Padovitz A., Zaslavsky A., 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.

A Unifying Model for Representing and Reasoning About Context under Uncertainty

Amir Padovitz[1] **Arkady Zaslavsky**[1] **Seng W. Loke**[2]
[1]Centre for Distributed Systems and Software Engineering, Monash University
900 Dandenong Rd., Caulfield-East, Victoria, Australia
{amirp, arkady.zaslavsky@csse.monash.edu.au}
[2]Department of Computer Science and Computer Engineering, LaTrobe University

Abstract

Modeling and reasoning about context under uncertainty is a major challenge in context-aware computing. This paper proposes a novel approach to represent context in a unifying way and to perform reasoning about context represented with that model, under uncertainty. We develop a novel reasoning approach based on Multi-Attribute Utility Theory as the means to integrate heuristics about the relative importance, inaccuracy and characteristics of sensory information. Our approach allows applying different reasoning approaches, and in this paper we qualitatively and quantitatively compare between our proposed reasoning approach and Dempster-Shafer sensor data fusion technique.

Keywords: context modeling and reasoning, context uncertainty

1. Introduction

Research in context-aware pervasive computing investigates the context in which entities in a pervasive system operate and their awareness to changes in that context. Research in Context-awareness progressively evolves towards dealing with major challenges originating from the underlying characteristics of pervasive systems. One such major challenge is dealing with high degree of uncertainty that is associated with the process of reasoning about context. Context-aware computing is challenged by the need to handle uncertainties that emerge when systems attempt to become aware (at runtime) of desirable situations but are unable to reason effectively about the correct situation [12, 13]. There is an inherent gap between the real-world and the world that can be perceived by computer systems, yielding uncertainty in system perceived context, with consequent effect on the performance of context-aware systems.

As a next step in modeling and reasoning about context, this paper presents a new approach to model context and situations, called “Context Spaces”. The model provides a unifying and insightful way to model context and enables consistent reasoning over the modeled information in uncertain conditions. Based on the model we apply different reasoning techniques, and in this paper we focus on two, namely, Dempster-Shafer integration of information [17] and a novel approach to reason about context using heuristics and Multi-Attribute Utility Theory [11]. In Section 2 we discuss related work in modeling and reasoning about context. In Section 3 we present our context modeling approach. Section 4 presents two reasoning approaches applied over the context model, namely, a novel heuristically-based technique and Dempster-Shafer-based integration. We evaluate these approaches, qualitatively and quantitatively in Section 5. We conclude in section 6.

2. Background

In recent years, research efforts have focused on various aspects of context, including context middleware and toolkits [2, 4, 1] for information acquisition, and ontologies that provide vocabularies to describe context [2, 3]. The task of abstracting and generalizing context has been a focus of attention in recent research, attempting to identify important contextual abstractions and important characteristics of context [e.g. in 9, 4, 15]. The issue of uncertainty, arguably, a fundamental concern in sensor-based pervasive computing ([21, 7]) has only been considered by a very limited number of models, e.g. [7, 8, 16]. We have also witnessed initial attempts to discover and reason about data inconsistencies with techniques which make use of ontologies that describe the context-aware application domain [e.g., 3, 18]. These approaches are suitable for discovering information discrepancies and reasoning is often applied with application-specific rules. Alternative approaches, attempting to address the challenge of reasoning in uncertain conditions, focus on sensor data fusion techniques in an attempt to achieve context and situation awareness (e.g., in [6, 5, 20, 19]).

3. Context Spaces model

The paradigm of context-aware computing can be thought of as an attempt to obtain information with limited sensing capabilities, but which nevertheless reflects circumstances useful to the application. The nature of context can, therefore, be considered as the constrained view that a system has of the world, which can either be immediately used (for triggering actions) or require additional computation for determining occurrences of situations (i.e. more elaborate reasoning). Hence, we fundamentally distinguish between a set of events that reflect a specific condition of a system, and the notion of situations that can be inferred using that contextual knowledge.

Consistent with this view, we express our context related philosophy in the Context-Situation pyramid. We observe a three-level hierarchy of concept abstractions. First is the basic level of raw data. This information (perhaps with some computation) is used to create a notion of context; i.e., context is the information used in a model for representing real world situations. Then, as a meta-level concept over context, we observe the notion of situations, which can be inferred by analyzing the contextual information. An illustration of this hierarchy is presented in Figure 1.

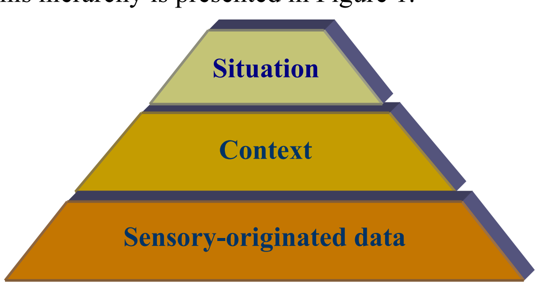

Fig. 1 – Context-Situation Pyramid, a three level hierarchy of concepts for modeled information

Many-to-many relationships can exist between modeled information and actual situations. Being in a specific context may indicate several possible situations (hence the need for additional reasoning) and different sets of modeled information can describe a specific situation.

3.1 Modeling principles

Context Spaces uses geometrical metaphors to describe context and situations as first-class objects of the model. We start by defining the *application space* – the universe of discourse in terms of available contextual information for an application. The application space comprises types of information that are relevant and obtainable to the system. An information type is termed a *context attribute* and is denoted by a_i. The value of a sensor reading at time t is the context-attribute value at time t and is denoted by a_i^t. The application space is a multi-dimensional space made up of a domain of values for each context attribute, in which context can be sensed. Within it we perceive subspaces (possibly defined in fewer dimensions), which reflect real-life situations. We call these subspaces *situation spaces*. Situation spaces are defined over regions of acceptable values in selected dimensions and represent collections of values that reflect real-life situations. An acceptable region of values is denoted by A_i^j and defined as a set of elements V that satisfies a predicate P, i.e. $A_i^j = \{V \mid P(V)\}$. The situation space is represented by a tuple of these regions and denoted by $S_j = (A_1^j, A_2^j, ..., A_n^j)$ (consisting of n acceptable regions for these attributes).

The actual values of sensory originated information are defined by the *context state*, e.g., the collection of current sensor readings.

A general illustration of these concepts is presented in Figure 2. A situation space is made up of three dimensions or context attributes, satisfying individual predicates. The context state is plotted at different times (C_i^{t1} and C_i^{t2}) representing a collection of different specific values. At time t_1 the state corresponds to (or contained within) the situation space definition and at time t_2 the context state position is outside the situation space definition.

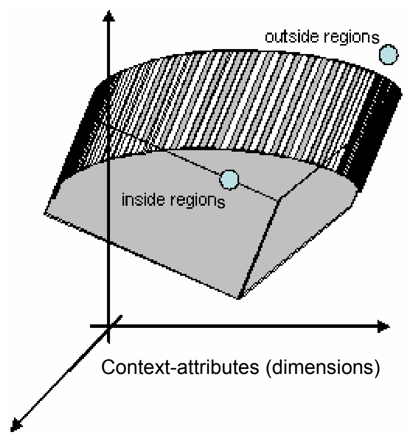

Fig. 2 – A visualization of a situation space and context state at different times.

4. Reasoning under uncertainty

To reason about context and situations represented with Context Spaces under uncertainty we can apply a number of reasoning approaches. We first develop a novel reasoning based on Multi-attribute Utility Theory (MAUT) [11]. Then we illustrate applicability of other reasoning techniques over the model with Dempster-Shafer integration approach [17]. We compare these reasoning approaches and highlight benefits of using the proposed MAUT-based algorithm for reasoning about context.

4.1 Reasoning based on MAUT

To reason effectively about context we have identified different heuristics that are applicable to context-aware computing. In artificial intelligence, heuristics represent rules of thumb, mostly based on expert experience or common sense used as guidelines for solving a problem.

We propose the use of MAUT as the means to integrate such heuristics into a confidence measure reflecting the degree of confidence in the occurrence of a situation. Consider the following extensions to the basic model.

Relevance function - In many cases some types of information are more important than others for inferring a situation, e.g., high body temperature may be a strong indication of a general sickness of a person while other attributes may not be so important in inferring that specific situation. To model this difference in the importance of context attributes for inferring a situation, we define the relevance function, which assigns weights $w_1, w_2 ..., w_n$, ($w_i \in [0,1]$, $\sum_{i=1}^{n} w_i = 1$) to context attributes. The weights reflect how important each attribute is (relative to other attributes) for describing a situation.

Contribution (utility value) function - In the relevance function, we model the relative importance between the attributes of a situation space, whereas in the contribution function we model the individual contribution (or impact) of elements within a specific region for inferring a situation. That is, rather than merely knowing that the sensed value is within or not within a region, if the value is within, we also consider the particular value itself. The fact that the value is within the region is indicative of the situation, and even more so if the value is in some particular range (within the region) - how much so (determining a value $c \in [0,1]$ for that element) is what the contribution function represents.

The contribution of a context attribute value can also be affected by the accuracy of sensor readings. The fact of an inaccurate sensor can be incorporated in the contribution function, which may provide low support levels for values that are similar but not actually contained within the specific region. This is similar to membership functions in Fuzzy Sets [22], where functions compute a degree of membership between a value and a known set. The contribution function can, thus, enable modeling of uncertainty about sensor readings and incorporate those as part of the reasoning process.

This feature can be used to incorporate sensor inaccuracies as part of the reasoning process. We illustrate this idea in Figure 3. The top left and bottom left diagrams illustrate contribution levels, assigned to values within the region; the top right and bottom right diagrams illustrate contribution functions that consider possible inaccuracy in the obtained context attribute value and therefore assign low support values for sensed information outside the region.

Using the above definitions we allow uncertainty or imprecision in determining situation occurrences based on modeled context. So, indicators (or evidential support) for the occurrence of a situation are represented by the values (of context attributes) in the context state being within the accepted regions of the

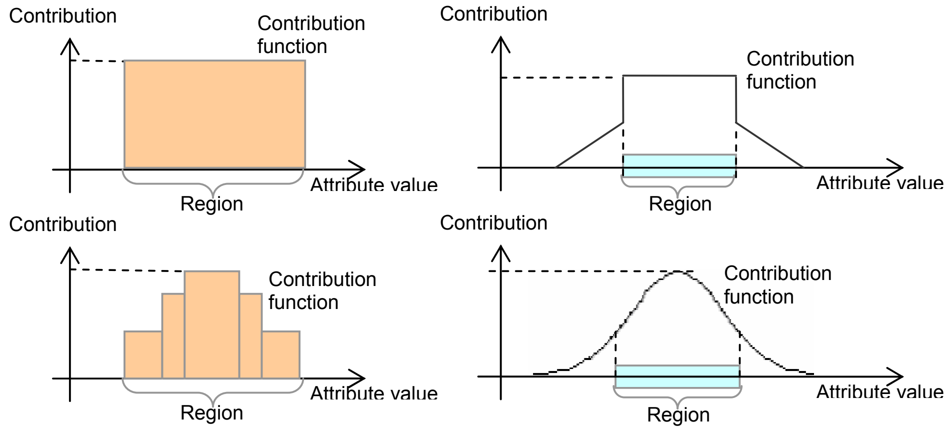

Fig. 3 – Examples of contribution functions defining the contribution level of a given value of a context attribute for inferring the occurrence of a situation

situation space and quite strongly indicative if they also fall within particular ranges. The fact of some context attribute value being outside its respective region in the situation space weakens the likelihood of that situation.

To consider such a view in practice we make use of Multi-Attribute Utility Theory (MAUT) [11] that takes the information represented by the model (i.e. the condition of the context state and the definition of the situation space to be inferred) and computes a measure of confidence in the occurrence of that situation. Computed confidence is then compared with a confidence threshold, to facilitate a decision regarding the occurrence of the situation. (We compare the computed confidence with the individual threshold of the particular situation, thereby gain the ability to compare outcomes computed for different situations.)

MAUT provides a convenient way for combining together seemingly different contributions into a single measure, expressing the result in terms of utility [11]. In our case, we see utility (or contribution towards our goal of determining the occurrence of a situation) as the degree of evidential support given to the hypothesis of a situation occurring when a context attribute value is within the corresponding region. The more indicators we have that the context state matches the definition of a situation space, the greater utility is gained.

MAUT is considered an evaluating scheme, which provides a general evaluation function *v(x)* over an object *x* to denote the overall object's utility. The evaluation function is traditionally defined as a weighted accumulation of evaluating the objects' value dimensions, which represents a combination of different contributions relevant to the object. The computation results in a single numerical measure ranging between 0 and 1.

A function computing the confidence in the occurrence of a situation, considering the concepts we discussed so far, and which results in a single numerical measure ranging between 0 and 1, is the following:

$$(2)\ Confidence = \sum_{i=1}^{n} w_i c_i$$

Where w_i denotes a weight assigned by the relevance function for a region i in a situation space, and c_i denotes the contribution level of context attribute *i*'s value in the definition of the situation space.

4.1.1 Incorporating Additional Heuristics

The power of our MAUT-based proposed integration approach is the ability to accommodate seemingly different heuristics into a single confidence measure. Consider the following additional heuristics.

(i) **Sensors inaccuracies -** We extend the reasoning procedure by incorporating into the confidence measure a heuristic that allows integration of additional knowledge about sensor inaccuracies as part of the reasoning process, at run-time. This heuristic state that the greater likelihood of a context attribute being contained within a region, the greater contribution should be evaluated for that context attribute, and vice-versa. The heuristics provides an approach to compute the contribution level of a sensor reading at run-time, rather than modeling it at design-time. So, for example when we sense dimmed lights in the smart room, it might be a strong indication of a presentation taking place. However, if the light sensor is inaccurate (and might actually sense normal light levels) then the contribution of sensing dimmed lights towards inferring a presentation should be reduced. This kind of heuristic enables more accurate distinction between available information for reasoning under uncertain condition. We represent the confidence measure using this heuristic as:

(2) $\mu(S) = \sum_{i=1}^{n} w_i \cdot \Pr(\hat{a}_i^t \in A_i)$, where the term $\Pr(\hat{a}_i^t \in A_i)$ represents the confidence of having the correct value being sensed contained within its corresponding region of acceptable values.

(ii) **Characteristics of context attributes** - We distinguish between two types of context attributes in regard to the definition of a situation space, which have different effects over the reasoning outcome, as follows.

Symmetrically Contributing – a context attribute that increases the confidence in a situation taking place if its value is within the corresponding region, and decreases the confidence if it is outside that region.

Asymmetrically Contributing - a context attribute that increases the confidence in a situation taking place if its value is within the corresponding region but sensing values outside the accepted region would not decrease the computed confidence.

To consider this heuristic for reasoning we evaluate the containment of asymmetric attributes in the corresponding acceptable region of values. If some asymmetrical attributes are not contained in their respective regions then they are ignored and the weights of the remaining context attributes (the symmetric ones) are recalculated to maintain their relative importance.

Reasoning with Dempster-Shafer

Dempster-Shafer [42] (hereafter DS) is a statistically based technique for combining evidence and can be considered a generalization of Bayesian theory as it allows assignment of probability to uncertain events, offering a way to represent ignorance or uncertainty [Q18]. In general terms, DS deals with a set of exclusive and exhaustive propositions, called the frame of discernment (denoted by Θ). In our case, these propositions are the possible inferred context situations known to the system and can also include unknown possible situations. An important ingredient in DS is the definition of a mass distribution function *m*( ), which provides a measure of uncertainty, applied over all the subsets of elements in the frame of discernment, and which satisfies the following properties:

(1) $m: 2^{\Theta} \rightarrow [1,0]$, (2) $m(\phi) = 0$, (3) $\sum_{A \subseteq \Theta} m(A) = 1$.

DS provides a rule, known as Dempster's rule of combination, for combining evidence, possibly originating from different sources (e.g. sensors). The combination yields a probability mass assigned to a subset of Θ (i.e., some situation or combination of situations), given a subset of propositions *A*, characterized by a mass distribution m_1 and subset of propositions *B*, characterized by a mass distribution m_2. The normalized version of the combination rule is the following:

(4) $$m(C) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \phi} m_1(A) m_2(B)},$$

where *m(C)* denotes the combined evidence.

A beneficial characteristic of DS is the ability to use partial knowledge over propositions and represent ignorance or uncertainty as part of the modeling process. For example, the knowledge relating the probability of having the union or disjunction of a specific subset of propositions, given the evidence can be modeled without the need to evaluate the mass for the individual elements in that set. A shortcoming of DS is related to the use of masses instead of probability measures and the difficulty to determine these values [10]. Masses can "only more or less be understood as probabilities" ([10]) and difficulties in coming up with these values arise when computing mass values to represent subsets of propositions and ignorance [10].

DS can be applied over the Context Spaces model by computing the mass distribution function for occurrences of events representing context attribute values contained in corresponding regions of values. This can be represented in Context Spaces terms as follows.

(5) $$m(C) = \frac{\sum_{A \cap B = C} m < a_1 > (A) \cdot m < a_2 > (B)}{1 - \sum_{A \cap B = \phi} m < a_1 > (A) \cdot m < a_2 > (B)},$$

where *m(C)* denotes the mass of the combined evidence supporting situation *C*, *A* and *B* are situation spaces or subsets of situation spaces, and $m < a_i > (A)$ represents mass value computed for situation *A* with sensory information about context-attribute a_i. In other words, whenever context attribute values satisfy specific predicates of regions of acceptable values, a mass probability is computed according to the prescribed properties and uncertainty estimation.

5. Evaluation of reasoning approaches

Governed by strict mathematical properties, Dempster-Shafer has been criticized on the difficulty in coming up with the values for the mass functions [10]. The way to assign values to the mass distribution functions may be unclear. For instance, how much of it supports the propositions and to what degree should ignorance be represented in the relation between the evidence and propositions? Masses can "only more or less be understood as probabilities" ([10]) and thus it can be difficult to incorporate uncertainty and subsets of situations into the model. Our proposed MAUT-based approach provides an alternative approach of modeling relevant information for the reasoning process, which is simpler and comprehensible. While DS provides a general purpose approach for reasoning, the heuristically-based reasoning is specifically designed for context-aware systems. It differs from DS in two notable properties. Firstly, it uses specific heuristics to determine occurrences of situations in context-aware settings. This makes our approach less general but more applicable to context-aware computing. Secondly, it uses a different approach to represent contextual information, which can be more easily used by context-aware systems.

The different approach of representing information also affects the characteristics of the reasoning and needs to be considered by the application. An example would be the flexibility or the ability to add new elements to a context-aware system. In DS, defining new situations requires examining all the rules associated with each evidence. In our proposed approach, adding new situations would be simple and straightforward as they represent the starting point of the modeling process, and are, therefore, decoupled from other modeled situations.

From a reasoning perspective, our algorithm offers a novel methodology for integrating context information for reasoning about situations. It offers the flexibility to choose between heuristics that are relevant to context-aware systems. By considering our proposed heuristics the reliability of the data fusion algorithm is enhanced. For example, characterizing the context attribute (i.e., symmetric or asymmetric) in relation to the situation, or integrating inaccuracy estimations in the data fusion algorithm makes the overall inference more reliable. The differences discussed so far affect the application of our approach, not only in its flexibility and ease of use, but have distinct impact over the performance of reasoning, which is more attuned to context related considerations.

To illustrate behavioral differences resulting from applying the heuristics, we illustrate an experimental comparison with a method that does not consider these heuristics (represented by DS). While it is difficult to quantitatively compare inherently different approaches (for instance, DS does not question the accuracy of the sensed evidence whereas our model does), we seek to show how the approaches behave differently, given different algorithmic considerations under unpredictable environmental changes.

We have simulated a scenario of a user presenting, attending another's presentation or participating in a meeting. We have used different context attributes in defining these activities, such as inferred user location, room light and noise levels, number of people in the room and user's notebook activity. In order to align DS results with ours we have evaluated the probability of having some evidence and incorporated it as part of the mass probability function assigned to situations. Our aim here is to compare the behavior of algorithms rather than the absolute outcome of the processes.

Figures 4a, 4b, 5a and 5b illustrate results of experimental runs with a sequence starting with the user first attending a presentation, then presenting and finally participating in a meeting. We have defined the context attributes: notebook activity, active presentation process

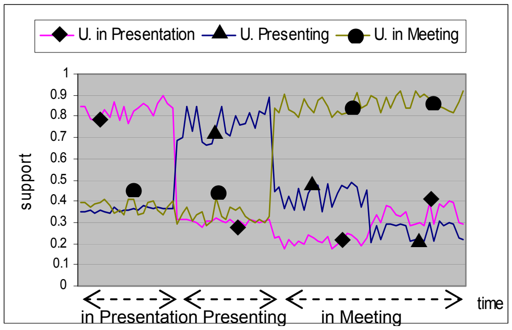

Fig. 4a - MAUT - notebook ON during meeting

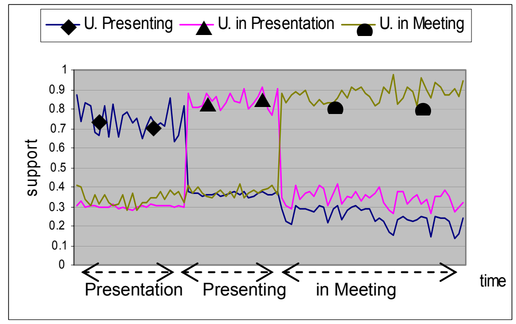

Fig. 5a - MAUT – PDA taken away during meeting

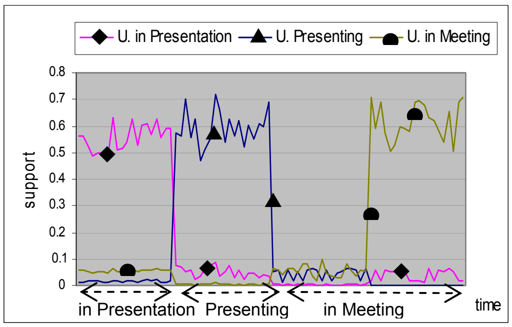

Fig. 4b - DS - notebook ON during meeting

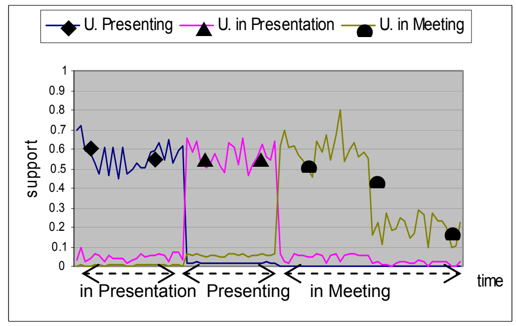

Fig. 5b - DS – PDA taken away during meeting

and personal PDA location as asymmetric. These definitions accommodate the possibility of the user forgetting or not immediately switching off his/her notebook or presentation process when joining the meeting or leaving his/her PDA elsewhere (e.g., in the office or at home).

The results clearly show the significance of context attributes characterization when the user activity is different than what is anticipated. During experimentation we have simulated the user switching off his/her notebook in the middle of the meeting or switching off/leaving the PDA at the office. In our approach, using the asymmetric attributes, the user is correctly inferred as being in the meeting during all the meeting time, whereas a sharp incorrect decline is observed in confidence levels in the other reasoning approach, when the notebook is still switched on during meeting or PDA is taken by another user elsewhere.

These results demonstrate the need to incorporate context-related heuristics such as symmetric and asymmetric context attributes. They also reflect distinct behavioral differences and actual different results during the computation of the two fusion approaches. The choice of technique needs to be determined by the specific application, judging the suitability of considering context-related information as part of the fusion process.

5 Conclusion

We have presented a unifying model for describing and consequently reasoning about context in a general way. The model's fundamental concepts make use of insights from geometrical spaces and provide an approach for reasoning about context and situations of interest of a context-aware system. We have described situations as geometrical structures in multidimensional space and investigated their relationships with the system state in a given context. We have examined two reasoning approaches and have highlighted the benefits of applying heuristics in reasoning about context. The fundamental method of performing reasoning remains, however, the same for any type of additional considerations, and based on the unifying characteristics of the model. It is built on a theoretical perspective about what it means for a situation to occur: the occurrence of a situation is represented by a tuple of values (i.e., the context state comprising values obtained via sensors (and perhaps some reasoning)) being within a tuple of accepted regions (i.e. the situation space representing the situation).

Acknowledgements

We thank Hewlett-Packard (HP) for sponsorship of this work.

References

[1] Campbell R. H., Ranganathan A., 2003, A middleware for Context-Aware Agents in Ubiquitous Computing Environments, ACM/IFIP/USENIX International Middleware Conference, Rio de Janeiro, Brazil.

[2] Chen H., Finin T., Anupam J., 2003, An Intelligent Broker for Context-Aware Systems, International Conference on Ubiquitous Computing (Ubicomp), Seattle, Washington.

[3] Chen H., Finin T., Anupam J., 2003, An Ontology for Context-Aware Pervasive Computing Environments, Workshop on Ontologies and Distributed Systems, IJCAI-2003, Acapulco, Mexico.

[4] Dey A. K., Salber D., Abowd G. D., 2001, A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications, Human-Computer Interaction, Vol. 16 pp. 97-166.

[5] Fox D., Hightower J., Liao L., Schulz D., Borriello G., 2003, Bayesian filtering for location estimation, IEEE Pervasive Computing Journal.

[6] Gellersen H.W., Schmidt A., Beigl M., 2002, Multi-Sensor Context-Awareness in Mobile Devices and Smart Artifacts, in Mobile Networks and Applications (MONET).

[7] Henricksen K., Indulska J., 2004, Modelling and Using Imperfect Context Information, workshop on Context Modeling and Reasoning (CoMoRea), at 2nd IEEE International Conference on Pervasive Computing and Communication (PerCom'04), Orlando, Florida.

[8] Judd G., Steenkiste P., 2003, Providing contextual information to pervasive computing applications, In proc. of 1st IEEE Conference on Pervasive Computing and Communications (PerCom), pp. 133-142, FortWorth.

[9] Kindberg, T., et al., 2000, People, places, things: Web presence for the real world. Technical Report HPL-2000-16, Hewlett-Packard Labs.

[10] Koks D., Challa S., An Introduction to Bayesian and Dempster-Shafer Data Fusion, *Technical report DSTO-TR-1436, DSTO Systems Sciences Laboratory*, Australia, August 2003, http://www.dsto.defence.gov.au/publications/2563/DSTO-TR-1436.pdf

[11] Winterfeld D. and Edwards W., 1986, Decision Analysis and Behavioural Research, Cambridge University Press, Cambridge, England.

[12] Satyanarayanan M., Pervasive Computing: Vision and Challenges, IEEE PCM August 2001, pp. 10-17.

[13] Satyanarayanan M Coping with Uncertainty, IEEE CS Pervasive computing Journal, August 2001.

[15] Roman M., Hess C., Cerqueira R., Ranganathan A., Campbell R. H., Nahrstedt K., A, 2002 Middleware Infrastructure for Active Spaces, IEEE Pervasive Computing, Special Issue on Wearable Computing, Vol. 1, Issue 4, pp.74-83.

[16] Schmidt A., Van Laerhoven K., 2001, How to build smart appliances, 2001, IEEE Personal Communications, Special Issue on Pervasive Computing, Vol. 8, Issue 4, pp. 66-71.

[17] Shafer G., 1976, A Mathematical Theory of Evidence, Princeton University Press, Princeton, NJ.

[18] Strang T., Linnohff-Popien C., Frank K., 2003, Integration Issues of an Ontology Based Context Modelling Approach, IADIS, International Conference WWW/Internet (ICWI), Argarve.

[19] Van Laerhoven K, Aidoo K, Lowette S, 2001, Real-time analysis of Data from Many Sensors with Neural Networks, In Proc. of 5th International Symposium on Wearable Computers, (ISWC'01), Zurich, Switzerland.

[20] Wu H., Siegel M., Stiefelhagen R., Yang J., 2002, Sensor Fusion Using Dempster-Shafer Theory, *In Proc. of IMTC'2002*, Anchorage, AK, USA.

[21] Yoshimi B., On Sensor Frameworks for Pervasive Systems, *Workshop on Software Engineering for Wearable and Pervasive Computing (SEWPC)* at ICSE, Limerick, Ireland.

[22] Zadeh, L., Outline of a New Approach to the Analysis of Complex Systems, *IEEE Transactions on System, Man and Cybernetics* Vol. 3, 1973.