Resource-Optimized Quality-Assured Ambiguous Context Mediation Framework in Pervasive Environments

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Abstract—Pervasive computing applications often involve sensor-rich networking environments that capture various types of user contexts such as locations, activities, vital signs, and so on. Such context information is useful in a variety of applications, for example monitoring health information to promote independent living in "aging-in-place" scenarios, or providing safety and security of people and infrastructures. In reality, both sensed and interpreted contexts are often ambiguous, thus leading to potentially dangerous decisions if not properly handled. Therefore, a significant challenge in the design and development of realistic and deployable context-aware services for pervasive computing applications lies in the ability to deal with ambiguous contexts. In this paper, we propose a resource-optimized, quality-assured context mediation framework for sensor networks. The underlying approach is based on efficient context-aware data fusion, information-theoretic reasoning, and selection of sensor parameters, leading to an optimal state estimation. In particular, we apply dynamic Bayesian networks to derive context and deal with context ambiguity or error in a probabilistic manner. Experimental results using SunSPOT sensors demonstrate the promise of this approach.

Index Terms—Context-awareness, Ambiguous contexts, Bayesian networks, Multi-sensor fusion, Information theory, SunSPOT.

1 Introduction

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 [28]. Essential to such applications is *human-centric* computing and communication, where computers and devices adapt to users' needs and preferences.

In this paper we focus on the computational aspect of user-centric sensory 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 more and more cost-effective and ubiquitous, the interpretation of sensed data as useful contexts, particularly in critical applications like healthcare or security, is still imperfect and ambiguous. Therefore, a significant challenge facing the development of realistic and deployable context-aware services lies in the ability to handle ambiguous contexts. The conversion of raw (sensed) data into high-level albeit meaningful context information requires middleware to pre-process the data collected from heterogeneous distributed sensors through filtering, transformation, and even aggregation, with a goal to minimize the ambiguity of the derived contexts. Only with reasonably accurate context(s) can the applications be accurate enough to make high quality adaptive decisions. The context processing could involve simple filtering based on a value match, or sophisticated data correlation, data fusion or information-theoretic reasoning techniques. Contexts may also include various aspects of relevant information that may be instantaneous or durative, ambiguous or unambiguous. Furthermore, heterogeneous sensors as the information source usually have different resolutions and accuracies, let alone different data rates and formats. Thus, the mapping from sensory output to the context information is a non-trivial task. We believe context-aware mediation plays an important role in improving the accuracy of the derived contexts by reducing their ambiguity (and hence error), although the exact fusion or reasoning techniques may be application and domain specific. This motivates our work in this paper.

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Digital Object Indentifier 10.1109/TMC.2011.20 1536-1233/11/$26.00 © 2011 IEEE

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.

1.1 Related Work

The *ubiquitous computing* paradigm [34] implies smart (i.e., pro-active) interaction of computing and communication devices with their peers and surrounding networks, often without explicit operator control. Hence, such devices need to be imbued with an inherent sentience about relevant contexts that include automatically or implicitly sensed information about the device states and the presence of the users (inhabitants). This concept has led to various projects in smart environments [6]. Existing work such as the Aware Home [24], Reactive Room [7], Neural Network House [21], Intelligent Room [4] and House_n [14] do not provide explicit reusable support for users to manage or correct the inherent uncertainty in the sensed data and its interpretation; instead these systems assume that the sensed contexts are unambiguous and error-free. The work reported in [9] provided a toolkit to enable the integration of context data into applications, however, no mechanism was proposed for sensor fusion or reasoning about contexts to deal with ambiguity. Although a mechanism is proposed in [32] to reason about contexts, it does not provide well defined context-aware data fusion models nor does it address the challenges associated with context ambiguity and situation prediction. Distributed mediation of ambiguous contexts in aware environments [8] has been used to allow the user to correct ambiguity in the sensed output.

Significant efforts have also been made to develop middleware systems that can effectively support efficient context-aware applications in the presence of resource constraints, such as sensory data acquisition or information fusion [1]. For example, DFuse [17] is a data fusion framework that facilitates dynamic transfer of different application level information into the sensor network to save power. In the adaptive middleware for context-aware applications [12] in smart home setups, the application's quality of context (QoC) requirements are matched with the QoC attributes of the sensors with the help of a utility function. Similarly, in MiLAN [11], the quality of service (QoS) requirements of the applications are matched with the QoS provided by the sensor network. Instead of looking into the network utility maximization problem with predefined utility functions, the quality of information-aware framework in [19] employs a runtime design perspective in which the wireless sensor network learns and optimizes the network utility by probing the satisfaction levels of the completed tasks. The notion of information quality in the form of application tolerance is introduced in [18], where the loss of information or data due to resource-constrained environments is addressed by the approximation. An information-directed sensor selection approach is proposed in [37] for a target tracking application. The work presented in [31] used a dynamic Bayesian network based model to provide the information quality of sensor network applications with minimal use of resources.

However, in all these schemes, the QoC requirements of the applications are assumed to be predetermined, and the applications should know both these requirements and the quality associated with each type of sensor in advance. Given that, in pervasive computing environments, the nature (number, types and cost of usage, and benefits) of such sensors available to the applications usually vary, it is impractical to assume a priori knowledge about them. Entropy-based sensor selection heuristic algorithms are also proposed in [10], [20], [33]. In these schemes, an information-theoretic approach is taken for specific application scenarios, where the belief state of the target value is gradually improved by repeatedly selecting the most informative unused sensor until the required information or context accuracy is achieved. The problem of distributed tracking using wireless sensor networks is formulated as an information optimization problem that quantifies several measurable information utility factors [36]. This information-driven approach to sensor querying and data routing balances the information gain provided by each sensor with the cost associated with information acquisition. The selection of proper sensors with the right information at the right moment was originally introduced in [30], while the structure of an optimal sensor configuration constrained by the wireless channel capacity was investigated in [2].

By eliminating the simplifying assumption that all contexts are certain, we design a context-aware data fusion algorithm to mediate ambiguous contexts using dynamic Bayesian networks. We also propose an approach to intelligent sensor management that provides optimal sensor parameter selection in terms of the reduction in the ambiguity or error in the state estimation process. Additionally, a quality of context model along with a fidelity function is proposed to satisfy the application quality requirements.

1.2 Our Contributions

In this paper, we propose a framework that fuses data from disparate sensors, derives the underlying *context state (activity)*, and reasons efficiently about this state in order to support context-aware services that handle ambiguity. For pervasive computing and smart environments with ambiguous contexts, our goal is to build a framework that resolves information redundancy, and also ensures the conformance to the application's quality of context (QoC) bounds based on an optimal sensor placement and/or configuration. For this purpose, we propose a layered and modularized system design using Dynamic Bayesian Networks (DBNs) [15] in which the sensed data is used to interpret context states through the fusion process.

Additionally, we use information-theoretic reasoning techniques to select the optimal values for *context attributes (sensor data)* to minimize the state ambiguity or error. We build a system using SunSPOT sensors for sensing and mediating the user context states or activities. Experimental results demonstrate that the proposed framework is capable of reducing the sensor overhead (measured in terms of communication cost) while ensuring an acceptable level of context accuracy. The framework is also capable of adaptively enhancing the effectiveness of the probabilistic sensor fusion scheme and the situation prediction of the user states by selectively choosing the proper sensors corresponding to the most cost-effective (i.e., efficient) disambiguation action.

The rest of the paper is organized as follows. Section 2 describes the basic concepts of our context model and the quality of context (QoC). Section 3 describes the context-aware (active) data fusion model based on DBNs for resolving ambiguity. In Section 4 we study the structure of an optimal sensor configuration to minimize the state estimation error from an information-theoretic point of view. The performance of our proposed framework is evaluated for a smart health monitoring application with a context sensing system in place, and the results are presented in Section 5. Finally, Section 6 concludes the paper.

2 Context Model

Context-aware sensory data fusion in the face of ambiguities is a challenging research problem. This is because the data sent to the sensor fusion mediator collected from a network of multiple (heterogeneous) sensors is often characterized by a high degree of complexity due to the following challenges: (i) data is often acquired from sensors of different modalities and with different degrees of uncertainty and ambiguity, (ii) decisions must be made quickly, and (iii) the situation as well as the sensory observations evolve dynamically over time. The paradigm of context-awareness demands systems to obtain real world information using limited available resources in a way that is useful for the applications at hand. The derived contexts can either be immediately used for triggering actions or representing real-life situations in which case further computation, such as data fusion techniques may be required to relate the contexts to the situations, leading to what is called *situation-awareness*. To model this fundamental nature of contexts and to enable context and situation-awareness for systems that are able to sense information in the presence of varying levels of data uncertainties requires a generic context model. Thus we make use of the space-based context model [25] and extend it to include quality of context (QoC) attributes. This extended model captures the underlying description of context related knowledge and attempts to incorporate various intuitions that should impact the context inference and produce better (more accurate) fusion results.

2.1 Space-based Context Model

We use the space-based context model as proposed in [25] that defines the following concepts.

Definition 1: Context Attribute: A context attribute, denoted by a_i, is defined as any type of data used for inferring situations. A context attribute is often associated with sensors, virtual or physical, where the sensor readings denote the context attribute values at a given time t, denoted by a_i^t. *For example, the body temperature "100° F" of a user measured by the i-th sensor at a given time t is an example of a context attribute.*

Definition 2: Context State: A context state describes the current state of the application or user in relation to a chosen context and is denoted by a vector S_i. It is a collection of N context attribute values that are used to represent a specific state of the user at time t. Thus, a context state is denoted as $S_i^t = (a_1^t, a_2^t, \ldots, a_N^t)$. *Suppose the body temperature is "100° F" and the user location is "gym", then the context state of the user may be inferred as "doing physical exercise"*. Later we will show how to infer the context state from the context attributes using a probabilistic framework such as dynamic Bayesian networks.

Definition 3: Situation Space: A situation space $\mathcal{R}$ represents a real-life situation. It is a collection of ranges of attribute values corresponding to some predefined situation (e.g., sickness or normal behavior) and is denoted by a vector space $\mathcal{R}_i = (a_1^{R_1}, a_2^{R_2}, \ldots a_{\mathcal{M}}^{R_{\mathcal{M}}})$ consisting of $\mathcal{M}$ acceptable ranges R_i for these attributes. An acceptable range $a_i^{R_i}$ is defined as a set of elements V (numerical or non-numerical) that satisfies a predicate $\mathcal{P}$, i.e., $a_i^{R_i} = V|\mathcal{P}(V)$. For example, in numerical form the accepted 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, containing any type of information, numerical or non-numerical. *For example, the context attribute "body temperature" can take values in the range "98° F" to "100° F" when the user context state is "doing physical exercise" with predefined situation space "normal". But if the body temperature takes values within the range "98° F" to "100° F" when the user context state is "lying on the bed", then the situation space is "not normal".* A hierarchical probabilistic framework incorporating context attributes, context states, and situation space is discussed in the next section.

2.2 Quality of Context Model

Despite recent developments in sensing and network technology, continuous monitoring of users' vital signs (in health care applications) and environmental context in normal settings is still challenging due to the resource constraints of sensor networks. Consequently, the amount of information transmitted to a sensor fusion mediator should be minimized in order to prolong the mediator's lifetime. The idea of exploiting temporal and spatial correlation among successive samples of individual sensors is addressed in [3]; this approach reduces the communication overhead for snapshot queries. The focus there was on meeting the quality requirements for a class of 'aggregation queries', whereas our model is on arbitrary relationships between a context state and its underlying sensor data. Thus we define the Quality of Context (QoC) [13] as a metric for minimizing resource usage (e.g., battery life and wireless communication bandwidth). We assume that the application processes 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 objective is to evaluate the update cost of a sensory action A for a given task while ensuring conformance to the application's QoC bound. Let us denote the update cost (in terms of communication overhead) as $\mathcal{U}_i$ if a sensor B_i has to report its sample value to the mediator and m is the subset of the reporting sensors. Then, the objective is to minimize

$$\sum_{B_i \in m} \mathcal{U}_i(q_i) \tag{1}$$

where $\mathcal{U}_i$ denotes the expected average update (data reporting) cost and explicitly indicates its dependence on the specified precision interval q_i (tolerance range). Intuitively, $\mathcal{U}_i$ is inversely proportional to q_i, since the value of the data reporting cost would be high as the precision interval continues to shrink. At any particular time instant t, we denote this update cost as $\mathcal{U}_i^t$.

This update cost also depends on the hop count h_i, the length of the uplink path from the sensor B_i to the fusion mediator. Accordingly, the update cost can be rewritten as:

$$\text{minimize} \sum_{B_i \in m} \mathcal{U}_i(q_i, h_i) \tag{2}$$

Claim *1:* The update cost $\mathcal{U}_i$ is inversely proportional to q_i and directly proportional to h_i.

A natural method for sampling sensor data is the use of random walks. In the sensor network domain, one could generate a random sample by propagating a request message along a randomly chosen h-hop path starting from the query sink, and sampling the h-th sensor reached. Here we model the variation of a given sensor's sampled values as a random walk without considering any temporal correlation among these samples. For such a model, it is well known that a sensor's sampled value deviates from the mean by more than $\pm q_i$ is proportional to $\frac{1}{q_i^2}$. We consider the random walk model because the sensor positions are unknown and the network may not always be connected. If the underlying data samples evolve as a random-walk model as shown in [13], we have $\mathcal{U}_i \propto \frac{h_i}{(q_i^2)}$ resulting in the following optimization function:

$$\text{minimize} \sum_{B_i \in m} \frac{h_i}{(q_i^2)} \tag{3}$$

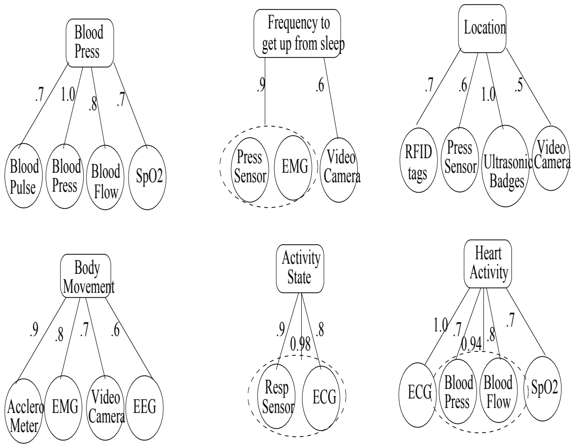

Fig. 1. Subset of sensors with required QoC with no consideration of tolerance range

For example, as shown in Fig. 1, using a respiratory sensor, the activity state of an individual may be computed with an inferencing accuracy of 0.9 (i.e., with 10% error rate), but only with 0.8 accuracy using data from a low-quality ECG sensor. However, by fusing the data available from the respiratory and ECG sensors, we can achieve an inferencing accuracy of 0.98 (i.e., only 2% error rate as per calculation based on Eq. 6). In Fig. 1, each edge from a sensor to the context attribute is associated with a function of three parameters: q_i (the tolerance range of sensory data from sensor B_i), Q (the accuracy range of the derived context attribute) and $\wp$ (the fidelity of the derived context attribute that lies within the range Q). Thus, the fidelity function is $\wp = f_i(q_i, Q)$ for sensor B_i. In other words, given tolerances on q_i and Q, we can say how often (in an ergodic sense), the fused context attribute estimation will lie within the true accuracy range $\pm Q$. Similarly, when we consider two sensors B_i and B_j jointly, the fidelity function should be $\wp = f_{ij}(q_i, q_j, Q)$. In this way, for m sensors, there are $2^m - 1$ (all possible combinations except when no sensor is selected) functions $f(.)$, indicating the relationship between the context attribute, the context fidelity and the precision range. Given these functions, the 'application' now says that it needs a precision bound (on the context attribute) of $\acute{Q}$ with a fidelity of at least $\acute{\wp}$. Then, the problem at hand is:

Problem *1:* Find the combination of tolerance ranges $q_1, q_2, ..., q_m$ of m selected sensors that satisfies the fidelity $f_{1,\ldots,m}(q_1, q_2, \ldots q_m, \acute{Q}) \geq \acute{\wp}$ and minimizes the update cost $\sum_{B_i \in m} h_i/(q_i)^2$.

In case the context attribute values are boolean, it may be hard to associate a bound Q with the accuracy of the context. However, this is a special case of the model proposed here.

The problem of optimally computing the q_i values can be represented by the Lagrangian:

$$\text{minimize} \sum_{i=1}^{m} \frac{h_i}{q_i^2} + \lambda \times \left[f_{1,\ldots,m}(q_1, q_2, \ldots q_m, \acute{Q}) - \acute{\wp} \right]. \tag{4}$$

where λ is the Lagrangian constant. Finding an exact solution to Eq. 4, for any arbitrary $f(.)$ is an NP-complete problem [3]. While a completely arbitrary $f(.)$ function requires a brute-force search, there are certain forms of $f(.)$ that prove to be more tractable. In particular, an attractive case occurs when the individual fidelity function of sensor B_i is represented by the form

$$f_i(.) = \nu_i * \exp^{-\frac{q_i^2}{\eta_i}}, \tag{5}$$

where η_i and ν_i are sensitivity constants for sensor B_i. A larger value of η_i indicates a lower contribution from sensor B_i to the inference of the context state S. In [22], a decision fusion rule with the counting policy has been proposed based on a Poisson sensor distribution model. Moreover, for selecting m sensors, assuming that the estimation error of each sensor is statistically independent of the other sensors (as in [16]), the resulting $f(.)$ function has the form:

$$f_{1,\ldots,m}(.) = 1 - \prod_{B_i \in m} [1 - f_i(.)] \tag{6}$$

We solve this by taking the Lagrangian optimization as follows.

$$\text{minimize} \sum_{B_i \in m} \frac{h_i}{q_i^2} + \lambda \left[1 - \prod_{B_i \in m} [1 - (\nu_i * \exp^{-\frac{q_i^2}{\eta_i}})] - \acute{\wp} \right]. \tag{7}$$

and prove the following Lemma.

Lemma *1:* The combination of tolerance ranges $q_1, q_2, ..., q_m$ of m sensors that satisfies the fidelity function $f_{1,\ldots,m}(q_1, q_2, \ldots q_m, \acute{Q}) \geq \acute{\wp}$ and minimizes the objective function in Expression (3) is given by

$$\frac{h_1 * \eta_1 * (1 - \nu_1 * exp(-\frac{q_1^2}{\eta_1}))}{q_1^4 * \nu_1 * exp(\frac{-q_1^2}{\eta_1})} = \cdots$$

$$= \frac{h_m * \eta_m * (1 - \nu_m * exp(-\frac{q_m^2}{\eta_m}))}{q_m^4 * \nu_m * exp(\frac{-q_m^2}{\eta_m})}$$

Proof: The proof is shown in the Appendix.

This optimization problem helps us choose the values of $q_1, q_2, \ldots, q_m$ for a given set of m sensors, such that we minimize the total update cost while ensuring the required accuracy level.

In the next section we propose a fusion scheme that can correlate with and reason about the context attributes and context states since the situation space in pervasive computing environments is often dynamic and unfolds over time. Thus we need a time varying dynamic model to reflect changes that captures the beliefs of the current events and predicts the evolution of different situations. An adaptive system is therefore needed so that it cannot only handle raw sensory data of different modalities systematically but also, perhaps more importantly, can reason over time to reduce the context ambiguity during the interpretation of the situation.

3 CONTEXT-AWARE DATA FUSION

A characteristic of a sensor-rich smart environment (e.g., health care) is that it senses and reacts to *contexts*, information sensed about the environment, its occupants (users), and their daily activities, by providing context-aware services with a goal to improve user experiences and interactions with the environment. In this section, we develop an efficient framework for sensor data fusion in a context-aware environment with the help of the underlying space-based context model. In the case of context-aware services, it is difficult to get an accurate and well defined context that can be classified as 'unambiguous' since the interpretation of sensed data as a context is mostly imperfect and ambiguous (or noisy). To alleviate this problem, we propose a dynamic Bayesian network (DBN) model.

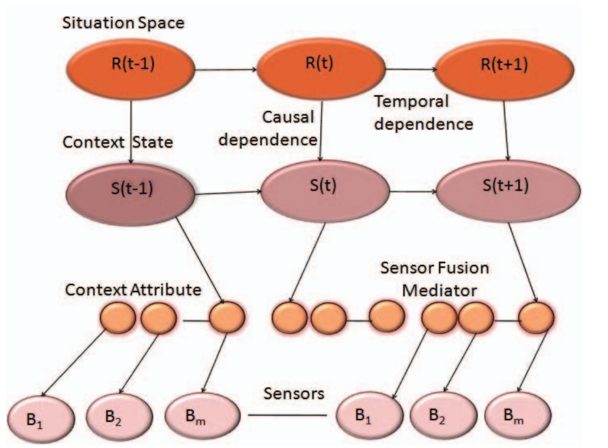

Fig. 2. Context-Aware Data Fusion Framework based on Dynamic Bayesian Networks

3.1 The DBN Model

Our motivation is to use the data fusion algorithm to develop a context-aware model to gather knowledge from the sensory data. A Dynamic Bayesian Networks (DBN) provides a coherent and unified hierarchical

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Procedure ACMA (input: context attribute a_i^t, confidence threshold τ;
output: subset of sensors m)
1. Initialize time stamp t = 0,
2. Compute ambiguity-reducing utility {V_1^t,...,V_m^t} by Eq.8
3. Calculate utility value {U_1^t,...,U_m^t} using Eq.10
4. Select the most efficient sensor action A* based on Eq.11
5. Instantiate the subset of corresponding sensors
6. Update probability distribution P(R, A) of situation space using Eq.12
7. If P(R, A*) ≥ τ, then terminate; otherwise
8. Increase time stamp t = t + 1, and go to step 1
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Fig. 3. Ambiguous Context Mediation Algorithm (ACMA)

probabilistic framework for sensory data representation, integration, and inference. Fig. 2 illustrates a DBN based framework for a context-aware data fusion scheme consisting of a situation space, context states, context attributes, and a sensor fusion mediator in a network of sensors. The data fusion scheme integrates both top-down and bottom-up inference mechanisms. The top-down inference can be used to predict the utility of a particular sensory action with respect to a goal at the top. For example, in the case of a given context state (going to the restroom), top-down inference will fuse the most relevant context attributes (time, frequency of getting up from bed, blood sugar level, etc.). The bottom-up inference integrates the context attributes from a sensory action and updates each node in the network.

Let us consider a situation space $\mathcal{R}$ resulting from the sensory information sources $\mathcal{B} = \{\mathcal{B}_1, \dots, \mathcal{B}_m\}$ where $\mathcal{B}$ is a set of measurements taken from sensors labeled 1 to m as shown in Fig. 2. The context attribute that is most relevant in our case should decrease the ambiguity of the situation space element $a_j^{R_j}$ the most; we will select that sensor which directs the probabilities of the situation space to near one (for maximum) or zero (for minimum). Let $\mathcal{V}$ be the ambiguity reducing utility to the situation space $\mathcal{R}$. Then the expected value of $\mathcal{V}$, given a context attribute a_k^t from a sensor B_k, providing L possible values, can be represented as

$$\mathcal{V}_i = \max_{k=0}^{L} \sum_{j=0}^{N} [P(a_j^{R_j}|a_k^t)]^2 - \min_{k=0}^{L} \sum_{j=0}^{N} [P(a_j^{R_j}|a_k^t)]^2 \quad (8)$$

where $i \in \{1, 2, \dots m\}$ is a sensor and N denotes the elements of the situation space. The context attribute can be measured by propagating the possible outcome of an information source, i.e.,

$$P(a_j^{R_j}|a_k^t) = \frac{P(a_j^{R_j}, a_k^t)}{P(a_k^t)} \quad (9)$$

However, the quantification of this conditional probability needs a detailed model depending upon the different types of sensors and their applications. Consider for example, an audio sensor. Evaluating the benefit of using audio in disambiguating a person's state (e.g., whether a person is moaning in pain or singing) is extremely challenging. It depends on how far the person is from the microphone, which way the person is facing, the time of the day (at night it is more quiet so sounds can be heard more clearly), and 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 affect the efficacy of the audio sensor.

Considering the information update cost from Eq. 2 and ambiguity reducing utility from Eq. 8, the overall utility can be expressed as

$$U_i = \alpha \mathcal{V}_i + (1 - \alpha)(1 - \mathcal{U}_i) \quad (10)$$

where $\mathcal{U}_i$ is the update cost to acquire the information by the sensor B_i with a knowledge of the QoC bound, and α denotes the balance coefficient between the ambiguity reduction and the cost of information acquisition. Eq. 10 represents the contribution to ambiguity reduction and the cost associated with information retrieval to achieve the desired level of confidence for the situation space. We can observe from Eq. 10 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. So the most efficient sensor action A^* can be chosen with the help of the following decision rule:

$$A^* = \arg\max_{A} \sum_{j} U(\mathcal{B}, a_j^{R_j}) P(a_j^{R_j}|\mathcal{B}) \quad (11)$$

where $\mathcal{B} = \{\mathcal{B}_1, \dots, \mathcal{B}_m\}$ is a set of measurements taken from sensors labeled from 1 to m respectively at a particular instant. Action A refers here the optimal sensor selection. To define the decision rule for selecting sensor, we consider utility of a situation space over all its acceptable ranges multiplied by the probability of the situation space over all its acceptable ranges with the given set of sensors. The subset of sensors (referred to as economically efficient disambiguation sensor action A^*) which maximizes this decision rule value is ultimately chosen. By incorporating the temporal dependence between the nodes as shown in Fig. 2, the probability distribution of the situation space can be described as:

$$P(\mathcal{R}, A) = \prod_{t=1}^{T-1} P(S_t|S_{t-1}) \prod_{t=1}^{T-1} P(\mathcal{R}_t|\beta_t) P(\mathcal{R}_0) \quad (12)$$

where T denotes the time, $\mathcal{R} = \{\mathcal{R}_0, \ldots, \mathcal{R}_t, \ldots, \mathcal{R}_T\}$ is the situation space and $\beta = \{\beta_0, \ldots, \beta_t, \ldots, \beta_T\}$ is the subset of sensed information on the time sequence of T. Here $S = \{S_0, \ldots, S_t, \ldots, S_T\}$ represents a context state relevant on the time sequence of T that has temporal links between corresponding nodes in two neighboring time steps. The sensor action strategy must be recalculated at each time step since the best action varies with time. The ambiguous context mediation algorithm is presented in Fig. 3. Next we propose an information theoretic reasoning technique to select the sensor parameters with a goal to reduce the ambiguity in the context estimation process.

4 Optimal Selection of Sensor Parameters

Energy-efficiency in wireless sensor networks is of utmost importance in addition to managing the QoC requirements. For example, a higher quality of context might be required for certain health-related context attributes during high stress situations such as medical emergency, while a lower quality may suffice during low stress situations such as sleep. Fig. 4 shows the context attributes 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. Specifically, the figure 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 0.8. So the problem here is to decide what type of information each sensor should send to the fusion mediator to estimate the best current state of the patient, satisfying the application QoC requirements for each context attribute while at the same time minimizing the state estimation error.

In this section, we formalize an optimal selection of sensor parameters for context state estimation. The optimality is defined in terms of the reduction in ambiguity or error in the estimation process. The main assumption is that state estimation becomes more reliable and accurate if the ambiguity or error in the underlying estimation can be minimized. We investigate this from an information-theoretic perspective [5], where information about the context attributes is made available to the fusion mediator by a set of selected sensors. The fusion mediator produces

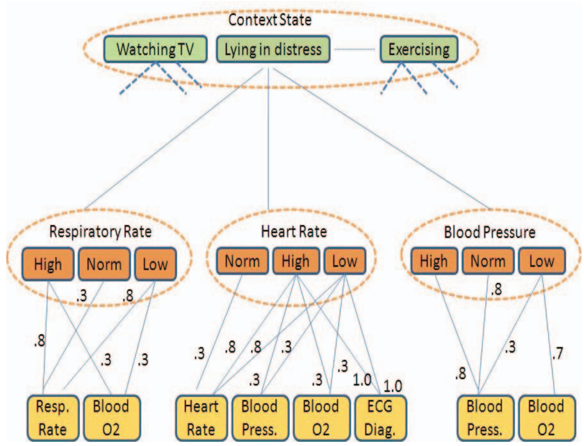

Fig. 4. State-based Context attribute graph with the required QoC

an estimate of the state of the situation by analyzing 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 $\mathcal{R}$ (we assume here the situation $\mathcal{R}$ as binary for ease of modeling). Each sensor attribute has a source entropy rate[1] $H(a_i)$. By $H(a_i)$ we mean the entropy rate of the i^{th} sensor as a source; $H(a_i)$ is the average number of bits needed to encode it; and a_i is the noisy observations across sensor i, mathematically refers the discrete random variable of a stochastic process. Any sensor wishing to report this attribute must send $H(a_i)$ bits per unit time, which is the source entropy being measured assuming that the sensor is sending the 'exact' physical state. Of course, different sensors contribute in different measures to the 'error' in the state estimation (e.g., due to their sensing limitations). So, the problem is to minimize the error (or keep it within a specified bound), while not exceeding the shared link rate $\mathcal{Q}$. 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 [2].

Problem 2: Let D be the vector of sensors and A be the set of attributes. Imagine a $(D \times A)$ matrix where $D_{mi} = 1$ when sensor B_m sends attribute a_i. Then, the goal is to find the matrix $(D \times A)$ within the link rate constraint $\mathcal{Q}$ representing the data that minimizes the

1. The entropy rate of a data source means the average number of bits per symbol needed to encode it. The entropy or source information rate of a stochastic process is the time density of the average information in that process. Mathematically, the entropy rate $H(X) = \lim_{n\to\infty} \frac{1}{n} H(X_1, X_2, ..., X_n)$ is the limit of the joint entropy of n members of the process X_k divided by n, as n tends to ∞.

estimation error of the situation space.

$$\sum_m \sum_i H(a_i) * D_{mi} < \mathcal{Q} \quad \text{and}$$
$$\texttt{minimize}\,[P_e = P\{\tilde{\mathcal{R}} \neq \mathcal{R}\}] \tag{13}$$

where $\tilde{\mathcal{R}}$ is an estimate of the original situation $\mathcal{R}$.

4.1 Problem Statement

We assume $\mathcal{R}$ to be a random variable drawn from the binary alphabet $\{\mathcal{R}_0, \mathcal{R}_1\}$ with prior probabilities p_0 and p_1, respectively. In our case, each sensor needs to determine a sequence of context attributes for a sequence of context states $\{S_{m,t} : \forall t = 1, 2, \ldots, T\}$ to determine the value of situation $\mathcal{R}$. We assume that the random variables $S_{m,t}$ associated with context states are i.i.d., given situation space $\mathcal{R}$, with conditional distribution $p_{S|\mathcal{R}}(.|\mathcal{R}_i)$. The sensors send a summary $Z_{m,t} = \pi_m(S_{m,t})$ of their own observations to a fusion center at discrete time t, where π is an admissible strategy (decision rule). Upon receiving the data, the fusion center produces an estimate $\tilde{\mathcal{R}}$ of the original situation $\mathcal{R}$. Thus we need to find an admissible strategy for an optimal sensor-attribute mapping matrix $(D \times A)$ that minimizes the probability of estimation error $P_e = P\{\tilde{\mathcal{R}} \neq \mathcal{R}\}$.

Definition 4: Consider a set of decision rules π_m for an observation $X \to \{1, 2, \ldots n_m\}$ where n_m is the number of messages admissible to sensor B_m with the admissible strategy denoted by π, consisting of M sensors in $(D \times A)$ matrix, such that

$$\sum_{m=1}^{M} \sum_i n_m \times H(a_i) * D_{mi} < \mathcal{Q}$$

A message in this case is a sequence of context attributes. But for a set of decision rules we have a set of messages. By admissible strategy in this definition we mean the strategy which minimizes the probability of estimation error of the situation space. The number of messages most relevant (admissible) to sensor B_m with the admissible strategy being maximum a posteriori detection probability are ultimately chosen. The evaluation of message $z_{m,t} = \pi_m(s_{m,t})$ by sensor B_m is forwarded to the fusion center at time t. Since we are interested in a continuous monitoring scheme, 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 data transmission scheme through the error exponent measure or Chernoff information:

$$E(\pi) = -\lim_{T \to \infty} \frac{1}{T} \log P_e^{(T)}(\pi) \tag{14}$$

where $P_e^{(T)}(\pi)$ denotes the probability of error at the fusion center for strategy π considering the maximum *a posteriori* detector probability. We use $\Pi(\mathcal{Q})$ to capture all admissible strategies corresponding to a multiple access channel with link rate capacity $\mathcal{Q}$ and redefine our problem as follows:

Problem *3:* Find an admissible strategy $\pi \in \Pi(\mathcal{Q})$ that maximizes the Chernoff information:

$$E(\pi) = -\lim_{T \to \infty} \frac{1}{T} \log P_e^{(T)}(\pi) \tag{15}$$

4.2 Analytical Results

Let us consider an arbitrary admissible strategy $\pi = (\pi_1, \pi_2, \ldots, \pi_M)$ and denote the space of received information corresponding to this strategy by

$$\gamma = \{1, 2, \ldots, n_1\} \times \{1, 2, \ldots, n_2\} \times \ldots \times \{1, 2, \ldots, n_M\} \tag{16}$$

where

$$(\pi_1(x_1), \pi_2(x_2), \ldots, \pi_M(x_M)) \in \gamma \tag{17}$$

for all observation vectors $(x_1, x_2, \ldots, x_M) \in X^M$. Since the maximization of the *a posteriori* detector is basically the minimization of the probability of estimation error at the fusion center, we could approximate this probability of error for a finite observation interval T and measure the error exponent corresponding to strategy π using Chernoff's theorem [5].

Let $p_{\tilde{Z}|\mathcal{R}}(.|\mathcal{R}_0)$ and $p_{\tilde{Z}|\mathcal{R}}(.|\mathcal{R}_1)$ denote the conditional probability mass functions on γ, given situations $\mathcal{R}_0$ and $\mathcal{R}_1$. Now for $\tilde{z} = (z_1, z_2, \ldots z_M)$ and $i \in 0, 1$:

$$\begin{aligned} p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_i) &= P_i\{\tilde{x} : (\pi_1(x_1), \pi_2(x_2), \ldots, \pi_M(x_M)) = \tilde{z}\} \\ &= \prod_{m=1}^{M} P_i\{\pi_m(u_m)\} \end{aligned} \tag{18}$$

where the probability of event W is $P_i\{W\}$ under situation $\mathcal{R}_i$, and $\pi_m(u_m) = \{x : \pi_m(x) = z_m\}$

Theorem *1:* Using Chernoff's theorem [5], the best achievable exponent in the error probability at the fusion center is given by

$$E(\pi) = -\min_{0 \le k \le 1} \log \left[\sum_{\tilde{z} \in \gamma} (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_0))^k (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_1))^{1-k} \right]$$

where $\pi \in \Pi(\mathcal{Q})$ is given. Using Theorem 1 we can restate our original problem as follows.

Problem *4:* Maximize the Chernoff information

$$E(\pi) = -\min_{0 \le k \le 1} \log \left[\sum_{\tilde{z} \in \gamma} (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_0))^k (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_1))^{1-k} \right]$$

corresponding to an admissible strategy $\pi \in \Pi(\mathcal{Q})$.

The problem of finding the optimal decision rules $\pi = (\pi_1, \pi_2, \ldots, \pi_M)$ is hard even when the assignment vector $(n_1, n_2, \ldots, n_M)$ is fixed *a priori*. Hence we try to derive a set of simplified conditions for Problem 4. For this purpose, we state the following lemma, where we obtain an upper bound on the contribution of a single sensor to the Chernoff information and find sufficient conditions for which having $\mathcal{Q}$ sensors in the

$(D \times A)$ matrix, each sending one bit of information, is optimal.

Lemma *2:* For strategy π, the contribution $E_{B_m}(\pi)$ from a single sensor B_m to the Chernoff information $E(\pi)$ is bounded above by the Chernoff information E^* contained in one context state S,

$$E_{B_m}(\pi) \leq E^* \equiv - \min_{0 \leq k \leq 1} \log \left[\int_X (p_{S|\mathcal{R}}(x|\mathcal{R}_0))^k . (p_{S|\mathcal{R}}(x|\mathcal{R}_1))^{1-k} dx \right] \quad (19)$$

Proof: The proof is shown in the Appendix.

Let us represent $E_1(\pi_m)$ as the Chernoff information corresponding to a single sensor with decision rule π_m, i.e.,

$$E_1(\pi_m) = - \min_{0 \leq k \leq 1} \log \left[\sum_{z_m=1}^{n_m} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right] \quad (20)$$

and let Γ_b be the set of binary functions on the observation space X.

Lemma *3:* Consider a binary function $\tilde{\pi}_b \in \Gamma_b$ such that $E_1(\tilde{\pi}_b) \geq \frac{E^*}{2}$. Then having $\mathcal{Q}$ identical sensors, each sending one bit of information is optimal.

Proof: Let strategy $\pi = (\pi_1, \pi_2, \ldots, \pi_M) \in \Pi(\mathcal{Q})$ and link rate capacity $\mathcal{Q}$ be given. We construct an admissible strategy $\pi' \in \Pi(\mathcal{Q})$ such that $E(\pi') \geq E(\pi)$. We divide the collection of decision rules $\{\pi_1, \pi_2, \ldots, \pi_M\}$ into two sets; the first set contains all of the binary functions, whereas the other is composed of the remaining decision rules. We also consider I_b to be the set of integers for which the function π_m is a binary decision rule:

$$I_b = \{m : 1 \geq m \geq M, \pi_m \in \Gamma_b\} \quad (21)$$

Similarly, we define $I_{nb} = \{1, 2, \ldots, M\} - I_b$. Considering the binary decision rule $\hat{\pi}_b \in \Gamma_b$, we express

$$E_1(\hat{\pi}_b) \geq \max\{\max_{m \in I_b}\{E_1(\hat{\pi}_b)\}, \frac{E^*}{2}\} \quad (22)$$

Since by assumption $\tilde{\pi}_b \in \Gamma_b$ and $E_1(\tilde{\pi}_b) \geq \frac{E^*}{2}$, we infer that such a function $\hat{\pi}_b$ always exists. Observing that $m \in I_{nb}$ implies that $n_m \geq 2$, which in turn yields $n_m \times H(a_i) \geq 2$. Hence without exceeding the capacity ($\mathcal{Q}$ bits per unit time) of the multiple access channel, we can replace each sensor with index in I_{nb} by two binary sensors. Considering the alternative scheme π', where π' is an admissible strategy, we replace every sensor with index in I_{nb} by two binary sensors with decision rule $\hat{\pi}_b$. This new scheme outperforms the original strategy π as shown below.

TABLE 1
Calibrated Accelerometer Sample Values for different Context States

Range($5-95$th percentile) of Tilt Values (in degrees)	**Context States**
85.21 to 83.33	*Sitting*
68.40 to 33.09	*Walking*
28.00 to -15.60	*Running*

$$\begin{aligned} E(\pi') &= (|\ I_b\ | + 2|I_{nb}|)\, E_1(\hat{\pi}_b) \geq |I_b| E_1(\hat{\pi}_b) + |I_{nb}| E^* \\ &\geq \sum_{m=1}^{M} \left[- \min_{0 \leq k \leq 1} \log \left[\sum_{z_m=1}^{n_m} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right] \right] \\ &\geq - \min_{0 \leq k \leq 1} \log \left[\sum_{\tilde{z} \in \gamma} \left(\prod_{m=1}^{M} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right) \right] \\ &= E(\pi) \end{aligned} \quad (23)$$

We observe that the Chernoff information at the fusion center is monotonically increasing with the number of sensors for a fixed decision rule $\tilde{\pi}_b$. The state estimation error can be minimized by augmenting the number of sensors in π' until the capacity constraint $\mathcal{Q}$ is met with equality. □

The strategy π being arbitrary, we conclude that having $\mathcal{Q}$ identical sensors in the $(D \times A)$ 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.

5 Experimental Study

We use the SunSPOT [29] sensors for evaluating our proposed framework for context sensing and mediation. Each free-range SunSPOT (Sun Small Programmable Object Technology) contains a processor, radio, sensor board, and battery; the base-station SunSPOT contains a processor and radio only. The SunSPOT uses a 32-bit ARM9 microprocessor running the Squawk VM and programmed in Java, supporting the IEEE 802.15.4 standard. In our context sensing and performance evaluation, we will use various built-in sensors available with the SunSPOT sensor board.

5.1 Determination of Context Estimates

We used the SunSPOT accelerometer sensor to measure the tilt value (in degrees) when a monitored user was in three different context states: *sitting*, *walking*, and *running*. From the collected samples, we computed the 5^{th} and 95^{th} percentile of the tilt readings corresponding to each state. Table 1 shows the resulting ranges in the accelerometer tilt readings observed for each of these three states. The results indicate that there is an observable separation in the ranges of the tilt values for the three different states.

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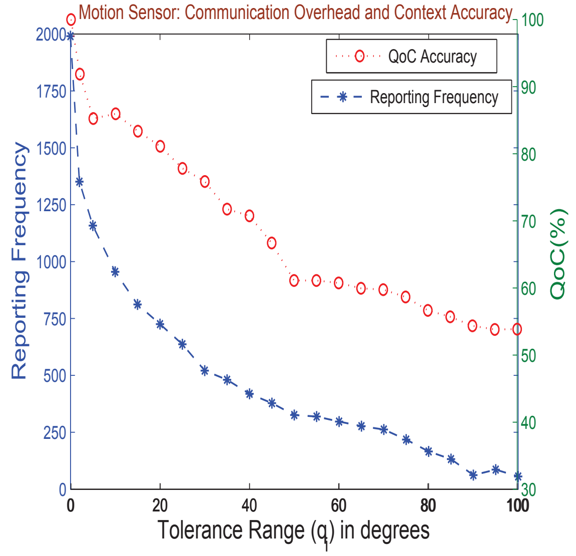

Fig. 5. Communication Overhead and QoC accuracy vs. Tolerance Range using Motion Sensor

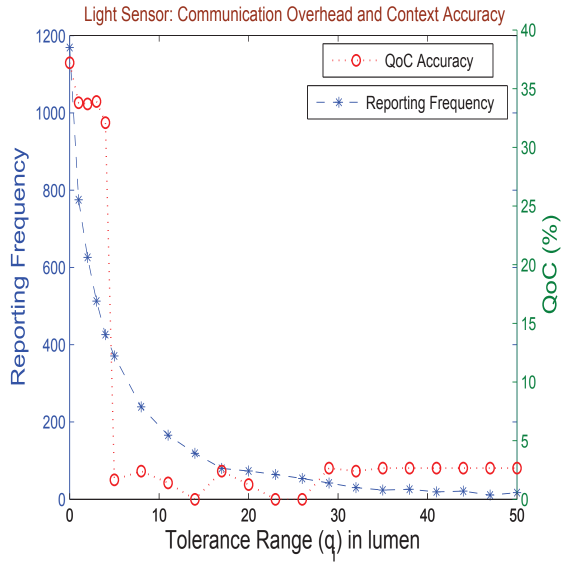

Fig. 6. Communication Overhead and QoC accuracy vs. Tolerance Range using Light Sensor

TABLE 2
Light Sensor Values (lumen) for different Context States

Avg. Range of Light level (lumen)	Context States
LightSensor.getValue() $= 10$ to 50	Turned on $\rightarrow$ active
LightSensor.getValue() $= 0$ to 1	Turned off $\rightarrow$ sleeping

This suggests that the states can be distinguished reasonably accurately even under moderate uncertainty in the sensor readings.

Similarly, we also used the SunSPOT light sensor to measure the light level (in lumen) for different user contexts. Intuitively, low values of ambient light intensity may be indicative of a *'sleeping'* state, while higher values of light intensity are likely to result when the individual is *'active'* (e.g., walking or running). Table 2 shows the observed ranges for the light values for each of these two states. The accuracy of context from the light sensor is much lower than that for the accelerometer sensor as users may often be inactive (e.g., sitting), even under high illumination.

5.2 Measuring QoC Accuracy and Sensor Overheads

To study the potential impact of varying the tolerance range of each sensor and the resulting tradeoff between the sensor reporting overhead, we collected traces for the SunSPOT motion and light sensors for a single user engaged in a mix of three different activities (*sitting*, *walking*, and *running*) for a total of ≈ 6 minutes (2000 samples at $5.5Hz$). We then used an emulator to mimic the samples that a sensor would have reported, given the trace, for a given tolerance range q, and compared the context inferred from the values reported by the emulation against the ground truth. Fig. 5 shows the resulting plots for the total number of samples reported (an indicator of the communication overhead) and the corresponding QoC (defined as *1 − error rate*) achieved, for different values of the tolerance range (q_{mo}) for the motion sensor. Fig. 6 plots the corresponding values vs. the tolerance range (q_l) for the light sensor.

As the figures demonstrate, in general, there is a continuous drop in the reporting overhead and the QoC as q increases. However, as seen in Fig. 5, a QoC accuracy of approximately 80% is achieved for $q = 40$, a modestly large value. Moreover, the use of this tolerance range reduces the reporting overhead dramatically by approximately 85% (from $1953 \rightarrow 248$). This suggests that it is indeed possible to achieve significant savings in cost, if one is willing to tolerate marginal degradation in the accuracy of the sensed context. A similar behavior is observed for the light sensor ($q = 4$ incurs a 5% loss in QoC accuracy vs. approximately 65% reduction in the reporting overhead). However, as the difference between the lumen ranges for $Active$ vs. $Inactive$ $(e.g., Sleeping)$ is only approximately 10 (Table 2), increasing q actually leads to a sharp fall in the QoC.

5.3 The Benefit of Joint Sensing

We also investigated how the use of joint readings from both sensors affects the inferencing accuracy vs. tolerance ranges. We consider the user in a *sitting*, *walking*, or *running* state whenever the motion sensor tilt values lie within the corresponding range and the light sensor values indicate an *active* state. Fig. 7 uses a three-dimensional plot to illustrate the observed inferencing accuracy when the tuple (q_{mo}, q_l) is jointly varied. This confirms the QoC is now less susceptible

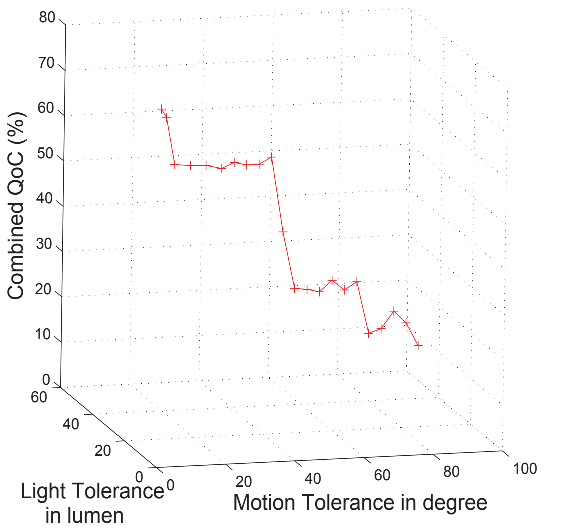

Fig. 7. QoC accuracy vs. Tolerance Range using Motion and Light Sensor Jointly

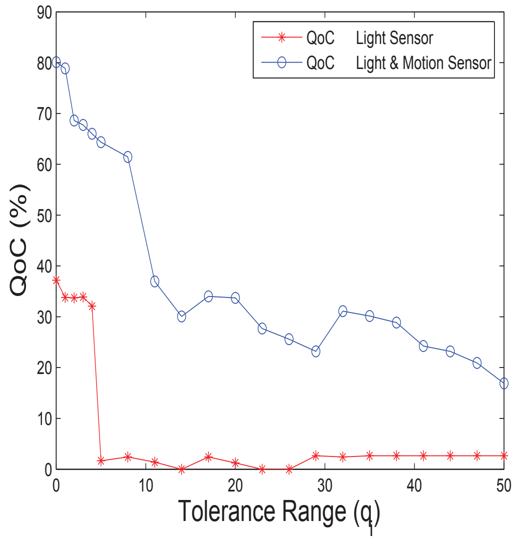

Fig. 8. Comparison of QoC accuracy Improvement using Multiple Sensors

to individual variations of q. Fig. 8 confirms this benefit by plotting the QoC vs. q obtained using the light sensor against that obtained by using both light and motion sensors (the tolerance ranges of both being identical). Clearly, the QoC accuracy from the combination of the two sensors is much higher than that of a single sensor.

5.4 Evaluation of Ambiguous Context Mediation

We conducted experiments to evaluate the performance of the proposed ambiguous context mediation framework in a smart home health monitoring environment. The ambiguous context mediation algorithm (ACMA) given in Fig. 3 was applied during the 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 efficient sensor action. Let us assume the situation space has three states, high, medium and low. Fig. 9 represents a snapshot of the Bayesian Network model for this application using Netica BN software [23]. In this figure we represent a situation space sickness and three context states – WatchingTV, Lying_in_Distress and Exercising. The conditional probabilities of these context states are empirically derived using the SunSPOT traces. The sensors selected by the ACMA algorithm 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. For example, given the ground truth of the patient exercising, we computed how many times the Body_Temp_Sensor report a reading above the threshold value. These conditional probability values

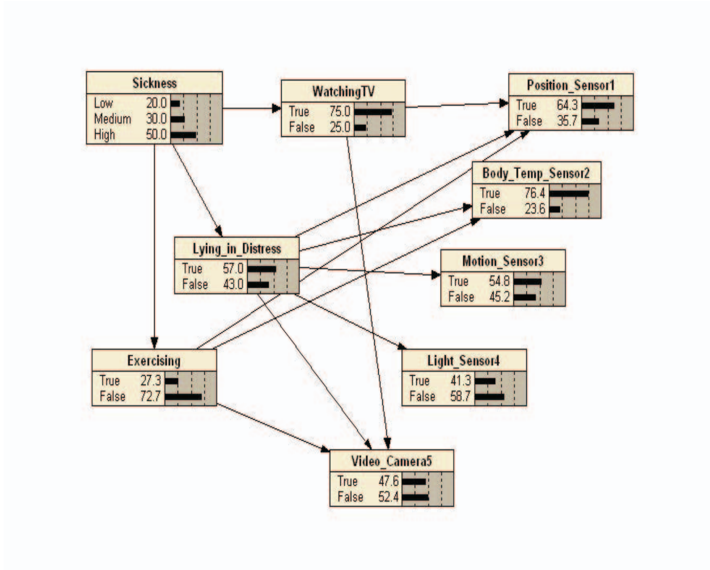

Fig. 9. Bayesian Network

at a particular state of the application are all shown in Fig. 9.

From Fig. 10, we observe that the utility increases (i.e., the ambiguity decreases) as the number of selected sensors increases for different states of the application. The initial utility is calculated using Eq. 8 considering a single sensor. The maximum utility values were obtained by increasing the sensor subset size for three different states (different probability values). With different balance coefficients as shown in Eq. 10, the best subset of sensors for an application having multiple states is also different. This demonstrates that the gain obtained by having multiple sensors

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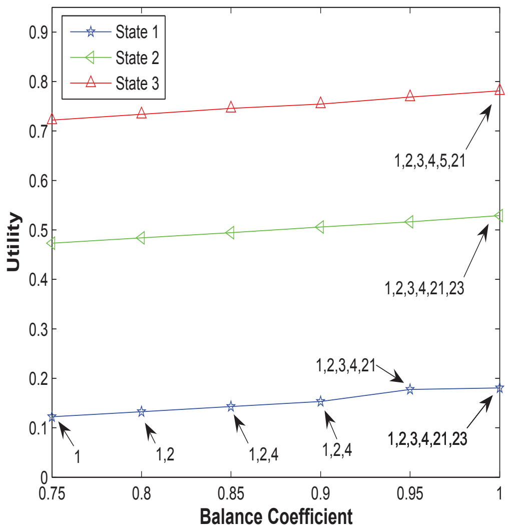

Fig. 10. Utility values (Best Sensor Subset) for different values of balance coefficient α

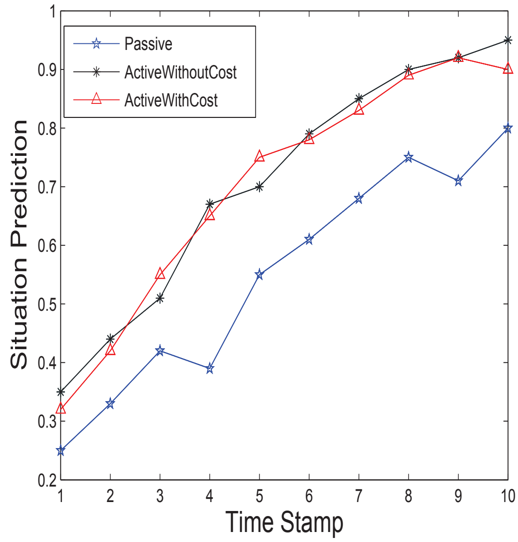

Fig. 11. Situation Prediction Probability using Passive and Active Fusion

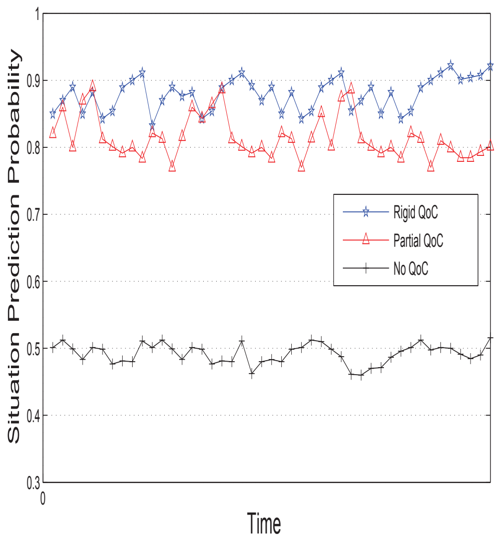

Fig. 12. Variation of Situation Prediction Probability using QoC constraint

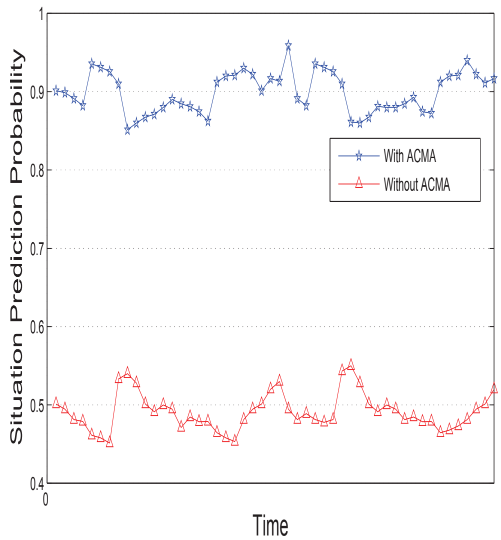

Fig. 13. Variation of Situation Prediction Probability using sensor values

exceeds the benefits of detailed information from each individual sensor, which is also in accordance with our information theoretic analysis.

Next we experimentally analyze the performance of *active* (context-aware) and *passive* (non context-aware) fusions to illustrate how the proposed active fusion scheme 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. We observe during our experiment that a few sensors dominate in active fusion compared to the others. This selection of sensors accelerates the decision to be taken on a situation space compared to the passive fusion as shown in Fig. 11. However, this sometimes leads to information redundancy if the same value of the attribute repeats consecutively. However, this approach may be beneficial for reducing imprecision and increasing reliability.

Fig. 11 shows no significant performance difference by considering the update cost. So the information redundancy can be overcome by frequently alternating between the active sensors with almost the same performance gain. Fig. 12 represents the confidence of situation prediction for different values of the QoC constraint. The confidence level achieves a higher value for a rigid (tight) QoC constraint as compared to a partial QoC. Though we achieved a better confidence level for a rigid QoC constraint, more uniformity is achieved for the partial QoC. This observation confirms that the participation of multiple sensors during the partial QoC bound fusion process yields a more stable value though fails to achieve a higher confidence gain. Next we examine the situation prediction when different sensors are selectively chosen with the help of using the context mediation framework. Fig. 13 depicts the variation of situation prediction with different sets of context attributes from different sensors. In the first scenario, all context attributes are fused following the specified algorithm according to their QoC specifications. 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 ones.

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

6 Conclusion

This paper presents a framework that supports ambiguous context mediation based on dynamic Bayesian networks and information-theoretic reasoning. We exemplified the proposed approach through context-aware healthcare applications in smart environments. Our framework satisfies the applications' quality requirements based on a resource optimized QoC function, provides a Bayesian approach to fuse context fragments and deal with context ambiguity in a probabilistic manner, and depicts an information theoretic approach to minimize the error in the state estimation process. A SunSPOT platform based context sensing system is developed and subsequent experimental evaluation is done to perform cost/benefit analysis to engage the most efficient actions for context disambiguation in resource constrained sensor environments.

Acknowledgement

The authors would like to thank the anonymous reviewers for their constructive comments which helped to improve the quality of the manuscript significantly. This work is partially supported by the AFOSR Grant FA9550-08-1-0260, and NSF Grants IIS-0326505 and CNS-0721951. The work of S. K. Das is also supported by (while serving at) the National Science Foundation. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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