Resource-Optimized Quality-Assured Ambiguous Context Mediation 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 paper, we propose a resource optimized quality assured 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. The proposed framework provides a systematic approach based on dynamic Bayesian networks to derive context fragments and deal with context ambiguity or error in a probabilistic manner. Experimental results using SunSPOT sensors demonstrate the promise of this approach.

Keywords: 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 [21]. Essential to such applications is *human-centric* computing and communication, 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

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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.

1.1 Related Work

Pervasive computing applications such as the Aware Home [18], Intelligent Room [5] and House_n [13] 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 [8], however, they do not provide mechanisms for sensor fusion or reasoning about contexts' ambiguity. Although other work has proposed mechanisms for reasoning about contexts [25], 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 [7] 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 [1]. DFuse [15] 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 [11], the application's quality of context (QoC) requirements are matched with the QoC attributes of the sensors through a utility function. Similarly, in MiLAN [10], 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 vary, and it is impractical to include a priori knowledge about them. Entropy-based sensor selection heuristic algorithms [9,16,26] 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 [24], 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 context using dynamic Bayesian networks. An approach to intelligent sensor management that provides optimal sensor parameter selection in terms of reduction in ambiguity in the state estimation process has not been considered before. We propose a quality of context function to satisfy the application quality requirements and take an information theoretic approach to decide an optimal sensor configuration.

1.2 Our 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. We state an optimization problem using a generic QoC function to determine the optimal tolerance range of the sensors that satisfy the specified quality of context at a minimum communication cost. Then we propose a Dynamic Bayesian Networks (DBNs) [14] 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. We build a system using various SunSPOT sensors for sensing and mediating user context state. Experiments demonstrate that the proposed framework is capable of determining the user context state and reducing the sensing overhead while ensuring acceptable context accuracy.

This paper is organized as follows. Section 2 describes the basic concepts of our context model and the quality of context (QoC) optimization problem. Section 3 describes the context-aware 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. We evaluate our approach in Section 5, and Section 6 concludes.

2 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 [19] 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 ($\mathcal{R}_i$), and attempts to incorporate various intuitions that should impact context inference to produce better fusion results as shown in Fig. 1. For specific definitions of these parameters see [22].

2.1 Quality of Context Model

Despite recent developments in sensing and network technology, continuous monitoring of context is still challenging due to resource constraints. Consequently, the amount of information transmitted to a fusion mediator should be minimized to prolong network lifetime. The idea of exploiting temporal correlation across successive samples of individual sensors to reduce communication overhead is addressed in [4]. The focus there was on meeting the quality requirements for a particular class of *aggregation queries*, whereas we focus on arbitrary relationships between a context state and the underlying sensor data. Thus we define Quality of Context (QoC) [12] as a metric for minimizing resource usage. 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 $\pm Q$.

We aim to evaluate the update cost of a sensory action A for a given task while ensuring the conformance to the application's QoC bound. Let us denote the update cost (in terms of communication overhead) as $\mathcal{U}_i^j$ if indeed sensor B_i has to report its sample value at time j. Then, we aim to minimize $\sum_{i \in B_m} \mathcal{U}_i(q_i)$, where $\mathcal{U}_i$ denotes the expected average update 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 reporting cost increases as the interval shrinks. This update cost also depends on the hop count h_i, the length of the uplink path from sensor B_i to the mediator. Accordingly, minimizing the update cost can be rewritten as: minimize $\sum_{i \in B_m} \mathcal{U}_i(q_i, h_i)$. If the underlying data samples evolve as a random-walk model [12], we have $\mathcal{U}_i \propto \frac{h_i}{(q_i^2)}$ resulting in the following optimization function: *minimize* $\sum_{i \in B_m} \frac{h_i}{(q_i^2)}$.

To define the QoC function, we consider three parameters associated with the context attribute: q (the accuracy range of sensor data), Q (the accuracy range of the derived context attribute) and $\wp$ (the fidelity of the context attribute being derived). Thus, the QoC function is $\wp = f_1(q_1, Q)$ for sensor B_1. In other words, given tolerances on q_1 and Q, we can say how often (in an ergodic sense), the fused context attribute estimation will lie within $\pm Q$. Similarly, when we consider two sensors B_1 and B_2 jointly, the QoC function should be $\wp = f_{12}(q_1, q_2, Q)$. In this way, for m sensors, there are $2^m - 1$ (all possible combinations except no sensors) functions $f(.)$, indicating the relationship between context attribute, context fidelity, and precision range. Given these continuous 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 is:

Problem 1. *Find the combination of* $q_1, q_2, ..., q_m$ *that satisfies* $f_{1,...,m}(q_1, q_2, \ldots q_m, \acute{Q}) \geq \acute{\wp}$, *and yet minimizes* $\sum_{i \in B_m} h_i/(q_i)^2$.

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

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

Finding an exact solution to Eqn 1 for any arbitrary $f(.)$ is an NP-complete problem [3], though there are certain forms of $f(.)$ that prove to be more tractable. An attractive case occurs when the i^{th} sensor's individual QoC function has the form $\mathrm{f}_S(i) = \nu_i * \exp^{-\frac{q_i^2}{\eta_i}}$, where η_i and ν_i are sensitivity constants for sensor s_i. A larger value of η_i indicates a lower contribution from sensor s_i to the inference of context state S. Moreover, for a selection of m sensors, the resulting $f(.)$ function has the form:

$$f_S(m) = 1 - \prod_{i \in m} (1 - \mathrm{f}_S(i)) \tag{2}$$

We solve this by taking the Lagrangian optimization, i.e, we solve for

$$\text{minimize} \sum_{i \in m} \frac{h_i}{q_i^2} + \lambda \left[1 - \prod_{i \in m} [1 - (\nu_i * \exp^{-\frac{q_i^2}{\eta_i}})] - \acute{\wp} \right]. \tag{3}$$

and prove the following Lemma.

Lemma 1. *The combination of* $q_1, q_2, ..., q_m$ *that satisfies the QoC function* $f_{1,\ldots,m}(q_1, q_2, \ldots q_m, \acute{Q}) \geq \acute{\wp}$ *and minimizes the objective function is*

$$\frac{h_1 * \eta_1 * (1 - \nu_1 * exp(-\frac{q_1^2}{\eta_1}))}{q_1^4 * \nu_1 * exp(\frac{-q_1^2}{\eta_1})} = \ldots = \frac{h_m * \eta_m * (1 - \nu_m * exp(-\frac{q_m^2}{\eta_m}))}{q_m^4 * \nu_m * exp(\frac{-q_m^2}{\eta_m})}$$

Proof. The above expression follows immediately by taking partial derivatives of the Lagrangian in Eqn 3 and setting them to 0 as shown below. In our case:

$$\textbf{minimize} \sum_{i \in B_m} \frac{h_i}{q_i^2} \quad \textbf{subject to}{:}1 - \prod_{i \in B_m} [1 - \nu_i * \exp^{-\frac{q_i^2}{\eta_i}}] \geq \acute{\wp} \tag{4}$$

Taking log we can rearrange the constraint of Eqn 4,

$$\log(1 - \acute{\wp}) \geq \sum_{i \in B_m} \log(1 - \nu_i * \exp^{-\frac{q_i^2}{\eta_i}}) \tag{5}$$

Considering this, we form the Lagrangian constraint,

$$\text{minimize} \sum_{i \in B_m} \frac{h_i}{q_i^2} + \lambda \left[\log(1 - \acute{\wp}) - \sum_{i \in B_m} \log(1 - \nu_i * \exp^{-\frac{q_i^2}{\eta_i}}) \right] \tag{6}$$

Taking the partial derivative of the Eqn 6 with respect to q_i and equating it to 0, we find

$$\lambda = \frac{h_i * \eta_i * (1 - \nu_i * exp(-\frac{q_i^2}{\eta_i}))}{q_i^4 * \nu_i * exp(\frac{-q_i^2}{\eta_i})} \tag{7}$$

which proves the optimal choices of q_i from Lemma 1.

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

3 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. We propose a DBN based model in our previous work [20] that we briefly outline in the remainder of this section.

3.1 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. Fig. 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.

Let us assume a situation space $\mathcal{R}_i$ to confirm using the sensory information sources $B = \{B_1, \ldots, B_m\}$, a set of measurements taken from sensors labeled from 1 to m. The context attribute most relevant should decrease the ambiguity of the situation space a_j^R the most; we will select the one that can direct the probabilities of the situation space to near one (for maximum) and zero (for minimum). Let $\mathcal{V}_i$ be the ambiguity reducing utility to the situation space $\mathcal{R}_i$. Then the expected value of $\mathcal{V}_i$, given a context attribute a_i^t from sensor B_i, which has K possible values, can be represented as:

$$\mathcal{V}_i = \max_{i=0}^{K} \sum_{j=0}^{N} [P(a_j^R | a_i^t)]^2 - \min_{i=0}^{K} \sum_{j=0}^{N} [P(a_j^R | a_i^t)]^2 \tag{8}$$

where $i \in \{1, 2, \ldots m\}$ identifies the sensor that provides the attribute. This context attribute can be measured by propagating the possible outcome of an information source, i.e., $P(a_j^R | a_i^t) = \frac{P(a_j^R, a_i^t)}{P(a_i^t)}$.

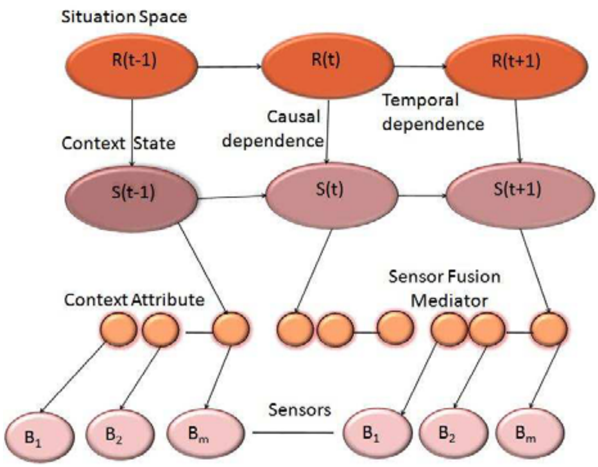

Fig. 1. Context-Aware Data Fusion Framework based on Dynamic Bayesian Networks

Considering the information update cost and ambiguity reducing utility, the overall utility can be expressed as:

$$U_i = \alpha \mathcal{V}_i + (1 - \alpha)(1 - \mathcal{U}_i) \tag{9}$$

where $\mathcal{U}_i$ is the update cost to acquire the information by sensor i with a knowledge of the QoC bound, and α denotes the balance between ambiguity reduction and cost. Eqn. 9 represents the contributions to ambiguity reduction and cost to achieve the desired level of confidence. We can observe from Eqn. 9 that the utility value of a_i increases with the ambiguity reducing utility and decreases with increasing acquisition cost. The most economically efficient disambiguation sensor action A^* can be chosen with the help of the following decision rule: $A^* = \arg\max_A \sum_j U(B, a_j^R)P(a_j^R|B)$; where $B = \{B_1, \ldots, B_m\}$ is a set of measurements taken from sensors labeled from 1 to m at a particular point of time. By incorporating the temporal dependence between the nodes as shown in Fig. 1, the probability distribution of the situation space we want to achieve can be described as: $P(\mathcal{R}, A) = \prod_{t=1}^{T-1} P(S_t|S_{t-1}) \prod_{t=1}^{T-1} P(\mathcal{R}_t|B_t)P(\mathcal{R}_0)$; where T is the time boundary. This sensor action strategy must be recalculated at each time slice since the best action varies with time.

4 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. Fig. 2 shows

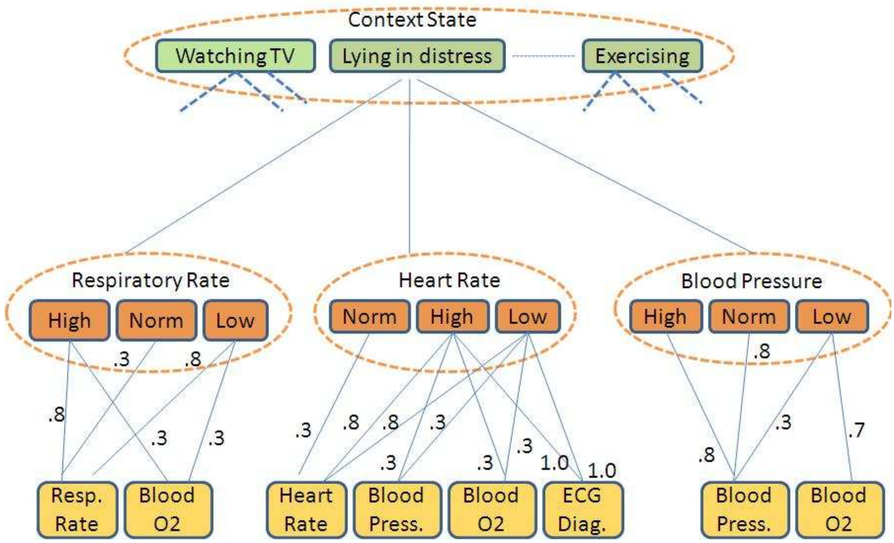

Fig. 2. State-based Context attribute requirement graph with the required QoC

the context attributes requirement graph for a personal health monitor and includes multiple states for each vital signs that can be monitored depending upon the context state of the patient. For example, the Fig. 2 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 .7 and the blood pressure must be monitored with a quality of .8. So the problem 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.

In this section, 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 [6] 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 on 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 situation $\mathcal{R}$ 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 $\mathcal{Q}$. 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 B be the vector of sensors and A be the set of attributes, then imagine a $(B \times A)$ matrix where $B_{mi} = 1$ where sensor m sends attribute a_i. Then, the goal is to find a matrix $(B \times A)$ within the capacity constraint $\mathcal{Q}$ which minimizes the estimation error of the situation space.*

$$\sum_m \sum_i H(a_i) * B_{mi} < \mathcal{Q} \quad \textit{and} \quad \texttt{minimize}\,[P_e = P\{\tilde{\mathcal{R}} \neq \mathcal{R}\}] \tag{10}$$

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

4.1 Problem Explanation

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 $\{S_{m,t} : \forall t = 1, 2, \ldots, T\}$ about the value of situation $\mathcal{R}$. We assume that random variables $S_{m,t}$ are i.i.d., given $\mathcal{R}$, with conditional distribution $p_{S|\mathcal{R}}(.|\mathcal{R}_i)$. The sensors could construct and send a summary $Z_{m,t} = \pi_m(S_{m,t})$ of their own observations to a fusion center at discrete time t. The fusion center then 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 $(B \times A)$ that minimizes the probability of estimation error $P_e = P\{\tilde{\mathcal{R}} \neq \mathcal{R}\}$.

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

$$\sum_{m=1}^{M} \sum_i H(\bar{a}_m.a_i) * B_{mi} < \mathcal{Q}$$

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 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:

$$E(\pi) = -\lim_{T\rightarrow\infty} \frac{1}{T} \log P_e^{(T)}(\pi) \tag{11}$$

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 an independent frequently varying multiple access channel with 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:*

$$E(\pi) = -\lim_{T\to\infty} \frac{1}{T} \log P_e^{(T)}(\pi) \tag{12}$$

4.2 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:

$$\gamma = \{1, 2, \ldots, \bar{a}_1\} \times \{1, 2, \ldots, \bar{a}_2\} \times \ldots \times \{1, 2, \ldots, \bar{a}_M\} \tag{13}$$

where $(\pi_1(x_1), \pi_2(x_2), \ldots, \pi_M(x_M)) \in \gamma$; 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 just approximate this probability of error for a finite observation interval T and measure the error exponent corresponding to strategy π using Chernoff's theorem [6].

Next we consider $p_{\tilde{Z}|\mathcal{R}}(.|\mathcal{R}_0)$ and $p_{\tilde{Z}|\mathcal{R}}(.|\mathcal{R}_1)$ as 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 $i \in 0, 1$:

$$\begin{aligned} p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_i) &= P_i\left\{\tilde{x} : (\pi_1(x_1), \pi_2(x_2), \ldots, \pi_M(x_M)) = \tilde{z}\right\} \\ &= \prod_{m=1}^{M} P_i\{\pi_m(u_m)\} \end{aligned} \tag{14}$$

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 [6], the best achievable exponent in the probability of error 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 $(\bar{a}_1, \bar{a}_2, \ldots, \bar{a}_M)$ is fixed a priori. Hence we try to derive a set of simplified conditions for Problem 4. Thus we state the following Lemma, where we obtain an upper bound of the contribution of a single sensor to the Chernoff information and find sufficient conditions for which having $\mathcal{Q}$ sensors in the $(B \times A)$ 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,*

$$E_{B_m}(\pi) \leq E^* \equiv -\min_{0 \leq k \leq 1} \log \left[\int_X (p_{S|\mathcal{R}}(x|\mathcal{R}_0))^k . (p_{S|\mathcal{R}}(x|\mathcal{R}_1))^{1-k} dx \right] \tag{15}$$

Proof. Proof 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.,

$$E_1(\pi_m) = -\min_{0 \leq k \leq 1} \log \left[\sum_{z_m=1}^{\bar{a}_m} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right] \tag{16}$$

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

Lemma 3. *Consider a binary function $\tilde{\pi}_b \in \Pi_b$ 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 rate $\mathcal{Q}$ 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: $I_b = \{m : 1 \geq m \geq M, \pi_m \in \Pi_b\}$. Similarly, we define $I_{nb} = \{1, 2, \ldots, M\} - I_b$. Considering the binary decision rule $\hat{\pi}_b \in \Pi_b$, we express $E_1(\hat{\pi}_b) \geq \max\{\max_{m \in I_b}\{E_1(\hat{\pi}_b)\}, \frac{E^*}{2}\}$. Since by assumption $\tilde{\pi}_b \in \Pi_b$ 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 $\bar{a}_m \geq 2$, which in turn yields $H(\bar{a}_m.a_i) \geq 2$. 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 in Eqn 17.

$$\begin{aligned}
&E(\pi') = (\mid I_b \mid + 2|I_{nb}|)\, E_1(\hat{\pi}_b) \geq |I_b| E_1(\hat{\pi}_b) + |I_{nb}| E^* \\
&\geq \sum_{m=1}^{M} \left[-\min_{0 \leq k \leq 1} \log \left[\sum_{z_m=1}^{\bar{a}_m} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right] \right] \\
&\geq -\min_{0 \leq k \leq 1} \log \left[\sum_{\tilde{z} \in \gamma} \left(\prod_{m=1}^{M} (P_0\{\pi_m(u_m)\})^k (P_1\{\pi_m(u_m)\})^{1-k} \right) \right] \\
&= E(\pi)
\end{aligned} \tag{17}$$

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

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

We use the SunSPOT [23] (Sun Small Programmable Object Technology) device for context sensing and mediation, which is a small, wireless, battery powered experimental platform. Each free-range SunSPOT contains a processor, radio, sensor board and battery; the base-station Sun SPOT 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 Empirical Determination of Context Estimates

We used the accelerometer to measure the tilt value of the SunSPOT (in degrees) when the monitored individual 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 the three states. The results indicate that there is an observable separation in the ranges of the tilt values for the three different states. This suggests that the states can be distinguished reasonably accurately even under moderate uncertainty in the sensor's readings.

Similarly, we also used the SunSPOT light sensor to measure the light level 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'*. 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, however, much lower, as users may often be inactive (e.g., sitting), even under high illumination.

5.2 Measurement of QoC Accuracy and Sensor Overheads

To study the potential impact of varying the tolerance range on 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 who engaged

Table 1. Calibrated Accelerometer Sample Values for different Context State

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

Table 2. Light Sensor Values (lumen) for different Context State

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

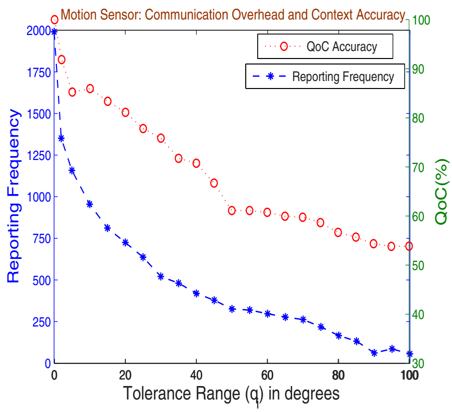

Fig. 3. Communication Overhead & QoC Accuracy vs. Tolerance Range using Motion Sensor

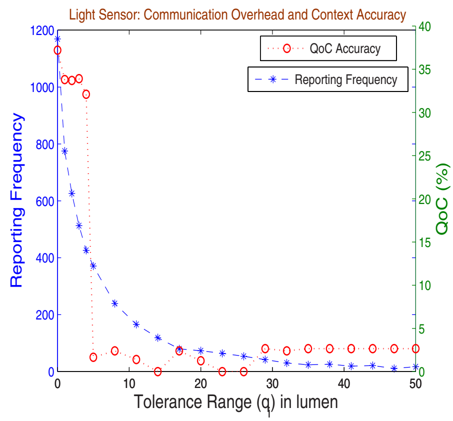

Fig. 4. Communication Overhead & QoC Accuracy vs. Tolerance Range using Light Sensor

in a mix of three different activities (*sitting, walking* and *running*) for a total of $\approx$ 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 q, and compared the context inferred from the values reported by the emulation against the ground truth. Fig. 3 shows the resulting plots for the 'total number of samples reported' (an indicator of the reporting overhead) and the corresponding QoC (defined as *1 - error rate*) achieved, for different values of the tolerance range (q_m) for the motion sensor. Fig. 4 plots the corresponding values vs. the tolerance range (q_l) for the light sensor.

As the figures demonstrate, there is, in general, a continuous drop in the reporting overhead and the QoC accuracy as q increases. However, as seen in Fig. 3, a QoC of $\approx 80\%$ is achieved for a modestly large q value of 40. Moreover, using this tolerance range reduces the reporting overhead dramatically by $\approx 85\%$ (from 1953 $\rightarrow$ 248). This suggests that it is indeed possible to achieve significant savings in bandwidth, 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 vs. a $\approx 65\%$ reduction in reporting overhead). However, as the difference between the lumen ranges for *Active* vs. *Sleeping* is only ≈ 10 (Table 2), increasing q actually leads to a sharp fall in the QoC.

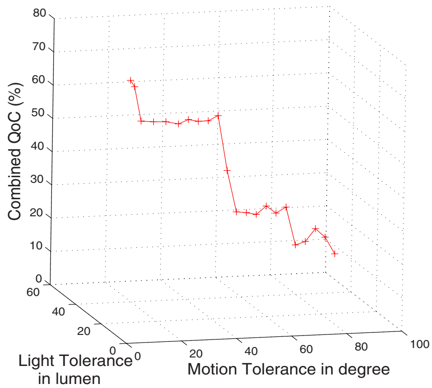

Fig. 5. QoC Accuracy vs. Tolerance Range using both Motion and Light Sensor Together

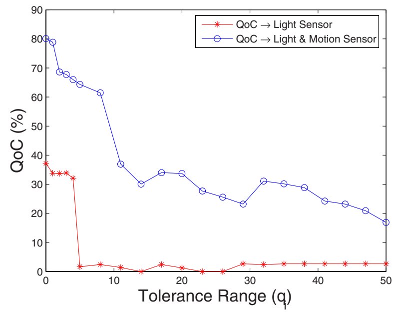

Fig. 6. Comparison of QoC Accuracy Improvement using Multiple Sensor

5.3 The Benefit of Joint Sensing

We also investigated how the use of readings jointly from both sensors affects the inferencing accuracy vs. tolerance ranges. We consider the individual to be 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. 5 uses a three-dimensional plot to illustrate the observed inferencing fidelity when the tuple (q_m, q_l) is jointly varied. This confirms the QoC accuracy is now less susceptible to individual q variations. Fig. 6 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 q ranges of both being identical). Clearly, the QoC obtainable from the combination of the two sensors is much higher than that of a single sensor. 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 information theoretic analysis. Through this evaluation we observed it is indeed possible to significantly reduce the sensors' resource usage while satisfying the application quality requirements in pervasive care environments.

6 Conclusion

This paper presents 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 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 context sensing system is developed and subsequent experimental evaluation is done.

References

1. Alex, H., Kumar, M., Shirazi, B.: MidFusion: An adaptive middleware for information fusion in sensor network applications. Elsevier Journal of Information Fusion (2005)
2. Chamberland, J., Verravalli, V.: Decentralized detection in sensor networks. IEEE Transactions on Signal Processing 51(2), 10 (2003)
3. Deshpande, A., Guestrin, C., Madden, S., Hellerstein, J.M., Hong, W.: Model-based Approximate Querying in Sensor Networks. Int'l Journal on Very Large Data Bases, VLDB Journal (2005)
4. Deshpande, A., Guestrin, C., Madden, S.: Using Probabilistic Models for Data Management in Acquisitional Environments. In: Proc. of the 2nd Biennial Conference on Innovative Data Systems Research (CIDR), January 2005, pp. 317–328 (2005)
5. Coen, M.: The future of human-computer interaction or how I learned to stop worrying and love my intelligent room. IEEE Intelligent Systems 14(2), 8–10 (1999)
6. Cover, T.M., Thomas, J.A.: Elements of Information Theory. Wiley, New York (1991)
7. Dey, A.K., Mankoff, J., Abowd, G.D., Carter, S.: Distributed Mediation of Ambiguous Context in Aware Environments. In: Proc. of the 15th Annual Symposium on User Interface Software and Technology (UIST 2002), October 2002, pp. 121–130 (2002)
8. Dey, A.K., Salber, D., Abowd, G.D.: A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications. Human-Computer Interaction (HCI) Journal 16(2-4), 97–166 (2001)
9. Ertin, E., Fisher, J., Potter, L.: Maximum mutual information principle for dynamic sensor query problems. In: Zhao, F., Guibas, L.J. (eds.) IPSN 2003. LNCS, vol. 2634, pp. 405–416. Springer, Heidelberg (2003)
10. Heinzelman, W., Murphy, A.L., Carvalho, H.S., Perillo, M.A.: Middleware to Support Sensor Network Applications. IEEE Network 18, 6–14 (2004)
11. Huebscher, M.C., McCann, J.A.: Adaptive Middleware for Context-aware Applications in Smart Homes. In: Proc. of the 2nd Workshop on Middleware for Pervasive and Ad-hoc Computing, October 2004, pp. 111–116 (2004)
12. Hu, W., Misra, A., Shorey, R.: CAPS: Energy-Efficient Processing of Continuous Aggregate Queries in Sensor Networks. In: Fourth IEEE Int'l Conference on Pervasive Computing and Communications (PerCom), pp. 190–199 (2006)
13. Intille, S.S.: The goal: smart people, not smart homes. In: Proc. of the Int'l Conference on Smart Homes and Health Telematics. IOS Press, Amsterdam (2006)
14. Jensen, F.V.: Bayesian Networks and Decision Graphs. Springer, New York (2001)
15. Kumar, R., Wolenetz, M., Agarwalla, B., Shin, J., Hutto, P., Paul, A., Ramachandran, U.: DFuse: a Framework for Distributed Data Fusion. In: Proc. of the 1st Int'l Conference on Embedded Networked Sensor Systems, November 2003, pp. 114–125 (2003)

16. Liu, J., Reich, J., Zhao, F.: Collaborative in-network processing for target tracking. EURASIP JASP: Special Issues on Sensor Networks 2003(4), 378–391 (2003)
17. Netica Bayesian Network Software, http://www.norsys.com
18. Orr, R.J., Abowd, G.D.: The Smart Floor: A Mechanism for Natural User Identification and Tracking. In: Proc. of 2000 Conference on Human Factors in Computing Systems (CHI 2000). ACM Press, New York (2000)
19. Padovitz, S., Loke, W., Zaslavsky, A., Bartolini, C., Burg, B.: An approach to Data Fusion for Context Awareness. In: Dey, A.K., Kokinov, B., Leake, D.B., Turner, R. (eds.) CONTEXT 2005. LNCS (LNAI), vol. 3554, pp. 353–367. Springer, Heidelberg (2005)
20. Roy, N., Pallapa, G., Das, S.K.: A Middleware Framework for Ambiguous Context Mediation in Smart Healthcare Application. In: Proc. of IEEE Int'l Conf. on Wireless and Mobile Computing, Networking and Communications (WiMob) (October 2007)
21. Roy, N., Roy, A., Das, S.K.: Context-Aware Resource Management in Multi-Inhabitant Smart Homes: A Nash H-learning based Approach. In: Proc. of IEEE Int'l Conf. on Pervasive Computing and Communications (PerCom), March 2006, pp. 148–158 (2006)
22. Roy, N., Julien, C., Das, S.K.: Resource-Optimized Ambiguous Context Mediation for Smart Healthcare. Technical Report TR-UTEDGE-2008-011, UT-Austin (2008)
23. SunSpotWorld - Home of Project Sun SPOT, http://www.sunspotworld.com/
24. Tenney, R.R., Sandell Jr., N.R.: Detection with distributed sensors. IEEE Trans. Aerosp. Electron. Syst. AES-17, 501–510 (1981)
25. Vurgun, S., Philpose, M., Pavel, M.: A Statistical Reasoning System for Medication Prompting. In: Krumm, J., Abowd, G.D., Seneviratne, A., Strang, T. (eds.) UbiComp 2007. LNCS, vol. 4717, pp. 1–18. Springer, Heidelberg (2007)
26. Wang, H., Yao, K., Pottie, G., Estrin, D.: Entropy-based sensor selection heuristic for target localization. In: Proc. of IPSN 2004 (April 2004)

Appendix

Proof of Lemma 2: We consider the contribution of sensor B_m. The Chernoff information for strategy $\pi = (\pi_1, \pi_2, \ldots, \pi_M)$ is given by

$$\begin{aligned}
E(\pi) &= -\min_{0\le k\le 1} \log \left[\sum_{\tilde{z}\in\gamma} (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_0))^k (p_{\tilde{Z}|\mathcal{R}}(\tilde{z}|\mathcal{R}_1))^{1-k} \right] \\
&= -\log \left[\prod_{m=1}^{M} \left(\sum_{z_m=1}^{\bar{a}_m} (P_0\{\pi_m(u_m)\})^{k^*} (P_1\{\pi_m(u_m)\})^{1-k^*} \right) \right] \\
&= -\sum_{m=1}^{M} \log \left[\sum_{z_m=1}^{\bar{a}_m} (P_0\{\pi_m(u_m)\})^{k^*} (P_1\{\pi_m(u_m)\})^{1-k^*} \right] \\
&= -\log \left[\sum_{z_1=1}^{\bar{a}_1} (P_0\{\pi_m(u_m)\})^{k^*} (P_1\{\pi_m(u_m)\})^{1-k^*} \right] \\
&\quad -\sum_{m=2}^{M} \log \left[\sum_{z_m=1}^{\bar{a}_m} (P_0\{\pi_m(u_m)\})^{k^*} (P_1\{\pi_m(u_m)\})^{1-k^*} \right] \qquad (18)
\end{aligned}$$

where the Chernoff information $E(\pi)$ is maximized at k^*. So we can conclude that contribution of sensor B_m to the Chernoff information $E(\pi)$ can not exceed

$$-\min_{0\leq k\leq 1}\log\left[\sum_{z_m=1}^{\bar{a}_m}(P_0\{\pi_m(u_m)\})^k(P_1\{\pi_m(u_m)\})^{1-k}\right] \tag{19}$$

which in turn is upper bounded by the Chernoff information contained in one context state S. So, the Lemma 2 confirms that the contribution of a single sensor to the total Chernoff information can not exceed the information contained in each observation. Hence we derive the sufficient condition based on the Lemma 2 for which having Q binary sensors is optimal.