Smart Healthcare Applications and Services:
Developments and Practices

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Chapter 6
Resolving and Mediating Ambiguous Contexts in Pervasive Environments

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ABSTRACT

Pervasive computing applications envision sensor rich computing and networking environments that can capture various types of contexts of inhabitants of the environment, such as their locations, activities, vital signs, and environmental measures. Such context information is useful in a variety of applications, for example to manage health information to promote independent living in "aging-in-place" scenarios. In reality, both sensed and interpreted contexts are often ambiguous, leading to potentially dangerous decisions if not properly handled. Thus, a significant challenge facing the development of realistic and deployable context-aware services for pervasive computing applications is the ability to deal with these ambiguous contexts. In this chapter, the authors discuss a resource optimized quality assured ontology-driven context mediation framework for resource constrained sensor networks based on efficient context-aware data fusion and information theoretic sensor parameter selection for optimal state estimation. It has the ability to represent contexts according to the applications' ontology and easily composable ontological rules to mediate ambiguous contexts.

INTRODCUTION

Recent research in ***smart environments*** offers promising solutions to the increasing needs of pervasive computing applications; our work has demonstrated the use of such environments to support the elderly in home based healthcare applications (Roy, Julien, & Das, 2009; Roy, N., Roy, A., & Das, 2006). Essential to such applications is human-centric computing and communication,

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where computers and devices adapt to users' needs and preferences.

We focus on the computational aspect of user-centric data to provide context-aware services; we demonstrate this through an application for intelligent independent living. Given the expected availability of multiple sensors of different types, we view context determination as an estimation problem over multiple sensor data streams. Though sensing is becoming increasingly cost-effective and ubiquitous, the interpretation of sensed data as context is still imperfect and ambiguous. Therefore, a critical challenge facing the development of realistic and deployable context-aware services is the ability to handle ambiguous contexts. The conversion of raw data into high-level context information requires processing data collected from heterogeneous distributed sensors through filtering, transformation, and even aggregation, with a goal to minimize the ***ambiguity*** of the derived contexts. This context processing could involve simple filtering based on a value match, or sophisticated data correlation, ***data fusion*** or information theoretic reasoning techniques. Only with reasonably accurate context(s) can applications be confident to make high quality adaptive decisions. Contexts may also include various aspects of relevant information; they may be instantaneous or durative, ambiguous or unambiguous. Thus, the mapping from sensory output to the context information is non-trivial. We believe context-aware mediation plays a critical role in improving the accuracy of the derived contexts by reducing their ambiguity, although the exact fusion or reasoning technique to use is application and domain specific.

RELATED WORK

Pervasive computing applications, such as the Aware Home (Orr & Abowd, 2000), Intelligent Room (Coen, 1999) and House_n (Intille, 2006), do not provide explicit reusable support for users to manage uncertainty in the sensed data and its interpretation and thereby assume that sensed contexts are unambiguous. Toolkits enable the integration of context into applications (Dey, Salber & Abowd, 2001), however, they do not provide mechanisms for sensor fusion or reasoning about contexts' ambiguity. Although other work has proposed mechanisms for reasoning about contexts (Vurgun, Philpose & Pavel, 2007), it does not provide well-defined context-aware data fusion models nor address the challenges associated with context ambiguity. Distributed mediation of ambiguous contexts in aware environments (Dey, Mankoff, Abowd & Carter, 2002) has, however, been used to allow the user to correct ambiguity in the sensed input.

Middleware has also effectively supported context-aware applications in the presence of resource constraints (e.g., sensor networks), considering requirements for sensory data or information fusion (Alex, Kumar & Shirazi, 2005). DFuse (Kumar, Wolenetz, Agarwalla, Shin, Hutto, Paul & Ramachandran et al., 2003) facilitates dynamic transfer of application level information into the network to save power by dynamically determining the cost of using the network. In adaptive middleware for context-aware applications in smart homes (Huebscher & McCann, 2004), the application's quality of context (QoC) requirements are matched with the QoC attributes of the sensors through a utility function. Similarly, in MiLAN (Heinzelman, Murphy, Carvalho & Perillo, 2004), applications' quality of service (QoS) requirements are matched with the QoS provided by the sensor network. However, the QoS requirements of the applications and available from the sensors are assumed to be predetermined and known in advance. In pervasive computing environments, the nature (number, types and cost of usage, and benefits) of such sensors available to the applications usually varies, and it is impractical to include a priori knowledge about them. Entropy-based sensor selection heuristic algorithms (Ertin, Fisher &

Potter, 2003; Liu, Reich & Zhao, 2003; Wang, Yao, Pottie & Estrin, 2004) take an information theoretic approach, where the belief state of a tracked object's location is gradually improved by repeatedly selecting the most informative unused sensor until the required accuracy level of the target state is achieved. The selection of the right sensor with the right information at the right moment was originally introduced in (Tenny & Sandell, 1981), while the structure of an optimal sensor configuration constrained by the wireless channel capacity was investigated in (Chamberland & Verravalli, 2003).

In (Patterson, Liao, Fox & Kautz, 2003), high-level user behavior is inferred from low-level sensor data by adding knowledge of real-world constraints to user location data. A variant of Dynamic Bayesian Networks (DBN) is used in an unsupervised way to predict transport routes based on GPS data. The Owl (Ebling, Hunt & Lei, 2001) context service supports heterogeneous context sources, privacy and meta information like age, i.e., the time since the sensor was last sampled, and confidence of context data. It is one of the earlier works that already mentions the possibility of inferring future user behavior from learned habits. To this end, their context service was designed to manage context history in addition to the current context. SOCAM (Gu, Pung & Zhang, 2004) proposed an OWL ontology based context model addressing context sharing, reasoning and knowledge reusing, and built a service oriented middleware infrastructure for applications in a smart home. It is based on an ontology-oriented approach, i.e., on a vocabulary for representing context, and its model of context is defined using the Web Ontology Language (OWL), allowing to share context between different entities and giving rise to reasoning about context. Their middleware provides the standard services of acquiring, interpreting and disseminating context, but also takes steps towards deriving high-level context from low-level context, which they call "context reasoning" and which can be performed in description logic and first-order logic. To cope with limited resources in mobile devices, the authors divide possible situations into sub-domains (e.g. home domain, office domain) and switch between the ontologies defined for these sub-domains. Adapting applications to changed context is performed via the standard way of predefined rules and triggers. The described implementation of the context interpreter, which performs the reasoning process within the OWL model, is suitable for infrastructure-based context services, but not for resource-limited devices. In recent work, the authors proposed a probabilistic extension to OWL and added a Bayesian Network approach to deal with uncertainty in sensor data (Gu, Pung & Zhang, Pervasive 2004). Although the ontology-based approach and its automatic transformation to a Bayesian Network to deal with uncertainty could offer distinct advantages, currently there does not seem to be a method for automatically deriving this structure of the ontology from sensor data.

However none of these applications consider a formal context fusion mechanism that can fuse high-level context for different applications in the same way so that the common module for fusing context can be viewed as a shared, highly reusable infrastructure. By eliminating the simplifying assumption that all contexts are certain, we design a context-aware data fusion algorithm to mediate ambiguous context using ***dynamic Bayesian networks***. We also design an ***ontological*** rule based approach using ***semantic web*** technology for further reduction of context ambiguity with applications to context-aware healthcare services. We propose an intelligent sensor management algorithm that provides optimal sensor parameter selection in terms of reduction in ambiguity in the state estimation using an ***information theoretic*** approach.

Contributions

Our approach fuses data from disparate sensors, represents abstract context state, and reasons efficiently about this state, to support context-aware services that handle ambiguity. Our goal is to build a framework that resolves information redundancy and also ensures the conformance to the application's quality of context (QoC) bound based on an optimal sensor configuration. For this purpose, we propose a Dynamic Bayesian Networks (DBNs) (Jensen, 2001) based model that uses the sensed data to interpret context state through fusion and an information theoretic reasoning technique to select the optimal sensor data values to minimize ambiguity (Roy, Pallapa & Das, WiMob 2007; Roy, Julien & Das, QShine 2009). However, our proposed technique cannot remove all the ambiguity in the sensed data, leaving it up to the programmer and inhabitants to deal with. To alleviate this problem, we propose to leverage off an ontology based context fusion with a rule based model and involve end users in removing any remaining ambiguity (Roy, Pallapa & Das, PETRA 2008; Roy, Gu & Das, PMC 2010). We use Semantic Web ('Semantic Web') technology to implement this rule based model to visualize wellness management services to the elderly person. We build a system using various sensors for sensing and mediating user context state. Experiments demonstrate that the proposed framework is capable of adaptively enhancing the effectiveness of the probabilistic sensor fusion scheme and situation prediction by selectively choosing the best set of sensors in each context.

This chapter is organized as follows. We first describe the basic concepts of our context model and the quality of context (QoC). We present the context-aware data fusion model based on DBNs for resolving ambiguity. An ontology-driven rule based model with its prototype for the realization of unambiguous context has been discussed. We study the structure of an optimal sensor configuration to minimize the state estimation error from an information theoretic point of view. We evaluate our approach and conclude the chapter with future research directions.

CONTEXT MODEL

Context-aware data fusion in the face of ambiguities is challenging because the data in sensor networks is inherently uncertain. We make use of a space-based context model (Padovitz, Loke, Zaslavsky, Bartolini & Burg, 2005) and extend it with quality of context (QoC) attributes. This model captures the underlying description of context related knowledge such as context attribute (a_i), context state (S_i), and situation space (R_i), and attempts to incorporate various intuitions that should impact context inference to produce better fusion results as shown in Figure 1.

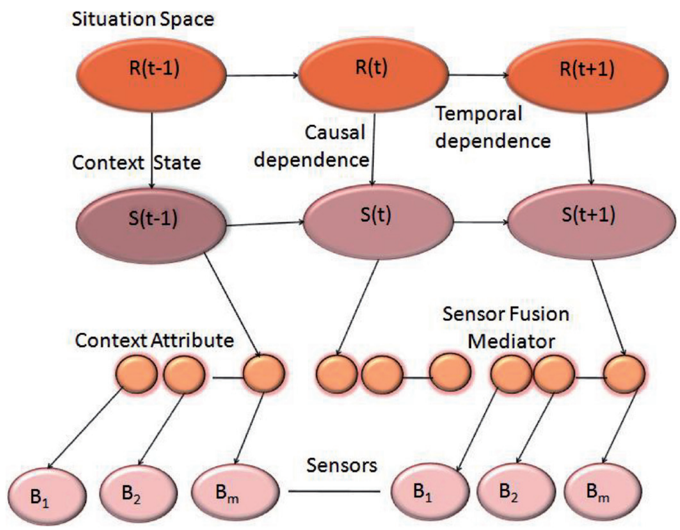
Space-Based Context Model

This model defines the following concepts:

Definition 1: Context Attribute:*A context attribute (denoted by a_i) is defined as any type of data used in the process of inferring situations. A context attribute is often associated with sensors, virtual or physical, where the value of the sensor readings denote the context attribute value at a given time t (denoted by a_i^t*). The body temperature "100^0 F" of a user measured by i_{th} sensor at a given time t is an example of a context attribute.

Definition 2: Context State:*A context state describes the application's current state in relation to a given context and is denoted by a vector S_i. It is a collection of Ncontext attribute values that are used to represent a specific state of the system at time t. A context state at time t is S_i^t =* $(a_1^t, a_2^t, \ldots, a_N^t)$. Suppose the body temperature is "100^0 F" and the location is in "gym", then the context state of the user is "doing physical exercise".

Figure 1. Context-Aware data fusion framework based on Dynamic Bayesian Networks



Definition 3: Situation Space: *A situation space represents a real-life situation. It is a collection of regions of attribute values corresponding to some predefined situation and denoted by a vector space* $R_i = (a_1^R, a_2^R, \ldots, a_M^R)$ (consisting of Macceptable regions for these attributes). An acceptable region a_i^R is defined as a set *of elements VthatsatisfiesapredicateP,i.e.,* $a_{\downarrow} i^{\uparrow} R = V \mid P(V)$. In numerical form the acceptable region would often describe a domain of permitted real values for an attribute a_i. A region of acceptable values is defined as a set that satisfies some predicate; hence, it can contain any type of information, numerical or non-numerical. For example the context attribute body temperature can take values from "98^0F" to "100^0F" when the user's context state is "doing physical exercise" with a predefined situation space – "normal". But if the context attribute – body temperature takes values in the range of "98^0F" to "100^0F" when the user's context state is "lying on the bed", then the situation space is "not normal". Again if we can use context attribute "PDA location" of a user to infer "user in a meeting" situation, then the accepted region for this attribute might be the location information of the PDA such as "at home", "at office" or "at meeting room".

Quality of Context Model

Despite recent development in sensing and network technology, continuous monitoring of individuals in normal setting is still challenging. We define the ***Quality of Context*** (QoC) (Hu, Misra & Shorey, 2006) as a metric for minimizing resource usage subject to maintaining a minimum quality of the context data received. QoC is essential to our model in choosing the best samples among the available ones for delivering a specific type of context. For example, if the blood pressure of an inhabitant in a smart home monitoring environment lies in between the predefined normal range, then the sensor needs not to report that value to the sensor fusion mediator again. But if the aggregated value computed at the mediator is beyond the tolerance level (QoC) then the sensor needs to report its samples back to the mediator for conformance, and the mediator in turn would help the application as needed to estimate the best possible situation of the inhabitant.

The sensor fusion mediator always ensures that the aggregated value computed does not diverge from the true reading by more than a specified "tolerance". The key is to have the mediator communicate a precision range or interval to an individual sensor, with an idea that a sensor need not report its samples back to the mediator as long as they fall into this specified range. Such tolerance is expressed in terms of a "Quality of Context" (QoC) metric, and is especially useful for applications issuing aggregation queries. But in the case of an emergency medical situation when all the sample values lie outside this range, the mediator gets updates from all available sensors in order to compute the best possible estimate of the patient's state. We assume that the information fusion issues an aggregation query with its QoC specified by a precision range Q, which implies that the aggregate value computed at the mediator at any instant should be accurate within $\pm Q$. Our primary objective is to evaluate the cost/benefit of a sensory action for a given task while ensuring the conformance to the application's QoC bound.

Let us denote the update cost (communication overhead) as $\mathbb{U}_i$ if indeed sensor B_i has to report its sample value at time j to the mediator. Then, the objective is to

$$minimize \sum_{i \in B_m} \mathbb{U}_i(q_i) \qquad (1)$$

where $\mathbb{U}_i$ denotes the expected average update (reporting) cost and explicitly indicates its dependence on the specified precision interval q_i. Intuitively, $\mathbb{U}_i$ is inversely proportional to q_i, since the value of the reporting cost would be high as the precision interval keeps on shrinking.

CONTEXT-AWARE DATA FUSION

A characteristic of pervasive computing is that applications sense and react to ***context***, information sensed about the environment and its occupants, by providing context-aware services that facilitate applications' actions. Here we develop an approach for sensor data fusion in a context-aware environment considering the underlying space-based context model and a set of intuitions it covers; we use a context-aware healthcare example to explicate our model.

In the case of context-aware services, it is really difficult to get an accurate and well defined context that we can classify as 'unambiguous'. In reality, both sensed and interpreted contexts are mostly imperfect and ambiguous. To alleviate this problem, we classify context information into ambiguous and unambiguous contexts and propose a DBN model for ambiguous contexts and a rule based mediation technique for unambiguous contexts. For example, a user location can be sensed using active badges, video cameras or GPS units. All of these sensors have some degree of ambiguity in the data they sense. Similarly, a video camera system which identifies the user posture based on the current position (sitting, standing, lying) may not be producing accurate results. The ambiguity problem becomes worse when the application derives implicit higher-level contexts based upon those inputs. For example, an application may infer that the person is lying in distress. However, there may be other explanation of this phenomenon such as the person might be lying to perform normal exercises. Thus, we design an active context-aware data fusion framework based on DBNs to reduce this ambiguity as much as possible during the situation inference process.

Dynamic Bayesian Networks

In this section we provide an overview of the DBNs. Before discussing DBNs, we first review basic concepts of Static Bayesian Networks (SBNs) (Pearl, 1988). A Bayesian network is a graphical model for representing probabilistic relationships among a set of variables. The network forms a directed acyclic graph (DAG), where nodes represent random variables and directed links between the nodes represent casual relationships. To simplify computation, conditional dependences are systematically built in the Bayesian networks. It is assumed that two nodes at the same level are conditionally independent given their parent node. Also, given the parent node, the child node is independent of the grandparent node. The SBNs work with evidence and beliefs from a single instant in time. As a result, SBNs are not particularly suited to systems that evolve over time. DBNs are developed to overcome this limitation. DBNs are an extension of SBNs specialized to better model real world domain with a unified model of time and uncertainty. Significant research has been done in this area (Provan et al., 1993; Nicholson et al., 1994; Pavolovic, 1999; Dean et al., 1989; Dagum et al., 1992; Young et al., 1996). In general, a DBN is made up of interconnected time slices of SBNs, and the relationships between two neighboring time slices are modeled by a Hidden Markov model, i.e., random variables at time t are affected by observable variables at time t, as well as by the random variables at time t-1 only. The evidence and inferred beliefs of previous time slices are used to estimate and predict beliefs in the current and future events through the causal links, as well as temporal links. Inference is performed by keeping in memory two slices at any one time, representing the previous discrete time and current time respectively. The slice at the previous time provides diagnostic support for current slice and it is used in conjunction with current sensory data to infer the current hypothesis. The two slices are such programmed that they rotate as old slices are dropped and new slices are used as time progresses. For convenience in belief propagation, at any time instant, the two time slices are treated as an extended SBN and the existing belief propagation for SBN can therefore be applied. There has been substantial research effort concentrated on reducing the computational complexity of performing inference on DBNs (Kanazawa et al., 1995; Jitnah et al., 1999; Koller et al., 1999).

Dynamic Bayesian Network Based Model

Our motivation is to use the data fusion algorithm to develop a context-aware model to gather knowledge from sensor data. ***Dynamic Bayesian Networks*** (DBNs) provide a coherent and unified hierarchical probabilistic framework for sensory data representation, integration and inference. Figure 1 illustrates a DBN based framework for a context-aware data fusion system consisting of a situation space, context states, context attributes, a sensor fusion mediator and a network of information sensors.

The selection of an information source or the activation of a process to compute new information is simply regarded as a set of actions available to the decision maker in decision theory. In our case, the information module needs to determine the next optimal context attributes and the corresponding sensory action. But selecting an action always has a consequence that, in this case, can be measured by the cost of information acquisition, varying the confidence of the situation space. If we can devise a benefit/cost measure to each possible consequence, this can be used by the system to decide what action to perform and what sensor to activate. We have to choose the action that maximizes the expected utility, which depends on the current available sensory data, the internal knowledge, and the current goal.

Let us assume that we have a situation space R_i to confirm using the sensory information sources $B=\{B_1,\ldots,B_m\}$, which is a set of measurements taken from sensors labeled from 1 to m respectively, as shown in Figure 1. The context attribute that is most relevant in our case should decrease the ambiguity of the situation space a_j^R the most and the one we will select that can lead the probabilities of situation space close to near one (for maximum) and zero (for minimum). Let V_i be the ambiguity reducing utility to the situation space R_i with N states. Then the expected value of V_i, given a context attribute a_i^t from a sensor B_i, which has M possible values, can be represented as

$$V_i = max_{i-0}^{k} \sum_{j=o}^{N} \left[P(a_j^R \mid a_i^t)\right]^2 - min_{i=o}^{k} \sum_{j=o}^{N} \left[P(a_j^R \mid a_i^t)\right]^2 \tag{2}$$

where $i=\{1,2,\ldots,m\}$ is a sensor tag that identifies the sensor that supplies the context attribute. This context attribute can be obtained by propagating the possible outcome of an information source, i.e.,

$$P(a_j^R \mid a_i^t) = \frac{P(a_j^R \mid a_i^t)}{P(a_i^t} \tag{3}$$

However, quantification of this conditional probability needs a detailed model depending upon the usage of different types of sensors and their applications. Consider, for example, an audio sensor. Evaluating the benefit of using audio in disambiguating whether a person is moaning in pain or singing, is really hard. It depends on how far the person is from the microphone, which way the person is facing, the time of day (at night it is more quiet so sounds can be heard more clearly), the state of other potentially interfering audio sources (such as air conditioning, TV, radio, refrigerator), etc. Computing the disambiguating utility therefore, needs very detailed models of how the above factors impact the efficacy of the audio sensor.

Considering the information update cost from Equation 1 and ambiguity reducing utility from Equation 2, the overall utility can be expressed as

$$U_i = \alpha V_i + (1-\alpha)(1-\mathbb{U}_i) \tag{4}$$

where $\mathbb{U}_i$ is the update cost to acquire the information by sensor with tag i with a knowledge of the QoC bound, and α denotes the balance coefficient between the ambiguity reduction and the cost of information acquisition. Equation 4 represents the contribution to ambiguity reduction and the cost associated with acquiring these information sources to achieve the desired level of confidence to the situation space. We can observe from Equation 4 that the utility value of a context attribute a_i increases with the ambiguity reducing utility and decreases as the cost to acquire that attribute increases. An optimal sensor action A can be chosen using the following decision rule

$$A^* = \arg max_A \sum_j U\left(B, a_j^R\right) P(a_j^R \mid B) \tag{5}$$

$B = \{B_1, \ldots \ \ldots \ \ldots \ . \ B_m\}$ is a set of measurements taken from sensors labeled from 1 to m at a particular point of time. By incorporating the time dimension, the probability distribution of the goal we want to achieve can be generally described as

$$P\left(R, A\right) = \prod_{t=1}^{T-1} P(S_t \mid S_{t-1}) \prod_{t=1}^{T-1} P\left(R_t | B_t\right) P(R_0) \tag{6}$$

where T is time boundary; the situation $R = \left\{R_{0,} \ldots, R_t, \ldots, R_T\right\}$ and the subset of sensed information $B = \left\{B_{0,} \ldots, B_t, \ldots, B_T\right\}$ on time sequence of T. S represents a set of context states $\left\{S_{0,} \ldots, S_t, \ldots, S_T\right\}$ relevant on time sequence of T based upon the situation we are looking for that has temporal links between corresponding nodes in two neighboring time frames. The sensor action strategy must be recalculated at each time stamp since the best action varies with time. The algorithm is presented in Figure 2.

ONTOLOGY BASED CONTEXT FUSION

We present our context ***ontology*** for modeling context fusion in Figure 3. We design our ontology in a hierarchical manner from a top-level ontology to a domain-specific ontology. The upper ontology is a high-level reusable ontology structure that captures general features of basic contextual entities. Domain-specific ontologies are a collection of ontology sets that define the details of general concepts and their features in each sub-domain. The context model is structured around a set of abstract entities, each describing a physical or conceptual object including location, Person, Computational Entity as well as a set of abstract subclasses. Each entity is associated with its context attributes (represented in owl:DatatypeProperty) and relations with other entities (represented in owl:ObjectProperty). Another flexible OWL property (owl:subClassof) helps us to add new concepts in a hierarchical manner that are required in a specific domain without any rigor. Figure 4 presents a partial context ontology for a healthcare application. The abstract class "device" has been classified into a handful sub-classes such as BSN (Body-area Sensor Network), TV and Cell phone, and BSN has been sub-grouped into two different sub-classes such as Ambient Sensor and Wearable Sensor. Context attributes (e.g., location, person, time, computational entity) are most fundamental contexts for taking a final decision about the executing situation. These contextual attributes not only form the skeleton of the context state but also conglomerate with a base context state to derive a composite context state.

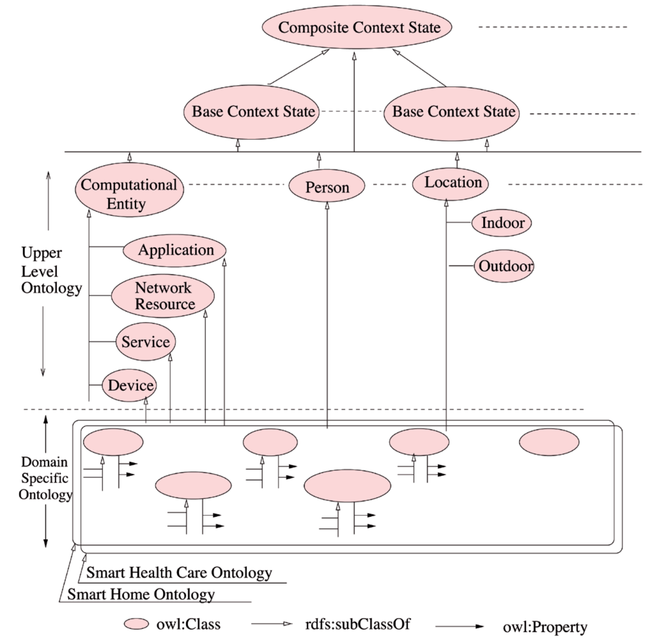
Our basic context model represents context attribute as Predicate (subject, value). We extend the basic model to derive a context state or a set of context states by combining the Boolean Operator such as union, intersection, complement, etc. We also extend the basic context model to incorporate probabilistic information for representing uncertain contexts. It has the form of Prob (Predicate (subject, value)), in which the probability measurement takes a value between 0 and 1. For example, Prob (BodyTemperature (John, HIGH)) = 0.9 means the probability that John's body temperature is currently high is 0.9.

We apply a Bayesian network (BN) approach to enable learning causal dependencies between various context events and obtaining probability distributions. In our model, each node corresponds to a context event, and directed arcs between nodes represent causal relationships between the contexts. The uncertainty of the causal relationship is represented by the conditional probability $P\left(a_j^R | a_i^t\right) = \dfrac{P\left(a_j^R | a_i^t\right)}{P(a_i^t)}$. After getting this conditional probability, we are able to compute the probability distribution of the BN. This DBN-

Figure 2. Ambiguous Context Mediation Algorithm (ACMA)

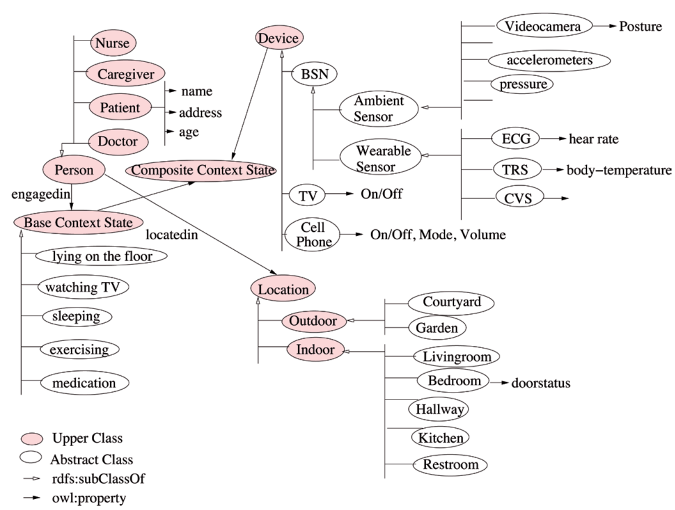
Procedure ACMA
1. t = 0, Compute ambiguity-reducing utility $\{V_1^t, \dots\dots, V_m^t\}$ by Eqn. 2
2. Calculate utility value $\{U_1^t, \dots\dots, U_m^t\}$ using Eqn. 3
3. Select the most economically efficient disambiguation sensor action based on Eqn. 5
4. Instantiate the subset of corresponding sensors B
5. Run ACMA inference algorithm to update probability distribution $P(R, A)$ of situation space
6. If $P(R, A^*) \geq$ confidence threshold, then terminate; otherwise
7. Add a new time stamp $t = t + 1$, and go to step 1

Figure 3. Context fusion Upper Ontology



based model can lead to a well-defined context fusion mechanism with the consideration of the inherent ontology associated with different states. With the help of the ontology, we can make uncertain context easily shared by different applications and enable our context fusion module to derive high-level composite context more accurately and timely. Context attributes (CA) are instances of the ontology and they can be fused to derive the context state (CS) or can be combined with a base context state to derive the composite or high-level context state. Hence, we have

Figure 4. Context Fusion Lower Ontology



$CA_1 \Lambda CA_2 \dots \Lambda CA_n => CS_i$ and $[\![(CA]\!]_1 \Lambda CA_2 \dots \Lambda CA_n)[\![\Lambda\ (CS]\!]_1 \Lambda CS_2 \dots \Lambda CS_n) => CS_i$.

The user defined context state derivation rules are shown in Table 1. Context states are derived only with the help of the different context attributes. In Table 2, the context fusion rules are defined from single/multiple context states and context attributes to predict the situation space.

Rule-Based Mediation Subsystem

In pervasive computing environments, the ambiguity of context may vary among different applications and users. If we can directly involve applications and users in the model to mediate the current associated ambiguity with the context, unambiguous context can be realized to some extent. An application can choose to ignore the ambiguity and take some action (e.g., act on the most likely choice) or can use rule-based techniques to ask the end user about his or her actual intent. We propose a rule-based mediation subsystem as follows. We define the following rule format derived from active database for identifying ambiguous contexts.

on <context attribute>
if <context state>
do <situation space>

The basic idea is as follows. The evaluation of a situation should be done if a particular context state is true on capturing some context attributes. Context attribute in our framework can be primitive (sensors in the smart home being activated) or non-primitive (complex or composite) which are derived from some other attributes as well. For example, the primitive ones can be location, time, etc., and non-primitive ones can be body temperature, respiratory rate, blood pressure, etc. They can also be instantaneous or durative. To illustrate, consider the following rules that can be used to actively monitor the elderly person in the smart home (Augusto, Nugent & Black, 2004).

Rule 1:

on Context Attribute (CA): <?user hasBodyTemperature 'VALUE1'>, <?user hasRespiratoryRate 'VALUE2'>, <?user hasBloodPressure 'VALUE3'>

if Context State (CS): <?user hasActivity 'EXERCISE'>,<?user hasActivity 'LIEDOWN'>

do Situation Space (SS): <?user inSituation 'SICKNESS'>

Table 1. User defined Context State Derivation Rules

Context State	Reasoning Rules
doing physical exercise	*(?x LocatedIn Gym)Λ(x BodyTemp HIGH) Λ(x RespiratoryRate HIGH) => (?x contextstate exercise)*
watchingTV	*(?x LocatedIn LivingRoom)Λ(TVSet LocatedIn LivingRoom) Λ (TVSet status ON)=> (?x contextstate watchingTV)*
lying on the floor	*(?x LocatedIn Kitchen) Λ(x posture lying) Λ(ElectricOven status ON) => (?x contextstate lying on the floor)*
walking	*(?x LocatedIn Courtyard) Λ (x motion ON) Λ(House doorstatus OPEN) => (?x contextstate walking)*
going to restroom	*(?x LocatedIn Bathroom) Λ(Flush status ON) Λ(Bathroom doorstatus CLOSED) => (?x contextstate going to restroom)*
lying on the bed	*(?x LocatedIn Bedroom) Λ(Bedroom lightlevel Low) Λ (Bedroom doorstatus CLOSED) => (?x contextstate lying on the Bed)*
talking	*(?x LocatedIn LivingRoom)Λ (y LocatedIn LivingRoom)Λ (x sound HIGH) => (?x contextstate talking)*

Table 2. User defined Context Fusion Rules

Situation State	Fusion Rules (Derived from a Single/Multiple Context State and Context Attribute)
sickness	*(?x contextstate lying on the floor) Λ(x BodyTemp HIGH) Λ(x RespiratoryRate HIGH) => (?x situationstate sick)*
behavior	*(?x contextstate walking)Λ(currenttime status midnight) =>(?x situationstate abnormal)*
behavior	*(?x contextstate restroom)Λ(?x contextstate watchingTV) =>(?x situationstate normal)*
sickness	*(?x contextstate going to restroom) Λ (?x contextstate lying on the Bed) Λ (?x leavingbed HIGH) => (?x situationstate sick)*

Suppose using some specific sensors in an indoor smart home environment, we obtain the value of context attributes such as body temperature, respiratory rate and blood pressure of a person. Now, if these measured values are higher than a specified range, we can infer about the situation of the person by observing the context state. If the context state is <?user hasActivity 'EXERCISE'> --"doing physical exercise", the situation is normal; otherwise, if the context state is <? user hasActivity 'LIEDOWN'> -- "lying on the bed", the situation is abnormal.

Let us consider another rule where we consider the context attribute as time instant, time span and location of the inhabitant in the home.

Rule 2:

on CA: <?user time '6AM'>, <?user locatedIn 'BACKYARD'>

if CS: <?user hasActivity 'WALKING'>

do SS: <?user inSituation 'NORMAL'>

If it is 6am in the morning and the location of the person is at backyard where the context state is "walking", then we can conclude that the behavior of the person is normal. But if it is 2am in the morning and the location of the person is outside the home where the context state is "sleeping", then we can conclude that the behavior of the person is not normal. We can make different variants of this rule by considering different context attributes with a different context state. Thus detecting that a person has been engaged in a specific activity for an unusual length of time may be an indicator of a health problem or a potentially hazardous situation.

Rule Based Engine Implementation

We represent the internal rule based model using ***Semantic Web*** Technology and ***OWL*** (Web Ontology Language) (Smith, Welty & McGuiness, 2004). OWL is an ontology markup language that enables context sharing and context reasoning. The ontology is described in OWL as a collection of ***RDF*** (Resource Description Framework) triples, each statement being in the form of *(subject, predicate, object),* where *subject* and *object* are the ontology's objects or individual and *predicate* is a property relation defined by the ontology.

RDF Vocabulary

We create an RDF vocabulary for our ambiguous context mediation subsystem based on the rule based approach using an ontology compliance level (OWL Lite) and create the model and generate the RDF/XML schema using the SemanticWorks interface from Altova Inc ('SemanticWorks Web'). We have defined three classes *ElderlyPerson*, *GrandParents* and *ContextAttribute* for the rules defined previously. We define *GrandParents* as a subclass of *ElderlyPerson*. The class (or classes) that the property applies to is called the property's domain, while the set of values the property can take is called the property's range. In our ontology, we deal with two properties:

(i) **Object property:***hasExercising, hasLying* to carry information about the type of the *ContextAttribute*. The *ContextAttribute* can be *BodyTemp, RespiratoryRate* and *BloodPressure*. We will create this property as an object property. Doing this enables us to relate one resource to another. In this case we wish to relate instances of the *GrandParents* class to instances of the *ContextAttribute* class via the *hasExercising*, *hasLying* property.

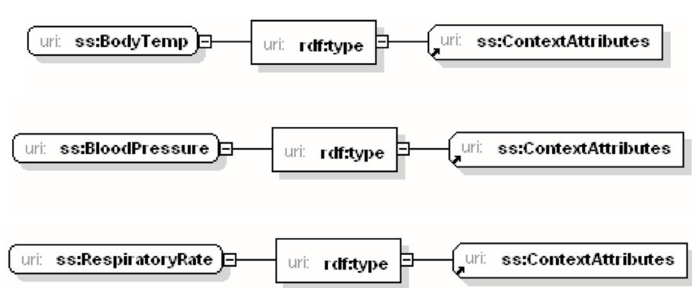
(ii) **Datatype property:***name*, which is a literal value indicating the name of the GrandParents. We will create this property as a datatype property.

We create three instances of the *ContextAttribute* class as shown in Figure 5, which will be simple instances like *BodyTemp, RespiratoryRate* and *BloodPressure*. Then we define three more instances of the *GrandParents* class as shown in Figure 6 and add predicates with them. The instance *GrandParentsBodyTemp, GrandParentsRespiratoryRate, GrandParentsBloodPressure* has therefore been defined to: (i) be an instance of the class *GrandParents,* (ii) have object property *hasExercising, hasLying* that takes the instance *ContextAttribute* as its object, and (iii) have a datatype property *name* that takes the string as its literal value.

Prototype Implementation

To validate our work and to demonstrate the expressiveness of the model, we implemented a reasoning component, which implements this rule model. The java based reasoning component gets RDF-information about these classes, available context state, and context attributes and can then trigger actions and provide prioritization information about the situation space. Jena 2.5.3, an open source Semantic Web Toolkit ('JENA Web') is utilized within the reasoning component for parsing the RDF descriptions. We implemented demonstration software, which can be used for experimenting with the reasoning component. The demonstration software includes the RDF vocabulary. This vocabulary has been converted to a java class file using the schemagen utility from the Jena API, which helps to get access to different properties of RDF graph based model. An RDF meta-database is developed that contains several data value used for querying context. We use ***SPARQL*** ('SPARQL Web'), a query language that can select RDF triples from this database. Applications based on our ambiguous context mediation subsystem can query contexts by specifying a SPARQL query. The queries are executed directly with Jena's SPARQL support for querying RDF models. Variables in the rules present the resources (users, situations), which are to be found with the SPARQL query. The

Figure 5. Different Instances of Context Attribute Class



RDF descriptions and rules in the demonstration were written by using an XML/RDF definition for presenting RDF models. Here is an example of a statement from a rule that is supported by our implementation:

string rules = "[Rule 1: *(?GrandParentsBodyTemp ss:hasLying ?BodyTemp)* Λ *(?BodyTemp ss:hasGreaterThan ?TempValue)* Λ*(?GrandParentsBloodPressure ss:hasLying ?BloodPressure)* Λ *(?Bloodpressure ss:hasGreaterThan ?BPValue) => (?GrandParents ss:hasSituation sick)*]"

Currently conditions in our model correspond to Boolean "and". "Or" can be achieved by creating several rules. Relational operations (>, <) are being implemented, as well as support for spatial and temporal reasoning, e.g., by introducing event sequences. The following is an example of a partial rule set based on the forward-chaining rule engine.

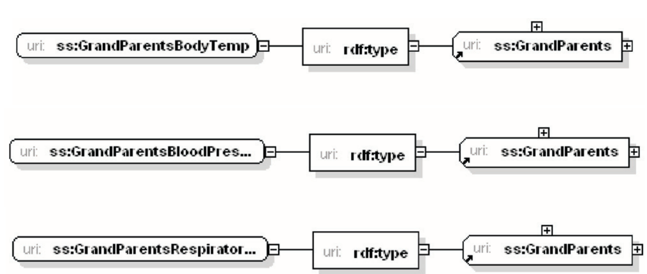
string rules = "[Rule 2: *(?ElderlyPerson ss:hasLocation ?location)* Λ*(?ElderlyPerson ss:hasTime ?time)*Λ*(?ElderlyPerson ss:hasWalking ?walking)=> (?ElderlyPerson ss:hasSituation parasomnias)*]"

The end-user UI demonstrates how the situations are presented to the user based on the prioritization obtained via reasoning. The UI also tells when context-based actions are triggered. The reasoning component uses SPARQL queries for checking if a rule presents a situation that can be found in the available RDF information. SPARQL queries are automatically generated from the rules of the user's or situation's description in order to find the relevant matches. If a match exists, the rule is true and the relevant actions can be triggered, and/or the matching situation can be categorized. In the demonstration implementation, a simple relevance metric is used for the situation prioritization; categories have different fixed priorities, but all the situations within a category are prioritized equally. Next we propose an information theoretic reasoning technique to select the sensor parameters which reduces the ambiguity in the context estimation process.

OPTIMAL SENSOR PARAMETER SELECTION

Considering that most sensors are battery operated and use wireless communication, energy-efficiency is important in addition to managing changing QoC requirements. For example, higher quality might be required for certain health-related context attributes during high stress situations such as a medical emergency, and lower quality during low stress situations such as sleep. Figure 7 shows the context attributes requirement graph for a personal health monitor and includes multiple states for each vital sign that can be monitored depending upon the context state of the patient. For example, Figure 7 shows that when a patient is lying in a distressed state and the blood pressure is low, the blood oxygen level must be monitored with a quality of 0.7, and the blood pressure must be monitored with a quality of 0.3. So the problem

Figure 6. Different Instances of GrandParents Class



here is to decide what type of information each sensor should send to the fusion center to estimate the best current state of the patient while satisfying the application QoC requirements for each context attribute by minimizing the state estimation error.

Here we introduce a formalism for optimal sensor parameter selection for state estimation. We define optimality in terms of reduction in ambiguity in the context estimation. The main assumption is that state estimation becomes more reliable and accurate if the ambiguity or error in the underlying state estimation process can be minimized. We investigate this from an ***information theoretic*** perspective (Cover & Thomas, 1991), where information about the context attribute is made available to the fusion center by a set of smart sensors. The fusion center produces an estimate of the state of the situation based on intelligent analysis of the received data. We assume that the noisy observations across sensors are independent and identically distributed (i.i.d) random variables conditioned on the binary situation R (we assume situation R here as binary for ease of modeling). Each sensor attribute has a source entropy rate $H(a_i)$. Any sensor wishing to report this attribute must send $H(a_i)$bits per unit time, which is the entropy of the source being measured assuming that the sensor is sending the exact physical state. Of course, different sensors contribute in different measures to the error in state estimation. So, the problem is to minimize the ambiguity (or keep it within a specified bound), while not exceeding the shared link rate Q. Thus by maximizing the a posteriori detector probability we can minimize the estimation error of the random variables based on noisy observations from a set of sensors at the fusion center to accurately reconstruct the state of the situation (Chamberland & Verravalli, 2003).

Problem 1: Let Bbe the vector of sensors and A be the set of attributes, then imagine a (B×A) matrix where B_{mi}=1when sensor m sends attribute a_i. Then, the goal is to find a matrix (B×A) within the capacity constraint Q that minimizes the estimation error of the situation space.

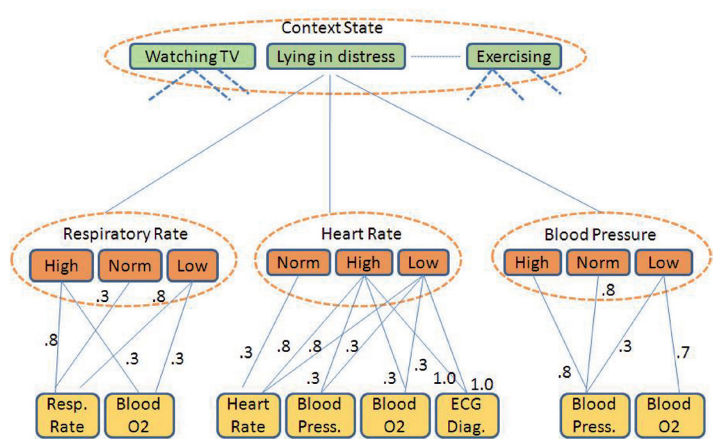
$$\sum_m \sum_i H\left(a_i\right) * B_{mi} < Q and minimize \; [P_e = P\{\, X \neq R\}]$$

where X is an estimate of the original state R.

Problem Explanation

We assume R to be a random variable drawn from the binary alphabet $\left\{R_0, R_1\right\}$ with prior probabilities P_0 and P_1, respectively. In our case, each sensor needs to determine a sequence of context

Figure 7. State-based Context attribute requirement graph with the required QoC



attributes for a sequence of context states $\left\{ S_{m,t} : \forall t = 1, 2, \ldots.., T \right\}$ about the value of situation R. We assume that random variables $S_{m,t}$ are i.i.d., given R, with conditional distribution $p_{(s \| R)(.|R_i)}$. The sensors could construct and send a summary $Z_{m,t} = \pi_m \left(S_{m,t} \right)$ of their own observations to a fusion center at discrete time t. The fusion center produces an estimate X of the original situation R upon reception of the data. Thus we need to find an admissible strategy for an optimal sensor-attribute mapping matrix (B x A) that minimizes the probability of estimation error $P_e = P\left\{ X \neq R \right\}$.

Definition 1: A set of decision rules π_m for an observation $X \rightarrow \{1, 2, \ldots, \overline{a}_m\}$ where $\overline{a}_m$ is the number of attributes admissible to sensor B_m with the admissible strategy denoted by π, consists of an integer M in the matrix (B x A), such that

$$\sum_{m=1}^{M} \sum_{i} H \left(\overline{a}_m . a_i \right) * B_{mi} < Q$$

The evaluation of message $z_{m,t} = \pi_m \left(s_{m,t} \right)$ by sensor B_m is forwarded to the fusion center at time t. Since we are interested in a continuous monitoring scheme here, we consider that the observation interval T tends to ∞. But the associated probability of error at the fusion center goes to zero exponentially fast as T grows unbounded. Thus we can compare the transmission scheme through the error exponent measure or Chernoff information:

$$E(\pi) = -lim_{T \rightarrow \alpha} \frac{1}{T} log P_e^{(T)}(\pi)$$

Where $E(\pi) = -lim_{T \rightarrow \alpha} \frac{1}{T} log P_e^{(T)}(\pi)$ $P_e^{(T)}$ denotes the probability of error at the fusion center for strategy π considering the maximum a posteriori detector probability. We use $\Pi(Q)$ to capture all admissible strategies corresponding to a multiple access channel with capacity Q and redefine our problem as follows:

Problem 2: Find an admissible strategy $\pi \in \Pi(Q)$ that maximizes the Chernoff information:

$$E(\pi) = \left(\pi \right) -lim_{T \rightarrow \alpha} \frac{1}{T} log P_e^{(T)}$$

We observe that the Chernoff information at the fusion center is monotonically increasing in the number of sensors for a fixed decision rule. State estimation error can be minimized by augmenting the number of sensors in π until the capacity constraint Q is met with equality. The strategy π being arbitrary, we conclude that having Q identical sensors in the (B×A) matrix, each sending one bit of information is optimal in terms of reducing the state estimation error. This configuration also conveys that the gain offered through multiple sensor fusion exceeds the benefits of getting detailed information from each individual sensor. For details of the model and its analysis, see (Roy, Julien & Das 2009).

EVALUATIONS

We also conducted experiments to evaluate the performance of the proposed ambiguous context mediation framework in a smart home health monitoring environment and report the results in this section. The ambiguous context mediation algorithm (ACMA) given in

Figure 2 was applied during our evaluation. In our application, the goal is to determine a set of sensors and the situation level (emergency or non-emergency) of a patient based on the most economically efficient disambiguation sensor action. Let us assume the situation level has three states, high, medium and low. Figure 8 represents a snapshot of the Bayesian Network model for this application using Netica BN software ('Netica Web'). In this figure we represent the situation space sickness and three context states

-- WatchingTV, Lying_in_Distress and Exercising. The conditional probabilities of these context states are empirically derived using SunSPOT ('SunSPOT Web') and other sensors traces. The sensors selected by ACMA for this application are Position_Sensor1, Body_Temp_Sensor2, Motion_Sensor3, Light_Sensor4 and Video_Camera5. We empirically derived the conditional probabilities of the context attributes from the raw readings of the sensors, e.g., given the ground truth of patient exercising, how many times did the Body_Temp_Sensor report a reading above the threshold value. These conditional probability tables at a particular state of the application are all shown in Figure 8.

The sensors used for our application are classified according to their numbers such as Sensor-1, Sensor-2, Sensor-3, Sensor-4, Sensor-5, Sensor-21 and Sensor-23 (for more details please see Roy, Pallapa & Das, WiMob 2007). We have calculated the expected profit utility value for different combination of sensors with varying set size through the successive iteration of the ACMA algorithm (Figure 2). The balance coefficient α is set to 1 to ignore the update cost of sensory information which in turn maps the utility value to the ambiguity reducing potential. The different sets of sensors are as follows:

Sets of 1: {1, 2, …, 21, 23}
Sets of 2: {1,2}, {1,3}, … {21,23}
Sets of 3: {1,2,3}, {1,2,4}, … {5,21,23}
Sets of 4: {1,2,3,4}, {1,2,3,5}, … {4,5,21,23}
Sets of 5: {1,2,3,4,5}, {1,2,3,4,6}, … {3,4,5,21,23}
Sets of 6: {1,2,3,4,5,21}, {1,2,3,4,23}, … {2,3,4,5,21,23}

From Figure 9, we observe that the utility increases (reduces ambiguity) as the number of selected sensors increases for different states of the application. The initial utility is calculated using Equation 2 considering a single sensor. The maximum utility values obtained by increasing the sensor set size for three different states (different probability values). With different balance coefficients, the best set of sensors for an application having multiple states is also different. This confirms that the gain obtained by having more sensors exceeds the benefits of getting detailed information from each individual sensor in accordance to our fusion model.

Next we experimentally analyze the performance of active (context-aware) and passive (non context-aware) fusion to illustrate how the proposed active fusion system works. The choice of which sensor to activate depends on the expected utility of each sensor. This repeats until we identify the situation type with sufficient confidence.

Figure 8. Bayesian Network

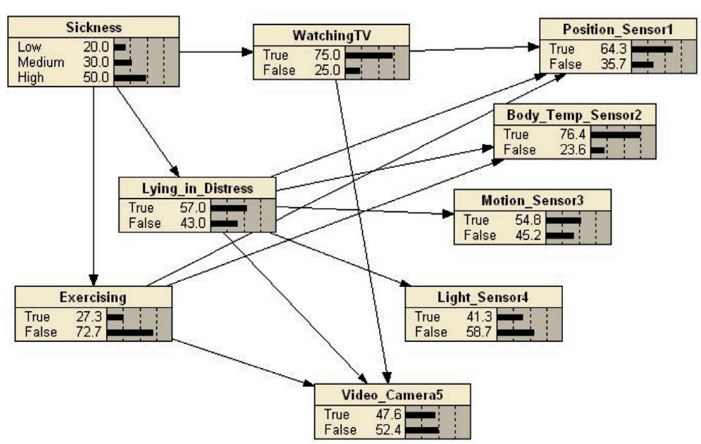
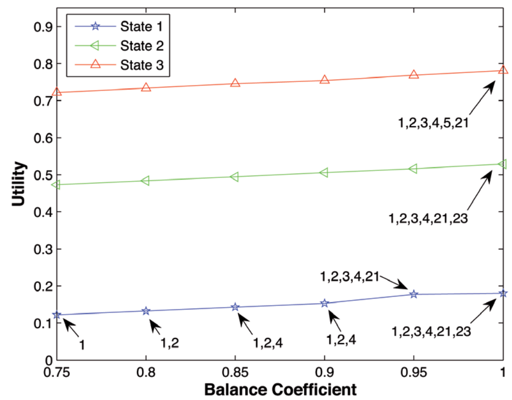


Figure 9. Best Sensor set for different values of balance coefficient α



We observe during our experiment that few sensors dominate in active fusion compared to the others. This repetition of sensors accelerates the decision to be taken on situation space compared to the passive fusion as shown in Figure 10. But sometimes it leads to information redundancy if it repeats the same value of the attribute consecutively. However, it may be beneficial for reducing imprecision and increasing reliability.

Figure 10 shows no significant performance difference by considering the acquisition cost. So the information redundancy can be overcome by frequently alternating between the active sensors with almost the same performance gain. Figure 11 represents the confidence of situation prediction for different specified QoC constraints. The confidence level achieves a higher value for a rigid QoC constraint compared to a flexible system. Though we achieved a better confidence level for a tight QoC constraint, more uniformity is achieved for the loosely bound system. This observation confirms that the participation of more sensors during the non-rigid QoC bound fusion process yields a more stable value though fails to achieve a higher confidence gain. Next we examine the situation prediction when we selectively choose the different sensors using the context mediation algorithm. Figure 12 depicts the variation of situation prediction with different sets of context attributes from different sensors.

Figure 10. Situation Prediction Probability using Multi Sensor Fusion

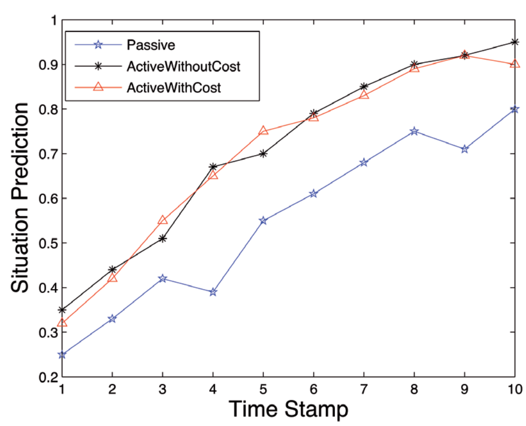
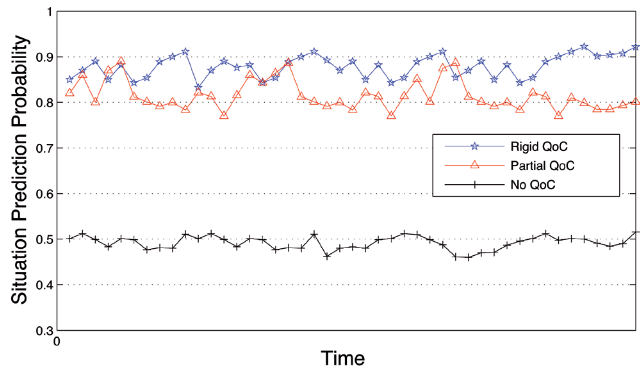


Figure 11. Variation of Situation Prediction Probability using QoC Constraint



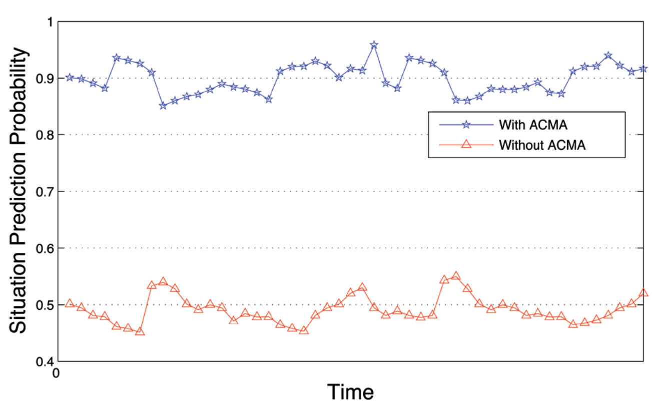
In the first scenario, all context attributes are fused following the specified algorithm according to their QoC specification. In the second scenario, values are only partially satisfied due to their inherent inaccuracy and experimental settings. The fusion of selective context attributes yields better results compared to the non-selective one.

Through this evaluation we observed that it is indeed possible to significantly reduce the sensors' resource usage while satisfying the application quality requirements in pervasive healthcare environments. It also attested the promise of context-aware multi-sensor fusion scheme for selecting a most economically efficient disambiguation action in a resource optimized quality assured model.

DISCUSSION

Dey (Dey, Salber & Abowd, 2001) proposed a toolkit which enables the integration of context data into applications and supports context-aware applications. The context fusion is based on simple name transformation and its context delivery assumes the a priori knowledge about the presence of a widget or a context broker. Multimodal Maps (Cheyer & Julia, 1993), a map based application for travel planning addresses ambiguity by using multimodal fusion to combine different inputs and then prompt the user for more information to remove the remaining ambiguity as much as possible. Remembrance Agent (Rhodes, 1997) uses context to retrieve information relevant to the user and explicitly addresses ambiguity in its manual

Figure 12. Variation of Situation Prediction Probability using Sensor Values



interface. Chen, et al. (Guanling, 2004) proposed a platform, named Solar, to support data fusion services and context dissemination to context-aware applications. Their fusion mechanism is based on an operator graph model, in which context processing is specified by application developers in terms of sources, sinks and channels. Solar also provides a policy driven data dissemination service based on a multicast tree. However, their fusion mechanism does not consider different type of contexts, and building a multicast tree may incur large overhead in the presence of node changes. Hong et al. (Hong & Landay, 2001) proposed Confab which includes a flexible and distributed data store and a context specification language. The context storage consists of a logical context data model which provides a logical representation of context information, and a physical data store where the context data is actually stored. Gaia (Roman, Hess, Cerqueira, Ranganathan, Campbell, Nahrstedt, 2002) is an infrastructure supporting the construction of applications for smart spaces. It consists of a set of core services for building distributed context-aware applications. However, these systems do not consider a formal context fusion mechanism which can fuse high-level contexts for different applications so that the common module for fusing context can be viewed as a shared and reusable service.

Many efforts have been made to develop middleware systems that can effectively support context-aware applications in the presence of resource constraints (e.g., sensor networks). For example, DFuse (Kumar, Wolenetz, Agarwalla, Shin, Hutto, Paul & Ramachandran et al., 2003) is a data fusion framework that facilitates transfer of different areas of application-level information fusion into the network to save power. DFuse does this transfer dynamically by determining the cost of network using cost functions. The tradeoff between communication overhead and the quality of the reconstructed data was first studied in (Olston & Widom, 2000), which envisioned the effect of tolerance ranges on the relative frequency of sink-initiated fetching versus source-initiated proactive refreshes. The focus, however, is on snapshot queries and not on continually satisfying the QoC bound of a long-standing subscription. The idea of exploiting temporal correlation across the successive samples of individual sensors for reducing the communication overhead for snapshot queries is addressed in (Deshpande, Guestrin, Madden, Hellerstein & Hong, 2005) which used training data to parameterize a jointly-normal density function. The CAPS algorithm (Hu, Misra & Shorey, 2006) is designed for long-running aggregation queries (such as *min, max*) and computes the optimal set of tolerance ranges for a given set of sensors that minimizes communication overhead while guaranteeing the accuracy of the computed response. However, our aim is to compute both the best subset of available sensors and most economically efficient disambiguating sensor actions that achieve the desired confidence of a situation space. Dielman et al. (Dielmann & Renals, 2004) proposed a statistical approach using DBN to infer the situation in a meeting scenario. They used both a two-level hidden Markov model (HMM) and a multi-stream DBN, and demonstrated that the DBN architectures are an improvement over a simple baseline HMM. Brdiczka et al. (Brdiczka, Reignier, Crowley, Vaufreydaz & Maisonnasse, 2006) proposed both a deterministic approach based on Petri nets and a probabilistic one based on HMM to represent abstract context in the situation model. Both approaches are well adapted for particular applications: Petri nets for parallelism and HMM for erroneous or uncertain input. MidFusion (Alex, Kumar & Shirazi, 2005) discovers and selects the best set of sensors on behalf of applications (transparently), depending on the QoS guarantees and the cost of information acquisition. They also provide a sensor selection algorithm to select the best set of sensors using the principles of Bayesian Networks (BN) and decision theories. Even though, the computation for all combinations of sensors requires only one set of BN inferencing for all the sensors, the computational complexity is still exponential in terms of the number of sensors. Therefore we investigate a linear algorithm for selecting sensors by considering the DBN based context fusion model as our baseline. Our experimental results also attest promise of this approach which is comparable to the results obtained in (Alex, Kumar & Shirazi, 2005) and (Zhang, Ji & Looney, 2002).

FUTURE RESEARCH DIRECTIONS

One of the main challenges in the application of quality assured ambiguous context mediation is the establishment of appropriate QoC (Quality of Context) functions for specific context variables. Indeed, much of the work on utility-based context models has failed to achieve the desired impact due to the difficulty of computing useful utility functions. To overcome this challenge, we would like to investigate statistical learning or regression techniques to construct the QoC functions from the empirically observed data. Such statistical techniques are needed to provide the necessary robustness in the face of sensor errors (due to noise and miscalibration) and incomplete data (due to network losses). However, the appropriate initial choice of a suitable QoC function is itself an open question; while ideally, we would like a common QoC function to model multiple sensor-to-context mappings, it is possible that the appropriate QoC function be different for different context state.

CONCLUSION

In this chapter, we presented a framework that supports ambiguous context mediation based on dynamic Bayesian networks and information theoretic reasoning, exemplifying the approach through context-aware healthcare applications in smart environments. Our framework provides a Bayesian approach to fuse context fragments and deal with context ambiguity in a probabilistic manner and a semantic web technology to easily compose rules to reason efficiently to mediate ambiguous contexts and depicts an information theoretic approach to minimize the error in the state estimation process. A demonstration software of our model has also been developed and subsequent experimental evaluation is done.

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KEYWORDS AND DEFINITIONS

Context-Awareness: knowledge about the presence of the surrounding contexts like location, activity, vital signs etc.

Ambiguous Contexts: Context associated with underlying noise and uncertainty.

Bayesian Networks: A probabilistic framework that represents a set of random variables and their conditional independence.

Multi Sensor Fusion: Data fusion based on multi-modal sensors.

Information Theory: Techniques for quantifying information and finding fundamental limits based on the theory of signal processing.

Semantic Web: Representation of the web information in a well defined way.

Ontology: Formal representation of the knowledge.