Reasoning About Context in Uncertain Pervasive Computing Environments

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Abstract. Context-awareness is a key to enabling intelligent adaptation in pervasive computing applications that need to cope with dynamic and uncertain environments. Addressing uncertainty is one of the major issues in context-based situation modeling and reasoning approaches. Uncertainty can be caused by inaccuracy, ambiguity or incompleteness of sensed context. However, there is another aspect of uncertainty that is associated with human concepts and real-world situations. In this paper we propose and validate a Fuzzy Situation Inference (FSI) technique that is able to represent uncertain situations and reflect delta changes of context in the situation inference results. The FSI model integrates fuzzy logic principles into the Context Spaces (CS) model, a formal and general context reasoning and modeling technique for pervasive computing environments. The strengths of fuzzy logic for modeling and reasoning of imperfect context and vague situations are combined with the CS model's underlying theoretical basis for supporting context-aware pervasive computing scenarios. An implementation and evaluation of the FSI model are presented to highlight the benefits of the FSI technique for context reasoning under uncertainty.

Keywords: context, fuzzy logic and pervasive computing

1 Introduction

In pervasive computing environments, applications need to be aware of the changes in their environment and adapt their behavior according to these changes. Pervasive systems use context-awareness to perform their tasks in an intelligent and efficient manner and maintain consistency and continuity of their operations. Context is a very broad term that encompasses different aspects and characteristics [1]. Context can be related to a network, application, environment, process, user or device. Contextual information collected from every single sensor or data source represents a partial view of the real-world. Aggregation of data from multiple sensors and sources provides a wider and more general view of surrounding environment and situations of interest [2]. For example, in a smart room scenario, rather than monitoring sensed context from light, noise and motion sensors individually, this information can be used to reason about situations such as ‘meeting’, ‘presentation’ or ‘study’ which provides a better understanding of the environment. As a meta-level concept over context, we define the notion of a situation that is inferred from contextual information [2]. Situation-awareness provides applications with a more abstract view of their environment rather than focusing on individual pieces of context.

One of the main challenges in enabling situation-awareness in pervasive applications is managing uncertainty. Uncertainty can be related to context imperfection such as sensors’ inaccuracy, missing information or imperfect observations [3-4]. However, there is another dimension of uncertainty that is inherent in human concepts and every day situations. In real-world, situations evolve and change into other situations (e.g. ‘walking’ changes to ‘running’). Changes that occur between situations of ‘walking’ and ’running’ are also good indicators of situations that may emerge – albeit with some vagueness and uncertainty. These uncertain situations can be of high importance to certain applications such as a health monitoring application that needs to monitor details of changes in a patient’s health situation. To model real-world situations, reasoning approaches need to be able to reflect this aspect of uncertainty in the situation reasoning results.

Reviewing recent works [5-14] in context reasoning under uncertainty reveals that these works have limited capability in dealing with vagueness of real-life situations and reflecting gradual and delta changes in the results of situation inference. More importantly, they lack a rich theoretical basic for supporting pervasive computing scenarios. A formal and general context modeling and reasoning approach that is specifically developed for context-aware computing environments and can deal with uncertain context and vague situations is still an open issue in this area of research.

In this paper we present a novel approach called Fuzzy Situation Inference (FSI) for situation modeling and reasoning under uncertainty. The FSI model integrates fuzzy logic principles into the Context Spaces (CS) model [2], a theoretical approach for modeling context and situations. The CS model provides heuristically-based sensor data fusion algorithm, specifically developed for pervasive computing environments to deal with inaccuracies of sensory originated information (i.e. reliability and error of reading) and characteristics of context [15-16]. The FSI technique incorporates the CS model’s underlying theoretical basis for supporting context-aware and pervasive computing environments while using fuzzy logic to model and reason about vague and uncertain situations.

This paper is structured as follows. Section 2 reviews the current state-of-the-art in context modeling and reasoning under uncertainty. Section 3 briefly discusses the Context Spaces (CS) model. Section 4 describes integration of fuzzy logic into the CS model as the FSI model. Section 5 and 6 present the implementation and evaluation of the FSI model respectively. Section 7 concludes the paper and discusses future work.

2 Related Work

Situation modeling and reasoning can range from simple conditional rules to more complex techniques. In a simple and basic way, Goslar and Schill [17] model context and situations using Topic Maps or Context Maps that represent real-world objects as topics. Schillit [18] captures the situational context using vectors that describe "the condition of situation, the sensing device, the required accuracy and update rate". In an object-oriented way, CoCo [19] represents context and situations using a graphical language and abstractions such as class, object, scales and factory. In the Context Modeling Language (CML) model, Henricksen [20-21] defines situations using predicate logic. Predicates are evaluated against a set of variable bindings and a context but the results are restricted to 'true', 'false' or 'possibly true'.

Situations are high level context that are inferred from low level context based on rules or reasoning algorithms. One of the major challenges in the situation reasoning is dealing with uncertainty. Bayesian reasoning is one of the methods used for dealing with uncertainty. In [5], Bayesian technique is applied for location tracking where location is computed by integrating readings of inaccurate sensors and in [6] it is used for estimation of indoor locations of devices. The probability model proposed in [7] extends an ontology-based model that uses Bayesian networks to reason about uncertainty. Applying Bayesian reasoning has the limitation of knowing prior probabilities in advance and this knowledge might not always be available.

The Dempster-Shafer theory is a well-known technique used for addressing uncertainty in context-aware computing. In [8], a weighted Dempster-Shafer evidence combining rule is introduced based on the historically-estimated correctness rate of sensors. A different approach proposed in [9] applies the Demspter-Shafer algorithm for context reasoning and the rough set technique for context aggregation.

Compared with other reasoning methods, the use of multi-value logic is appealing feature of the fuzzy logic for modeling uncertainty. In [10], a fuzzy representation of context is introduced for adaptation of user interface application on mobile devices and the same fuzzy concept has been used in [11] for providing the user with an explicit and meaningful explanation for the system's proactive behavior. Alternatively, in [12-13] fuzzy logic is used for defining the 'context situations' and the rules for adaptation of the service policies according to their fitness degree. The concept of situational computing using fuzzy logic presented in [1] is based on pre-developed ontologies and a similarity-based situation reasoning. Ranganathan et al. in [14] apply probabilistic logic when there is precise knowledge of event probabilities and fuzzy logic when this knowledge is not available.

Review of context modeling and reasoning approaches shows that most of these works do not provide a general approach that can be applied to different domains and have limited support for context-aware pervasive computing scenarios. A formal and unified context modeling and reasoning approach that can address different aspects of uncertainty in pervasive computing environments has not been introduced in the current state-of-the-art. The next section discusses the Context Spaces (CS) model and its underlying concepts and introduces the heuristics of CS for context reasoning.

3 The Context Spaces (CS) Model

The CS model represents contextual information as geometrical objects in multidimensional space called situations [2]. The basic concepts of the CS model are the context attribute, application space, context state and situation space.

A ‘context attribute’ describes any data used in the situation reasoning. The term ‘application space’ defines the universe of discourse and ‘context state’ refers to a collection of context values in CS. The concept of a ‘situation space’ is characterized by a set of regions. Each ‘region’ is a set of acceptable values of a context attribute that satisfies a predicate. A region is a crisp or conventional set of context attribute values such that any element is its member or not.

For example, a situation space called ‘healthy’ can be defined with a context attribute of heart rate. The region of values of heart rate can be between 45 and 85 bpm that satisfy two predicates of ≥45 bpm and ≤85 bpm. A context state with the value of 78 for heart rate is contained in the situation space of healthy and a context state with the value of 104 is not contained in that situation space.

In addition to basic concepts and techniques for situation modeling and reasoning, the CS model provides heuristics developed specifically for addressing context-awareness under uncertainty. These heuristics are integrated into reasoning techniques that are utility-based data fusion algorithms and compute the confidence level in the occurrence of a situation [14-15]. The two main heuristics of the CS model are as follows:

1. Individual significance (i.e. weight) and contribution of context attributes in the situation space
2. Inaccuracies of sensory originated information

These two heuristics deal with importance of each context attribute and sensors’ inaccuracies. To enable situation-awareness in pervasive applications, it is imperative to address the issue of uncertainty. The CS deals with uncertainty mainly associated with sensors’ inaccuracies. Yet there is another aspect of uncertainty in human concepts and real-world situations that needs to be represented in a context model and reflected in the results of situation reasoning. Fuzzy logic has the benefit of representing this level of uncertainty using membership degree of values.

The next section introduces the FSI model and discusses the CS model’s heuristics in more detail.

4 The Fuzzy Situation Inference (FSI)

The FSI model maps situation modeling concepts and reasoning methods of the CS model into a fuzzy structure and tailors them to conform to fuzzy logic principles. The following subsections discuss situation modeling and reasoning in the FSI model.

4.1 Modeling Situations

In the FSI model, the term linguistic variable is used to express a ‘context attribute’. Unlike context attributes, values that linguistic variables take are not numeric and are called terms (also known as fuzzy variables) [22]. Each term of a linguistic variable represents a fuzzy set that takes a pair of numeric values (i.e. a value and its membership degree). In a fuzzy set, unlike a region, membership of an item is gradual and is represented by a membership degree between 0 and 1 [23-25].

Definitions of ‘application space’ and ‘context state’ are applied similarly to the FSI model but the ‘situation space’ is differently defined. In FSI, a situation is defined by a set of fuzzy sets that are expressed as a FSI rule. Unlike CS, a situation can also be defined using multiple rules that have dependent or overlapping conditions to provide more flexibility in representing situations.

A FSI rule consists of multiple conditions joined with the AND operator where each condition can itself be a disjunction of conditions (i.e. using the OR operator) [26]. Each condition tests the input value using a membership function that corresponds to a fuzzy term. The consequent of the rule represents the output that suggests the degree of confidence in the occurrence of a situation. If the output of a rule evaluation for the ‘hypertension’ situation yields the value of 0.885, we can suggest that the level of confidence in the occurrence of ‘hypertension’ is 0.885. This value can be compared to a confidence threshold ε between 0 and 1 (i.e. predefined by the application’s designers) to determine whether a situation is occurring.

4.2 Situation Reasoning

The two reasoning methods of the CS model that we discuss here are based on the first and second heuristics introduced in Section 3.

Situation reasoning based on weights and contribution level. The first heuristic of CS deals with the weights of context attributes and the level of confidence of attributes’ values. Weights are values between 0 and 1 that are assigned to context attributes and represent relative importance of each context attribute for inferring a situation. A level of confidence is assigned to each element and reflects how that element relates to the modeled situation. The reasoning computation method based on weights and contribution levels of elements is as follows.

$$\text{Confidence} = \sum_{i=1}^{n} w_i c_i \ . \tag{1}$$

where w_i presents the weight assigned to context attributes and c_i denotes the confidence level of a context attribute. The contribution function that assigns the confidence values is proposed at a conceptual level and its implementation is later introduced in the second reasoning method based on sensors’ inaccuracy.

In FSI, the concept of weights is associated with the conditions of a rule but the concept of a contribution level is implemented in a different way. The FSI equivalent to the equation (1) is a rule evaluation method that computes a level of certainty between 0 and 1 using membership functions and presented as follows.

$$\text{Certainty} = \sum_{i=1}^{n} w_i \mu(x_i) \ . \tag{2}$$

where $\mu(x_i)$ denotes the membership degree of the element x_i and w_i represents a weight assigned to a condition. If the OR operator is used it will be evaluated using the maximum function. The result of $w_i\mu(x_i)$ represents a weighted membership degree of x_i and n represents the number of conditions in a rule (1≤i≤n).

Situation reasoning based on sensors' inaccuracy. To provide automatic computation of the contribution level at run-time, the second reasoning technique of CS incorporates the heuristic of sensors' inaccuracy presented as follows.

$$\text{Confidence} = \sum_{i=1}^{n} w_i . \Pr(\hat{a}_i^t \in A_i) \cdot \tag{3}$$

where $\Pr(\hat{a}_i^t \in A_i)$ presents the confidence level of a context attribute value by computing the probability of a context attribute correct value $\hat{a}_i^t$ being contained in the region A_i. To compute the probability value based on the reliability of a sensor, the reliability of reading (e.g. 95%) is used to represent the probability value (i.e. $\Pr(\hat{a}_i^t \in A_i)$=0.95). Second option to compute the probability value is to integrate the sensors' inaccuracy of reading rather than the reliability of reading. Using this option, the probability value is calculated in the following format:

$$\Pr(e_j \le a_i^t - \min(A_i^j)) - \Pr(e_j \le a_i^t - \max(A_i^j)). \tag{4}$$

where a_i^t denotes the sensed value of the context attribute, e_j denotes the sensor reading error (i.e. a_i^t - $\hat{a}_i^t$) and $\min(A_i^j)$ and $\max(A_i^j)$ represent minimum and maximum values of the region. This reasoning technique requires the estimation of the reading error distribution of sensors.

The CS equation (3) deals with uncertainty factoring in inaccuracies of sensors however this equation does not reflect delta changes of values in the equation and is not adequate to reason about vague situations. The FSI equivalent to the CS equation (3) not only incorporates the contribution level associated with sensors' inaccuracy but includes the membership of the values as another factor affecting the contribution level. In the FSI model, we first calculate the correct value based on the reliability or error rate and then pass it to the membership function as follows.

$$\text{Certainty} = \sum_{i=1}^{n} w_i \mu(f(x_i, e_i)) \tag{5}$$

where w_i represents a weight assigned to a condition and $\mu(f(x_i, e_i))$ denotes the membership degree of the element x_i . The function *f* calculates the correct value of the context based on the inaccuracy value e_i. If e_i is a reliability rate, the sensed value is multiplied by it and if it is an error rate (i.e. ±) it is added to the sensed value.

Although the CS model's heuristics and reasoning techniques deal with sensors' inaccuracy and characteristics of context attributes (i.e. not discussed in this paper), they are inadequate to represent the uncertainty associated with real-life and human concepts which tend to be abstract and imprecise.

The CS model computes a contribution level of context attribute values based on sensors' inaccuracy. This information might not be always available and obtainable but, more importantly, it is not sufficient for computing contribution levels of continuous values. This is due to the fact that there is an uncertainty factor related to the values that are near the boundaries of a region (i.e. maximum and minimum values). Using a fuzzy approach, this type of uncertainty can be represented and reflected in the situation reasoning results [3, 24-25]. The next section presents the implementation of the FSI model.

5 Implementation

We have implemented a prototype of health monitoring application based on FSI in J2ME and deployed it on a Nokia N95 (shown in Fig.1). The prototype reasons about situations of 'normal', 'pre-hypotension', 'hypotension', 'pre-hypertension' and 'hypertension'. This application can be used by patients who suffer from blood pressure fluctuations. A trapezoidal membership function is used to compute membership degree of context values. Contextual information used for reasoning includes systolic and diastolic blood pressure (SBP and DBP) and heart rate (HR).

Fig. 1. The prototype of a FSI-based health monitoring application running on a Nokia N95 with an ECG biosensor

To capture the patient's heart rate, we have used a two lead ECG biosensor from Alive Technologies [27] that transmits ECG signals using Bluetooth to the mobile phone. For the blood pressure, we have used randomly generated data that simulates blood pressure fluctuations. The health monitoring application performs situation reasoning in real-time on the mobile device. Status bars on the mobile phone displays the level of certainty and confidence in the occurrence of each situation.

To evaluate the FSI model we have conducted a comparative evaluation of the FSI, CS and Dempster-Shafer techniques that is presented in the next section.

6 A Comparative Evaluation

To evaluate the FSI model, we have compared the FSI situation reasoning technique to the CS and Dempster-Shafer (hereafter DS) reasoning approaches. The purpose of this evaluation is first to validate the FSI model against a well-known reasoning technique such as DS and a context model developed for pervasive computing environments such as the CS model. The second objective of the evaluation is to highlight the benefits of the FSI for reasoning about uncertain situations.

In this evaluation, we have considered situations of 'hypotension', 'normal' and 'hypertension'. These situations are defined using context attributes of systolic blood pressure (SBP) with the scale of 40-170 mm Hg, diastolic blood pressure (DBP) with the scale of 20-150 mm Hg and heart rate (HR) with the range of 20-150 bpm.

Table 1 depicts modeling of the three situations in the CS model including the weights of attributes and their corresponding regions of values. Unlike FSI, the CS model uses crisp boundary for regions. To provide a similar and balanced range of data for evaluation of these approaches, the boundaries of regions are selected in a way that they match the values of fuzzy sets with membership degree of 0.5.

Table 1. Situation definitions in the CS model.

Situation	Context attribute	Region of values	Weight
Hypotension	1=SBP	≤85	0.4
	2=DBP	≤60	0.4
	3=HR	≤45	0.2
Normal	1=SBP	>85 and ≤135	0.4
	2=DBP	>60 and ≤110	0.4
	3=HR	>45 and ≤85	0.2
Hypertension	1=SBP	>135	0.4
	2=DBP	>110	0.4
	3=HR	>85	0.2

Although FSI can represent a situation with multiple rules and each condition can be joined by the OR operator, we use one rule to define a situation and do not include the OR operator so that both models can be closely compared. The modeling of the three situations in the FSI model is presented in Table 2. Weights of conditions for the FSI rules conform to the weights specified for the context attributes in the CS model.

Table 2. Situation definitions in the FSI model.

Situation	Linguistic Variable	Terms	Fuzzy set
represented below via FSI rules	1=SBP 2=DBP 3=HR	low, normal, high low, normal, high slow, normal, fast	trapezoidal membership functions used
Rule1: if SBP is low and DBP is low and HR is low then situation is hypotension Rule2: if SBP is normal and DBP is normal and HR is normal then situation is normal Rule3: if SBP is high and DBP is high and HR is high then situation is hypertension			

To apply the DS algorithm for reasoning about situations, we use the Dempster's rule of combination. The normalized version of the combination rule is as follows.

$$m(R) = \frac{\sum_{P \cap Q = R} m_i(P).m_j(Q)}{1 - \sum_{P \cap Q = \phi} m_i(P).m_j(Q)} \tag{6}$$

where m(R) denotes the mass value computed for a proposition R given the evidences i and j. If R represents a situation, considering all existing propositions, the intersection of some of these propositions denoted as P and Q results in the proposition R (i.e. $P \cap Q = R$) and the intersection of other combinations of propositions results in an empty set.

To model the three situations of Hypotension (L), Normal (N) and Hypertension (H) with DS, we first need to define propositions and events. Since all three situations are incompatible we include a proposition of Unknown (U) that would consist of three situations. Then we identify the events and mass values that reflect the association of an event with the occurrences of each proposition. An example of the events and mass values are depicted in Table 3. Mass values are assigned in a way that they reflect to what degree each event indicates a situation.

Table 3. Definitions of events and mass values.

Event	Mass values for Normal	Mass values for Hypotension	Mass values For Hypertension	Mass values for unknown	Total mass
SBPLow (40-85)	0	0.7	0	0.3	1
SBPMed(86-135)	0.7	0	0	0.3	1
SBPHigh(136-170)	0	0	0.7	0.3	1
DBPLow(20-60)	0	0.7	0	0.3	1
DBPMed(61-110)	0.7	0	0	0.3	1
DBPHigh(110-150)	0	0	0.7	0.3	1
HRSlow(20-45)	0.2	0.4	0	0.4	1
HRMed(46-85)	0.4	0.2	0.2	0.2	1
HRFast(86-150)	0.2	0	0.4	0.4	1

Since we have based our situations on three context attributes, we define three mass functions of m_1, m_2 and m_3 corresponding to each context attribute. Then we apply DS combination over all propositions and available evidence. For example, if we have the context values of 82 for SBP, 52 for DBP and 58 for HR, we combine evidence for the occurrence of hypotension (L) as follows.

$$m_{12}(L) = \frac{\sum_{Q\cap R=L} m_1(A).m_2(B)}{1-\sum_{Q\cap R=\phi} m_1(A).m_2(B)} = \frac{m_1(L).m_2(L)+m_1(L).m_2(U)+m_1(U).m_2(L)}{1-m_1(L).m_2(H)-m_1(H).m_2(L)-m_1(L).m_2(N)-m_1(N).m_2(L)} = \frac{0.7\cdot 0.7+0.7\cdot 0.3+0.3\cdot 0.7}{1-0.7\cdot 0-0\cdot 0.7-0.7\cdot 0-0\cdot 0.7} \approx 0.91$$

$$m_{12}(H) = \frac{\sum_{Q\cap R=H} m_1(A).m_2(B)}{1-\sum_{Q\cap R=\phi} m_1(A).m_2(B)} = \frac{m_1(H).m_2(H)+m_1(H).m_2(U)+m_1(U).m_2(H)}{1-m_1(H).m_2(L)-m_1(L).m_2(H)-m_1(H).m_2(N)-m_1(N).m(H)} = \frac{0\cdot 0+0\cdot 0.3+0.3\cdot 0}{1-0\cdot 0.7-0.7\cdot 0-0\cdot 0-0\cdot 0} = 0$$

$$m_{12}(N) = \frac{\sum_{Q\cap R=N} m_1(A).m_2(B)}{1-\sum_{Q\cap R=\phi} m_1(A).m_2(B)} = \frac{m_1(N).m_2(N)+m_1(N).m_2(U)+m_1(U).m_2(N)}{1-m_1(N).m_2(L)-m_1(L).m_2(N)-m_1(N).m_2(H)-m_1(H).m(N)} = \frac{0\cdot 0+0\cdot 0.3+0.3\cdot 0}{1-0\cdot 0.7-0.7\cdot 0-0\cdot 0-0\cdot 0} = 0$$

$$m_{12}(U) = \frac{\sum_{Q\cap R=U} m_1(A).m_2(B)}{1-\sum_{Q\cap R=\phi} m_1(A).m_2(B)} = \frac{m_1(U).m_2(U)}{1-m_1(H).m_2(L)-m_1(L).m_2(H)-m_1(N).m_2(H)-m_1(H).m(N)-m_1(N).m_2(L)-m_1(L).m_2(N)} = \frac{0.3\cdot 0.3}{1-0\cdot 0.7-0.7\cdot 0-0\cdot 0-0\cdot 0-0.0.7-0.7.0} \approx 0.09$$

$$m_{123}(L) = \frac{\sum_{Q\cap R=L} m_1(A).m_2(B)}{1-\sum_{Q\cap R=\phi} m_1(A).m_2(B)} = \frac{m_{12}(L).m_3(L)+m_{12}(L).m_3(U)+m_3(U).m_{12}(L)}{1-m_{12}(L).m_3(H)-m_{12}(H).m_3(L)-m_{12}(L).m_3(N)-m_{12}(N).m_3(L)} = \frac{0.91\cdot 0.2+0.91\cdot 0.2+0.09\cdot 0.2}{1-0.91\cdot 0.2-0\cdot 0.2-0.91\cdot 0.4-0\cdot 0.2} = \frac{0.382}{0.454} \approx 0.841$$

The same DS reasoning computation presented above is used in our evaluation. Although, the DS theory has the strength of representing unknown or uncertainty, determination of mass values for propositions can be a difficult task, particularly that they can have impact on the other situations. For evaluation of CS and FSI, we use the equations (1) and (2) (discussed earlier). These techniques do not include the sensor's inaccuracy and could be compared to the DS method more accurately.

The dataset used for evaluation is generated continuously (data rate is 30 records/minute) in ascending order. For this set of experiments, we have used our data synthesizer to represent the different events defined in Table 3 that contribute to the occurrence of each pre-defined situation as well as the uncertain situations. Table 4 depicts a snapshot of 131 context states that is used along with their scales.

Table 4. The data used for the comparative evaluation.

Context attribute scales	Corresponding DS events
SBP:40-65, DBP: 20-45, HR: 20-45	**SBPLow, DBPLow, HRSlow**
SBP:66-80, DBP: 46-60, HR: 46-60	SBPLow, DBPLow, HRMed
SBP:81-85, DBP: 61-65, HR: 61-65	SBPLow, DBPMed, HRMed
SBP:86-105, DBP: 66-85, HR: 66-85	**SBPMed, DBPMed, HRMed**
SBP:106-130, DBP: 86-110, HR: 86-110	SBPMed, DBPMed, HRHigh
SBP:131-135, DBP: 111-115, HR: 111-115	SBPLow, DBPHigh, HRHigh
SBP:136-170, DBP: 116-150, HR: 116-150	**SBPHigh, DBPHigh, HRHigh**

Fig. 2 presents the results of comparative evaluation of three reasoning approaches of CS, DS and FSI for situations of ‘hypotension’, ‘normal’ and ‘hypertension’.

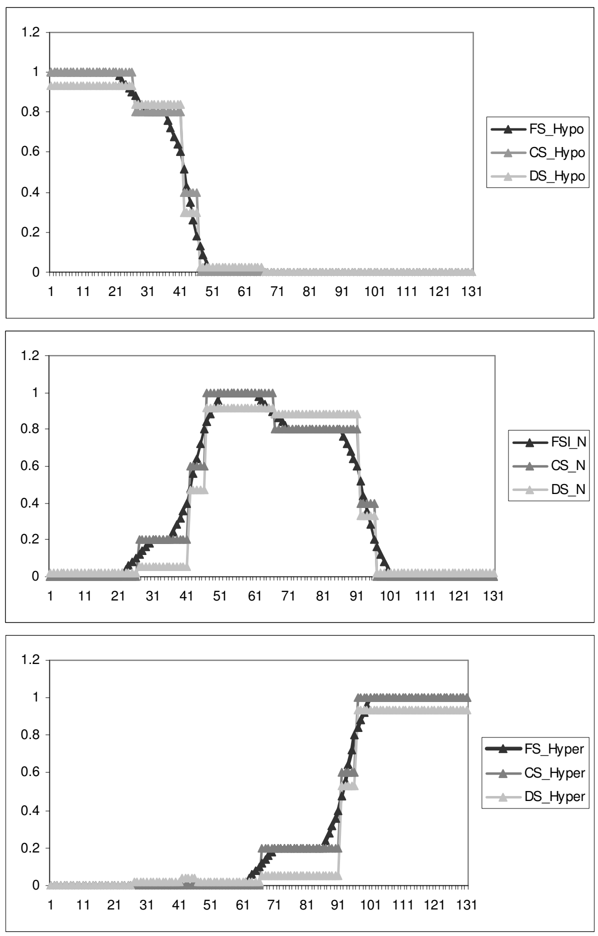

Fig. 2. Results of the comparative evaluation of the CS, DS and FSI reasoning approaches

Fig. 2 shows three approaches of CS, DS and FSI have a relatively similar trend according to context changes. When the data corresponds to a pre-defined situation the results of three approaches almost overlap. This overlapping is more noticeable with the CS and FSI models as they are based on similar heuristics.

However, when changes of data indicate the occurrence of an unknown and uncertain situation, differences of reasoning results between CS, DS and FSI are more apparent. Compared to FSI, the results of situation reasoning by the CS and DS methods show sudden rises and falls with sharp edges when situations change which do not match the real-life situations. This is because the DS and CS approaches do not deal with delta changes of the values and are not able to reflect the gradual evolution of one situation to another situation. When the value of context attributes decreases or increases, its membership degree also increases and decreases accordingly and gradually. This enables FSI to provide more accurate situation reasoning results in terms of reflecting very minor changes of context.

The evaluation validates the accuracy of the FSI model for situation modeling and reasoning and it also shows that FSI is able to reflect very minor changes of context in situation inference and represent changes in a more gradual and smooth manner.

The evaluation shows that the FSI model is more appropriate approach for representation of human concepts and for reasoning about the real-world situations that are defined by continuous values. Health-related situations are examples of these types of scenarios where FSI can prove to be more fitting approach compared to the DS and CS reasoning approaches.

7 Conclusion

Situation modeling and reasoning under uncertainty are challenging research tasks in context-aware pervasive computing. Fuzzy logic has the potential to represent the fuzziness and uncertainty that is associated with real-world situations. However, application of a fuzzy approach per se can not be adequate for situation modeling and reasoning in pervasive computing environments. Therefore, it is imperative that a fuzzy modeling and reasoning method to be combined with a rich theoretical basis for supporting context-aware scenarios.

In this paper, we proposed a Fuzzy Situation inference (FSI) model that integrates fuzzy logic into the CS model, a formal and general context reasoning and modeling technique for pervasive computing environments. The strengths of fuzzy logic for modeling imperfect context and reasoning about vague situations are combined with the CS model's underlying theoretical basis for supporting context-aware and pervasive computing scenarios. An implementation and evaluation of the FSI model were presented through a scenario in health monitoring to highlight the benefits of the FSI technique for context reasoning under uncertainty.

The FSI model is a part of our architecture for adaptive mobile data stream mining. In this project, we use the results of FSI for gradual tuning of parameters of data stream mining algorithms and perform intelligent and real-time analysis of data stream generated from sensors on mobile devices. The analysis is underpinned using situation-aware adaptation. In the future, we intend to explore and model relationships between situations, and extend FSI with learning capabilities so the system can predict situations.

References

1. Haghighi, P., Zaslavsky, A., Krishnaswamy, Sh.: An Evaluatation of Query Languages for Context-Aware Computing, in the 1st International Workshop on Flexible Database and Information Systems Technology (FlexDBIST-06), Held in conjunction with DEXA-06 International Conference on Database and Expert Systems Applications, IEEE Computer Society Press: Crakow, Poland (2006).
2. Padovitz, A., Loke, S., Zaslavsky, A.: Towards a Theory of Context Spaces. In Proceedings of the 2nd IEEE Annual Conference on Pervasive Computing and Communications, Workshop on Context Modeling and Reasoning (CoMoRea), IEEE Computer Society, Orlando, Florida (2004).
3. Anagnostopoulos, C.B., Ntarladimas Y., Hadjiefthymiades, S.: Situational Computing: An Innovative Architecture with Imprecise Reasoning, the Journal of Systems and Software vol. 80, pp. 1993-2014 (2007).
4. Satyanarayanan M.: Coping with Uncertainty, IEEE CS Pervasive computing Journal, Modeling uncertainty in context-aware computing, (2001).
5. Fox, D., Hightower, J., Liao, L., Schulz, D., Borriello, G.: Bayesian filtering for location estimation, IEEE Pervasive Computing, 2003.
6. Castro, P. Munz, R.: Managing context data for smart spaces, IEEE Personal Communications, vol. 7(5), pp. 4-46, (2000).
7. Gu, T., Pung, H., Zhang, D.: A Bayesian approach for dealing with uncertain contexts. In: The Proceeding of the Second International Conference on Pervasive Computing (2004).
8. Wu, H., Siegel, M., Stiefelhagen, R., Yang, J.: Sensor Fusion Using Dempster-Shafer Theory, In Proc. of IMTC'02, Anchorage, AK, USA (2002).
9. Jian, Z., Yinong, L., Yang, J., Ping, Z.: A Context-Aware Infrastructure with Reasoning Mechanism and Aggregating Mechanism for Pervasive Computing Application, Proceedings of the 65th IEEE Vehicular Technology Conference (VTC Spring 2007), pp. 257-261, Dublin, Ireland (2007).
10. Mäntyjärvi, J., Seppanen, T.: Adapting Applications in Mobile Terminals Using Fuzzy Context Information, In the Proceedings of 4th International Symposium on Mobile HCI2002, pp. 95-107, Italy (2002).
11. Byun, H., Keith, C.: Supporting Proactive 'Intelligent' Behaviour: the Problem of Uncertainty, Proceedings of the UM03 Workshop on User Modeling for Ubiquitous Computing, pp. 17–25, Johnstown, PA (2003).
12. Cao, J., Xing, N., Chan, A., Feng, Y., Jin, B.: Service Adaptation Using Fuzzy Theory in Context-aware Mobile Computing Middleware, In Proceedings of the 11th IEEE Conference on Embedded and Real-time Computing Systems and Applications (RTCSA'05) (2005).
13. Cheung, R.: An Adaptive Middleware Infrastructure Incorporating Fuzzy Logic for Mobile computing, In Proceedings of the International Conference on Next Generation Web Services Practices (NWeSP'05) (2005).
14. Ranganathan, A., Al-Muhtadi, J., Campbell, RH.: Reasoning about Uncertain Contexts in Pervasive Computing Environments. In IEEE Pervasive Computing, vol. 3, No. 2, pp. 62-70 (2004).

15. Padovitz, A., Loke, S.W., Zaslavsky, A., Burg, B. and Bartolini, C.: An Approach to Data Fusion for Context-Awareness. Fifth International Conference on Modeling and Using Context, CONTEXT'05, Paris, France (2005).
16. Padovitz, A., Zaslavsky, A. and Loke, S.W.:. A Unifying Model for Representing and Reasoning About Context under Uncertainty, 11th International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems (IPMU), July 2006, Paris, France (2006).
17. Goslar, K., Schill, A.: Modeling Contextual Information Using Active Data Structures. In Workshop for Pervasive Information Management (PIM), International Conference on Extending Database Technology (EDBT), Heraklion, Crete, Greece (2004).
18. Schilit, B.N., Theimer, M.M., Welch, B.B.: Customizing Mobile Applications. In Proceedings USENIX Symposium on Mobile and Location-Independent Computing, (USENJX Association) (1993).
19. Buchholz, T., Krause, M., Linnhoff-Popien, C., Schiffers, M.: CoCo: dynamic composition of context information. In the 1st Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services (MOBIQUITOUS 2004) Boston, Massachusetts (2004).
20. Henricksen, K., Indulska, J.: Modelling and Using Imperfect Context Information. In Proceedings of the 2nd IEEE Annual Conference on Pervasive Computing and Communications. Workshop on Context Modelling and Reasoning (CoMoRea'04), Orlando, Florida: IEEE Computer Society (2004).
21. McFadden, T., Henricksen, K. and Indulska, J. (2004). Automating context-aware application development. In UbiComp 1st International Workshop on Advanced Context Modelling, Reasoning and Management, pp. 90-95, Nottingham (2004).
22. Zadeh, L.A.: The Concept of a Linguistic Variable and Its Application to Approximate Reasoning Information Systems, pp. 199-249 (1975).
23. Mendel, J.M.: Fuzzy Logic Systems for Engineering: A Tutorial. Proceedings of the IEEE, 83(3): pp. 345-377 (1995).
24. Jang, J.R., Sun, Ch., Mizutani, E.: Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice-Hall: Upper Saddle River, NJ, (1997).
25. Zimmermann, h.J.: Fuzzy Set Theory - and Its Applications. Kluwer Academic Publishers, Norwell, Massachusetts (1996).
26. Bruce, G., Buchanan, B.G., Shortliffe, E.D.: Rule-based expert systems : the MYCIN experiments of the Stanford Heuristic Programming Project. Reading, Mass.: Addison-Wesley (1984).
27. Alive Technologies, http://www.alivetec.com