

# A Framework for Imprecise Context Reasoning

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**Abstract** — The knowledge about the user context refers to a sequence of activities performed in a pervasive computing environment. Such sequence and the corresponding context transitions typically constitute the up-to-now user situation, thus, clusters of similar situations can be formed. A framework that represents and infers the current user context and reasons about user situations through approximate reasoning and clustering techniques is proposed.

**Key terms**— fuzzy sets-based context representation and inference, context clustering, approximate reasoning

## I. INTRODUCTION

In a Pervasive Computing Environment (PCE) certain user activities (e.g., working in office, attending a meeting) may take place. Context-aware applications should be capable of determining that, the user is engaged in various situations at different time. Therefore, *context* refers to the current values of specific parameters that represent a user activity while *situation* refers to the history of such activities that have occurred during a certain time frame. Hence, situation represents transitions among pieces of context, e.g., the transition from the context: *a user is attending a meeting* to the context: *a user is presenting a report during a meeting* initiates an application to prepare the environment for the user's presentation (e.g., disseminating the presentation files to the attendants of the meeting and setting up the projector device). Moreover, as people group together in a PCE, they may desire to carry out *similar* activities thus are involved in *similar* context (e.g., a group of persons interested in the same topic in a conference). The idea of clustering user context transitions enables context-aware applications to initiate certain actuation rules and to reason about user behavior.

The process of sensing, interpreting and reasoning about context is called context determination. The more contextual data is sensed the greater the possibility of a *correct* determination becomes. Nevertheless, context is not always complete or accurate instead, it is degraded by several kinds of imperfections, e.g., missing information, unreliability of the sources and possible conflicting observations of the same phenomena. Determining context and, consequently, reasoning about it, introduces several types of uncertainty in context and situation representation. Such uncertainty is more effectively represented with the aid of the fuzzy set theory and the possibility theory [1]. By applying a degree of fuzziness not only to the determination phase but also to reasoning about context makes context-aware applications more robust, flexible and capable of handling a wide range of contextual attributes.

We propose a framework for determining and reasoning about context based on clustering (unsupervised learning). The contribution of such framework is two-fold: (i) context and situational context representation and (ii) context inference and reasoning about situation transitions under uncertainty. Two types of determination rule are introduced:

(i) the *context determination* rule and (ii) the *situational context determination* rule. The former rule infers the current user context and the latter one refers to the user situation classification. Our framework adopts possibility theory to capture uncertainty while it includes hierarchical context modeling through fuzzy sets-based modeling. In addition, it clusters similar situations through the Fuzzy C-Means clustering algorithm (FCM) where each user situation is associated with a cluster.

## II. CONTEXT REPRESENTATION

A fuzzy set  $A$  is defined over a subset of a universe of discourse  $U$  through a membership function,  $\mu_A: U \rightarrow [0, 1]$ . An element  $a \in U$  belongs to  $A$  to a certain degree  $\mu_A(a)$ . The higher a value of  $\mu_A(a)$  the higher degree of membership of  $a$  to  $A$ .  $A$  is represented as  $A = \{\mu_A(a_1) / a_1 + \dots + \mu_A(a_n) / a_n\}$  if  $U$  is measurable,  $a_i \in U, i = 1, \dots, n$ . Let  $B$  be a fuzzy set then, the possibility that “ $B$  is  $A$ ” is the number in  $[0, 1]$  given by  $Pos(B \text{ is } A) = \max_a(\min(\mu_A(a), \mu_B(a)))$ ,  $a \in U$ . We adopt fuzzy set theory for representing contextual attributes and values. Consider the following fixed set  $P(0) = \{p_1, \dots, p_m\}$  of  $m > 0$  attributes.  $P(0)$  represents the *ground* context, which means that each  $p_i \in P(0), i = 1, \dots, m$ , cannot be inferred (determined) by any  $p_j \in P(0), j \neq i$ . Any set  $P(k)$  is called a  $k$ -level set,  $k > 0$ , and represents an *inferred* context. Each attribute  $p \in P(k)$  is associated with a domain  $Dom_p$ , which is a set of values that  $p$  may take. The attribute  $v$ , which is constrained to assume values in the subset  $Dom_v \subseteq Dom_p$ , is defined as the *term* for  $p$  over the  $Dom_v$  domain. Such term characterizes  $p$  when it assumes values in  $Dom_v$ .  $v$  is represented by the fuzzy set  $A_v = \{(\mu_v / u) \mid u \in Dom_v, \mu_v: Dom_v \rightarrow [0, 1]\}$ , where  $\mu_v$  is the possibility distribution function [1] in  $Dom_v$ . An attribute  $p$  is *instantiated* as  $v$  when referring to the “ $p$  is  $v$ ” proposition. Let  $v^* \in Dom_p$  be a value (observation) for the  $v$  term related to  $p$  attribute then, the *degree of fulfillment*  $d \in [0, 1]$  of the “ $p$  is  $v$ ” proposition is defined as:  $d(p \text{ is } v) = Pos(p \text{ is } v \mid v^*)$  i.e., the possibility of “ $p$  is  $v$ ” given the observation  $v^*$  and equates to  $d(p \text{ is } v) = \max_u(\min(v(u), v^*(u)))$ ,  $u \in Dom_p$ . Consider a logical conjunction of terms of instantiated attributes then, the production rule,  $R_n: (p_1 \text{ is } v_1) \wedge (p_2 \text{ is } v_2) \wedge \dots \wedge (p_n \text{ is } v_n) \rightarrow (p_m \text{ is } v_m)$  constitutes the *context determination rule* with which  $p_m$  of a higher level set is concluded. The concluded  $p_m$  is called *context* of  $m$ -level. The value of the degree of the conclusion  $d(p_m \text{ is } v_m)$  is calculated as by a fuzzy inference engine.  $R_n$  combines contextual information from several knowledge sources (e.g., user location, time, people proximity). Therefore, such information may be imprecise (inexact) due to limited sources. Once the antecedent part of  $R_n$  holds true to a degree then, the user involvement in a certain context is inferred, at most, with that degree.

Pieces of context structure hierarchies denoting that, some context is more generic than other forming generalization relations among them. A transitive relation between  $p_n$  and  $p_m$  context has the form  $p_n \subseteq p_m$  with the associated semantics:  $p_n \subseteq p_m \Leftrightarrow \{\exists R_n, R_m \mid (R_n \rightarrow p_n) \wedge (R_m \rightarrow p_m) \wedge (Dom_{p_n} \supseteq$

$Dom_{p_m} \wedge (n \geq m)$ .  $p_n, p_m$  pieces of context define a hierarchy iff (i)  $p_m$  derives from a set of attributes of lower level than those of  $p_n$  (i.e.,  $n \geq m$ ) and (ii) the antecedents of  $p_m$  are less than those of  $p_n$ . Although  $p_m$  represents a more abstract context than  $p_n$ , i.e.,  $p_n$  is-a  $p_m$ , the opposite implication does not always hold.

**Notice:** One could deduce that, such hierarchical modeling avoids cycles but also weakens possibilities in forming other terms and thus would lead to greater generality. Instead, a thorough examination on such representation would lead to the conclusion that: different combinations among attributes result in different context determination rules thus, a low-level context extends more than one high-level pieces of context. Hence, a multi-resolution context representation is achieved, which forms a lattice of network (graph) of pieces of context in various levels and not a tree-based knowledge representation.

### III. SITUATIONAL CONTEXT REPRESENTATION

In the discussed framework the user involvement in  $p \in P(k)$  context exclusively implies that the user is not involved in  $q \in P(k)$ . All pieces of context of the same  $k$ -level are not compatible i.e., they do not co-occur. A transition from  $p$  to  $q$  with  $p, q \in P(k)$ , is called context transition of  $k$ -level, with the notation  $p \Rightarrow q$ . Let  $\mathbf{\Pi}(k)$  be the Markov chain for  $k$ -level pieces of context that is:  $\mathbf{\Pi}(k) = \{p \in P(k)\}$  provided that,  $Prob(p(t+1) \text{ is } v(t+1) \mid p(0) \text{ is } v(0), \dots, p(t) \text{ is } v(t)) = Prob(p(t+1) \text{ is } v(t+1) \mid p(t) \text{ is } v(t))$ ,  $t \in \mathfrak{X}$ . Then,  $\mathbf{\Pi}(k)_{N \times N}$  is the transition matrix of  $\mathbf{\Pi}(k)$  for  $k$ -level context.  $\mathbf{\Pi}(k)_{N \times N}$  contains  $N^2$  elements  $Prob(p_i \Rightarrow p_j)$  with  $N = |P(k)|$ ,  $p_i, p_j \in P(k)$  and it is not necessarily symmetrical. A user relates to a set of matrices for each  $k$ -level. The context transitions in  $\mathbf{\Pi}(k)$  represent the *situational context* or *situation* over time, i.e., the  $k$ -level *situation*. The  $\subseteq$  relation between  $p \in P(k)$  and  $q \in P(m)$  context,  $m > k$ , results analogously in a hierarchy of matrices.  $m$ -level situations are more abstract than those of  $k$ -level situations. Consequently, the  $m$ -level situation is a generalization of the  $k$ -level situation. The hierarchy of matrices assumes the constraint:  $Prob(p_i \Rightarrow p_j) \geq Prob(q_i \Rightarrow q_j)$ ,  $p_i, p_j \in P(k)$ ,  $q_i, q_j \in P(m)$ ,  $k < m$ , for all pairs  $(i, j)$ .

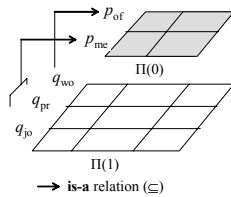


Fig. 1. Hierarchical structure of matrices

**Example:** Consider the pieces of context  $p_{me}, p_{of}, q_{wo}, q_{pr}, q_{jo}$ , which stand for the context *user is located in a meeting room* (0-level), *user is located in an office* (0-level), *user is working in her office* (1-level), *user is presenting a report during a meeting* (1-level) and *user joins a meeting* (1-level), respectively. Hence,  $Prob(p_{of} \Rightarrow p_{me}) \geq Prob(q_{wo} \Rightarrow q_{pr})$ . That is because the probability of a user being in  $p_{me}$  is the maximum possibility of the user being either in  $q_{pr}$  or in  $q_{jo}$  [1]. Fig. 1 depicts the two matrices  $\mathbf{\Pi}(0)_{2 \times 2}$  and  $\mathbf{\Pi}(1)_{3 \times 3}$  forming a hierarchy.  $\mathbf{\Pi}(0)$  refers to low-level situations and  $\mathbf{\Pi}(1)$  refers to more specific ones. A transition between pieces of context belonging to  $\mathbf{\Pi}(1)$  represents also a transition between pieces of context belonging to  $\mathbf{\Pi}(0)$ , but the opposite implication does not always hold.

### IV. SITUATIONAL CONTEXT CLUSTERING

The situation of a user in a PCE is represented by a set of matrices each belonging to different levels of specialization. In order to reason about situations, the framework groups the matrices (of a specific level) into clusters. Hence, the matrix of the master-cluster (centroid) is a representative situation of a user (e.g., user behavior) whose matrix is *similar* to the centroid. Subdividing a set of matrices of  $k$ -level context  $\mathbf{X}(k) = \{x_1, \dots, x_n\}$ ,  $x_i \in \mathbf{\Pi}(k)_{N \times N}$ ,  $i \in \mathfrak{X}_+$  into groups of *similar* matrices is called *context clustering* of  $\mathbf{X}(k)$ . Given a set  $\mathbf{C} = \{c_1, \dots, c_m\}$  of centroids, a distance function,  $\delta$ , is defined as  $\delta: \mathbf{\Pi}(k)_{N \times N} \times \mathbf{C} \rightarrow [0, 1]$ . A value of  $\delta(x, c) = 0$  means that  $x$  matches the centroid  $c$  perfectly. A value of 1 implies the opposite. The relationship between matrix and centroid is interpreted by means of a membership matrix  $\mathbf{U}_{n \times m}$  where  $u_{ij} \in \mathbf{U}_{n \times m}$  indicates the *degree of membership* of  $x_i$  to  $c_j$ .  $u_{ij} \in [0, 1]$  is a measure of how strongly a matrix (situation) is member of a particular centroid. Such measure denotes that, there are not *sharp* boundaries among matrices and centroids. A matrix possibly belongs to more that one centroids but to a certain degree. Hence, a user might be involved in diverse situations (e.g., a user might demonstrate diverse behaviors) represented by centroids with different degrees. The framework uses the FCM algorithm [2] in order to calculate such measure for each situation.

Two situations are *similar* according to  $\delta$ . A classical distance metric is the Euclidean distance between the  $A$  and  $B$  situations. We introduce a distance metric that exploits the semantics of context transitions when referring to similar situations. Consider the  $A$  and  $B$  situations and let  $p_i$  be the  $i^{\text{th}}$  context in the  $A_{ij}$  and  $B_{ij}$  vectors,  $j = 1, \dots, N$ . Let context  $p_k$  and  $p_m$ ,  $k, m < N$ , of  $A$  and  $B$ , respectively, that both maximize the transition probability  $a_{ik} = Prob(p_i \Rightarrow p_k)$  and  $\beta_{im} = Prob(p_i \Rightarrow p_m)$ , respectively, i.e.,  $p_k = \text{argmax}_{i \in \mathfrak{X}_+} a_{ik}$ , and  $p_m = \text{argmax}_{i \in \mathfrak{X}_+} \beta_{im}$ ,  $x = 1, \dots, N$  for a given  $p_i$ . Hence,  $A$  and  $B$  are considered close (in distance  $\delta$ ) with respect to  $p_i$  if  $k = m$ . The distance  $\delta_i$  w.r.t.  $i^{\text{th}}$  context is  $|a_{ik} - \beta_{im}|$ . The lower the value of  $\delta_i$ , the closer  $A$  is to  $B$  w.r.t.  $p_i$ , denoting same transitions with similar transition probabilities. If  $k \neq m$  then  $A$  is not close to  $B$  w.r.t.  $p_i$  thus  $\delta_i = 1$ . Hence, the distance  $\delta$  between  $A$  and  $B$  is the minimum  $\delta_i$  distance between  $A$  and  $B$  with regard to all  $p_i$ , i.e.,  $\delta = \min \delta_i$ ,  $i = 1, \dots, N$ .

#### A. Degree of Centroid Membership

For each centroid  $c_j \in \mathbf{C}$ , a fuzzy set  $B_j$  is defined as the fuzzy variable *inherence* denoting the *degree of centroid membership of a situation* to  $c_j$ . Let  $\mu_{B_j}: \mathbf{C} \rightarrow [0, 1]$  be the membership function of  $B_j$ ;  $\mu_{B_j}$  is the possibility of a situation  $x$  belonging to  $c_j$  defined in (1).

$$\mu_{B_j}(x) = \begin{cases} k_j = \max_{i=1, \dots, n} u_{ij}, & \text{if } x = c_j \\ \frac{1 - k_j}{m - 1}, & \text{else} \end{cases} \quad (1)$$

$$B_j = \left\{ \frac{1 - k_1}{m - 1} / c_1 + \dots + k_j / c_j + \dots + \frac{1 - k_m}{m - 1} / c_m \right\} \quad (2)$$

Hence,  $B_j$  for the  $c_j$  centroid is defined in (2), where  $m = |\mathbf{C}|$ ,  $n = |\mathbf{X}(k)|$ .  $|\mathbf{C}|$  is the cardinality of the  $\mathbf{C}$  set.  $B_j$  is the fuzzy representation of the  $u_{ij}$  value (fuzzification). Specifically, the *degree of inherence* denotes the degree of membership of a user situation to the  $j^{\text{th}}$  situation / centroid thus the supremum of  $B_j$  is  $u_{ij}$ . It should be noted that,  $\mu_{B_j}$  indicates how much the set  $\mathbf{X}(k)$  of situations supports the degree of membership of a user situation to  $c_j$ . Hence, the greater the value of  $k_j$  becomes the more representative the  $c_j$  situation is. The quantity  $(1 - k_j) / (m - 1)$  indicates the importance of the rest centroids with

regard to  $c_j$ . Such quantity is uniformly distributed to each centroid  $d \neq c_j, d \in C$ . If  $k_j = 1$  then at least a user situation totally belongs to  $c_j$  (and only to this centroid) thus  $\mu_{B_j}$  is a possibility distribution function [1].

The introduction of the  $B_j$  fuzzy set in the situational context reasoning is essential since a matrix, which represents a user situation, belongs to all centroids to a certain degree. The membership degree of the  $i^{\text{th}}$  situation to the  $c_j$  centroid represented by the quantity  $u_{ij}$  is expressed through the degree of the centroid membership (*inherence*) to  $B_j$ . A high value of  $k_j$  means that the  $i^{\text{th}}$  situation is sufficiently believed to be represented by  $c_j$ . For this reason, we require that  $k_j \rightarrow 1$ .

## V. IMPRECISE REASONING ABOUT SITUATIONAL CONTEXT

Each centroid represented by a matrix constitutes situational context with regard to a set of context transitions. Centroids denote diverse *types* of user situation. Users with similar situations are clustered into similar centroids. One can reason about situations since situation determination rules correspond to each centroid. The reasoning process takes into consideration the degree of centroid membership (*inherence*) of a user situation to a centroid.

Consider a set of *types* (classes or terms)  $\mathbf{T} = \{t_1, \dots, t_L\}, L > 0$ . Then, a *situation classification*  $Q$  is defined as a fuzzy subset over  $\mathbf{T}$  that is:  $Q = \{\mu_Q(t_1) / t_1 + \dots + \mu_Q(t_L) / t_L\}, \mu_Q \in [0, 1]$ . For instance, let  $\mathbf{T} = \{t_1, t_2, t_3\}$  with  $t_1, t_2, t_3$  stand for *normal, dubious* and *weird* user behavior, respectively. Then,  $Q = \{0.8 / t_1 + 0.1 / t_2 + 0.0 / t_3\}$  expresses a kind of situational context that  $t_1$  type is concluded to a high degree by the situation determination rule (discussed later) and  $t_2$  type is concluded to a low degree. Situation classification represented by fuzzy set can be processed by a context-aware application in order to take decisions [3]. The situation classification types are application specific.

Consider the generalized modus ponens rule:  $(p^* \wedge (p \rightarrow q)) \rightarrow q^*$ . Such rule denotes that when  $p^*$  is an *approximation* of  $p$  then  $q^*$  is concluded also as an *approximation* of  $q$  since  $p^*, p, q$ , and  $q^*$  are fuzzy sets. Let  $Q$  be a situation classification and  $B_j$  be the inherence of a situation to the  $c_j$  centroid. Hence, the situational context determination rule is:  $B_j \rightarrow Q$  denoting that, *if the user situation belongs to a centroid  $c_j$  then,  $Q$  is the concluded classification type*. Let  $A_i^*$  be the fuzzy set that represents the  $i^{\text{th}}$  situation membership degrees to each centroid  $c_j$ , i.e., for all  $u_{ij}, A_i^* = \{u_{i1} / c_1 + \dots + u_{im} / c_m\}$ . Then the generalized modus ponens rule is as follows:  $(A_i^* \wedge (B_j \rightarrow Q)) \rightarrow Q_i^*$ , where  $Q_i^*$  represents the concluded classification types for the  $i^{\text{th}}$  situation. The inference of  $Q_i^*$  given an observation  $A_i^*$  is computed according to the Mamdani inference scheme [4] as the cross-product  $\otimes$  of  $C$  and  $\mathbf{T}$  defined in (3). Hence, the concluded fuzzy set  $Q_i^* = \{(\mu_{Q_i^*}(t) / t) \mid t \in \mathbf{T}\}$  is calculated in (4).

$$\mu_{\otimes}(c, t) = \min(\mu_{B_j}(c), \mu_Q(t)), \forall c \in C, t \in \mathbf{T} \quad (3)$$

$$\mu_{Q_i^*}(t) = \max_{c \in C} \min(\mu_{B_j}(c), \mu_{\otimes}(c, t)), \forall c \in C, t \in \mathbf{T} \quad (4)$$

## VI. DISCUSSION ON THE FRAMEWORK EXPERIMENTS

Context clustering results in situation classification. Such classification forms a Knowledge Base of situation determination rules denoting what action a context-aware application could carry out. For instance, an actuation rule could be: *If the user attends to a meeting then, forward important calls only*, where the considered context could be the user involvement in a meeting. In addition, a specific user behavior or a activity pattern could be concluded by context

transitions, e.g., *If the user behavior is weird then, trigger the system to terminate all unsecured connections and lock all private areas or If the user behavior is normal, increase the degree of trust to her*.

The discussed framework is applied on real context data [5]. Each user carries a Personal Digital Assistant (PDA). The PDA is equipped with sensors for illumination, noise, position, a galvanometer for sensing touch and a three-axis accelerometer. Information concerning the user profile (e.g., agenda entries and private data) is obtained from the agenda application. The areas used are the office, the meeting room, the computer-room, the café, and a private area. Context values were recorded with a frequency of 1Hz approximately. Certain pieces of context forming hierarchy were used like *walking indoors while carrying her PDA, using elevator or stairs, sitting in the café and browsing, entering the private area, locates in the computer-room, attending a meeting and presenting a report during a meeting*. Three classification types of user behaviors represented by three fuzzy sets  $Q_1, Q_2$  and  $Q_3$  are used. Specifically,  $Q_1$  is represented by the fuzzy set:  $\{1.0 / \text{friendly} + 0.4 / \text{neutral} + 0.0 / \text{unsympathetic}\}$ ,  $Q_2 = \{0.1 / \text{friendly} + 0.9 / \text{neutral} + 0.1 / \text{unsympathetic}\}$  and  $Q_3 = \{0.0 / \text{friendly} + 0.1 / \text{neutral} + 1.0 / \text{unsympathetic}\}$ . Each  $Q_i$  associates with (at least) a situation determination rule. The FuzzyCLIPS<sup>1</sup> fuzzy inference engine is used for evaluating the context determination rules. The fuzzy clustering algorithm is the FCM and the evaluation of the situational context determination rules is an implementation of the Mamdani [4] inference scheme. Fig. 2 depicts the membership degrees of 100 users involved in situations to each centroid using the Euclidean distance ( $\epsilon$ ) and the proposed one ( $\delta$ ). Evidently,  $\delta$  assumes better fuzzy partition since there is more than one matrix in each cluster ( $Q_1, Q_2$  and  $Q_3$ ) that their membership degree has values near 1. This means that, all situation determination rules are equivalently important on the fuzzy reasoning since the maximum value of their corresponding degree of centroid membership  $k_j \approx 1, j = 1, \dots, 3$ .

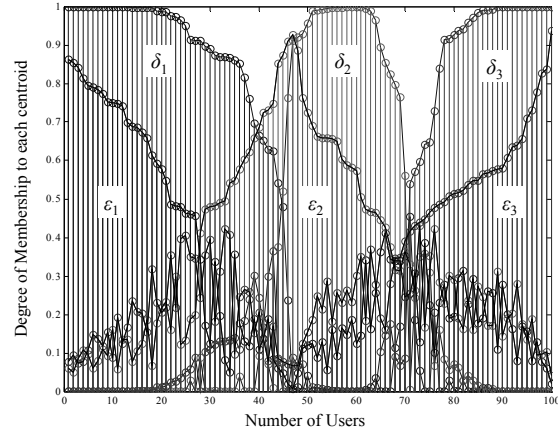


Fig.2. The degrees of membership after the fuzzy partition

## VII. PRIOR WORK

Research on context sensing, fusion, interpretation, representation, reasoning and actuation covers a wide variety of issues related to information management. The model in [6] processes situational information using rule-based constructs by using two concepts: *evidence* and *situation*. Such concepts play a key role in an evidence-based belief formation process since it is based on rule-based representation and forward

<sup>1</sup> www.iit.nrc.ca/IR\_public/fuzzy/fuzzyClips/

reasoning. Nevertheless, the evidential reasoning in such model is missing. Various context models use not only contextual information for triggering actions but also for enhancing the reasoning capability of a system. In [7], context is represented as object in a multidimensional Euclidean space, where each dimension constitutes an attribute. Any subspace comprises the situation space, in which several attributes represented by interval values are defined. Although such model deals with merged subspaces (complex situations) no semantics related to generalization relations among situations is considered. The work in [5] represents situational context as a multidimensional vector of fuzzy sets. Principal Component Analysis and Independent Component Analysis are used for discovering context that is not explicitly available, resulting in context inference. All detected pieces of context are disjoint and, thus, no hierarchically structured representation and reasoning is attained. In addition, fuzzy sets are only considered to represent context and not to reason about it, as supported in the proposed framework. In [8], context is modeled as predetermined fuzzy sets referring to specific attributes. Such sets constitute the input for a Fuzzy Logic Controller, which provides continuous control signals for applications. Therefore, each fuzzy set is predetermined (defined by human expert) thus it does not reflect the actual information since no learning process is considered. In our model, FCM is used as an unsupervised learning process where user situations are constructed reflecting the behavior of a specific user.

Most context models mainly focus on how to sense and infer context or a situation [9]. Therefore, issues related to enhancing the reasoning capability of a context-aware system, i.e., enhanced semantics among context (e.g., generalization relations) are essential. The work in [10] refers to a context model based on declarative-logic programming. However, such model deals only with high-level context representation (Prolog predicates) and reasoning. Consequently, it does not take into account contextual reasoning under uncertainty, as provided from our model. Moreover, using propositional logics, the authors in [11] describe situations as concepts considering the compatibility relations among situations, thus it could be considered as an extension to our representation in terms of conceptual context modeling. Related work on conceptual contextual reasoning is that of [12], which uses ontologies from the Semantic Web framework for context representation lacking of enhanced semantics thus, restricted knowledge reasoning capability. Moreover, the conceptual context model in [13] represents situational context through ontology-based modeling and is capable of Description-Logics reasoning about situations generalization, compatibility and similarity. However, our research is complementary to such work, since unsupervised fuzzy context clustering results into centroids, which could be regarded as situations (concepts) in a taxonomy of concepts.

#### VIII. CONCLUSIONS

We propose a framework for context and situation representation, inference and reasoning over context clustering. Our context model provides a hierarchical representation of pieces of contexts. The multi-level context representation supports context-aware applications to handle both specific and abstract knowledge about context. Production rules of contextual attributes form the user

context. Moreover, the discussed framework captures uncertainty by using possibility theory and fuzzy sets-based modelling and deals with historical context by adopting a Markov chain model. Changes of user context over time (i.e., a sequence of context transitions) constitute the situational context. Fuzzy clustering among transitions of pieces of context is adopted in order to group users with similar situations. A situation is classified with respect to certain situation classification types, which are application specific. Hence, situation determination rules can be exploited by context-aware applications in order to either perform actions related to a user (or a group of users) or autonomously adapt to the current user context.

The scalability of the discussed framework refers to the definition of multiple situation classification types, the selection of the context representation model and inference engine, and the choice of the clustering algorithm and the situational reasoning process. Various fuzzy clustering algorithms could be also used in the discussed framework (e.g., Fuzzy Adaptive Algorithm) while the reasoning process about situational context could be also any fuzzy inference engine (e.g., Tagaki – Sugeno [14]). The proposed framework handles uncertainty in context representation and enhances the reasoning capability of a system exploiting enhanced context semantics derived from the unsupervised learning of the contextual information clustering.

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