UC axis.

The context matching process initially produces 3 semantic results {"LQ", "GQ", "HQ"} (step 7). Step 6 extends the semantic metrics using the uncertainty boundary (**t4**); the results are: ("U-LQ", "U-GQ", "U-HQ", "C-LQ", "C-GQ", "C-HQ" where "U" and "C" represent *uncertainty* and *certainty*. These extensions to the range of semantic descriptions of the context match increase markedly the granularity of the results obtained. The *partitioning* approach (for the UC axis) shares with the previous discussion the lack of ***a priori*** knowledge therefore a heuristic approach is required based on domain specific expert knowledge. In this research **t4** has been set at {0.70} based on the analysis set out for the CM axis partitioning.

V. DISCUSSION

This paper has set out an overview of context with an introduction to intelligent context processing. The CM algorithm has been presented with an overview of fuzzy systems as applicable to the CM problem. The design of the membership function (a core function in fuzzy rule-based systems where predictable decision support is required) has been discussed with consideration of the decision boundary issue and a brief overview of CM under uncertainty. It has been shown that CM using a semantic membership function provides a basis upon which the granularity of the CM result can be improved. The CM algorithm lies at the core of the generic rule-based intelligent context-aware decision-support system which has been shown in this paper and in [1] to provide an effective solution to personalization in information systems in a broad range of domains, systems and technologies where decision support under uncertainty forms a systemic requirement.

Space restricts a detailed discussion on the analysis of the posited approach however in summary the results support the conclusions that: (1) the increasing degrees of membership (within the classifications defined in the solution space and as an overall CM result) reflect increasing degrees of confidence in the CM, and (2) Notwithstanding the observations in section IV(*A*) (t*he design of the membership function*) relating to the number of context properties in a context and the reliability of the CM result, the identification of the DB's remains generally consistent irrespective of the number of context properties that combine to create a context. These observations support the conclusion that the posited approach using CM implemented in the *extended* CM algorithm using the semantic classifications has the potential to improve the targeting of service provision based on an entities context and improve decision support under uncertainty in a broad range of domains and systems.

Investigations are currently addressing a range of domains including: (1) e-learning, (2) financial applications with group decision support, and (3) health monitoring systems including physical and age-related conditions such as dementia in both hospital settings and in patients homes.

While the research has resolved many the issues in the processing of contextual information a number of challenges have been identified including: (1) persistent storage of dynamic contextual information, (2) the approach to prioritization of context properties in the CM algorithm, and (3) the optimal design of the membership function used in the CM algorithm. A discussion on the challenges identified is beyond the scope of this paper however consideration of the nature and scope of the challenges identified, the design choices that influenced the context processing strategy adopted, and the use of ontology-based context modeling can be found in [1][5]. The challenges identified have grown out of the research and are open research questions which form the basis for future lines of research.

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