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# Quality and context-aware smart health care: Evaluating the cost-quality dynamics

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Many emerging pervasive health-care applications require the determination of a variety of context attributes of an individual's activities and medical parameters and her surrounding environment. Context is a high-level representation of an entity's state, which captures activities, relationships, capabilities, etc. In practice, high-level context measures are often difficult to sense from a single data source and must instead be inferred using multiple sensors embedded in the environment. A key challenge in deploying context-driven health-care applications involves energy-efficient determination or inference of high-level context information from low-level sensor data streams. Because this abstraction has the potential to reduce the quality of the context information, it is also necessary to model the tradeoff between the cost of sensor data collection and the quality of the inferred context. This article describes a model of context inference in pervasive computing, the associated research challenges, and the significant practical impact of intelligent use of such context in pervasive health-care environments.

The wide availability of smart health-care appliances and a variety of standalone and integrated sensor devices makes it increasingly easy to ubiquitously and continuously monitor an individual's health-related vital signals and her activity behavior and to integrate such medical and activity data into health-care information systems. We are already witnessing early commercial activity in this space, centered on remote monitoring of elderly individuals and chronically ill patients within smart assisted-living homes. A combination of body-worn medical and nonmedical sensors (e.g., sensors to monitor blood oxygenation or accelerometers to monitor movements) and in situ sensors (e.g., thermal and motion detectors) is used to continuously monitor and automatically determine an individual's context in such smart environments. Broadly speaking, context here refers to a variety of dynamically changing states, related to either an individual's specific activities (e.g., walking versus sleeping) or biomedical conditions (e.g., elevated blood pressure, shortness of breath, or arrhythmia), or to surrounding environmental conditions (e.g., atmospheric ozone levels or ambient temperature). In many health- and wellness-related applications, such context is the critical enabler of various capabilities, such as alerting a first responder if the individual is judged to be sleeping for an abnormal period of time or flagging a potential health risk by analyzing wellness data to detect shortness of breath after everyday physical activities.

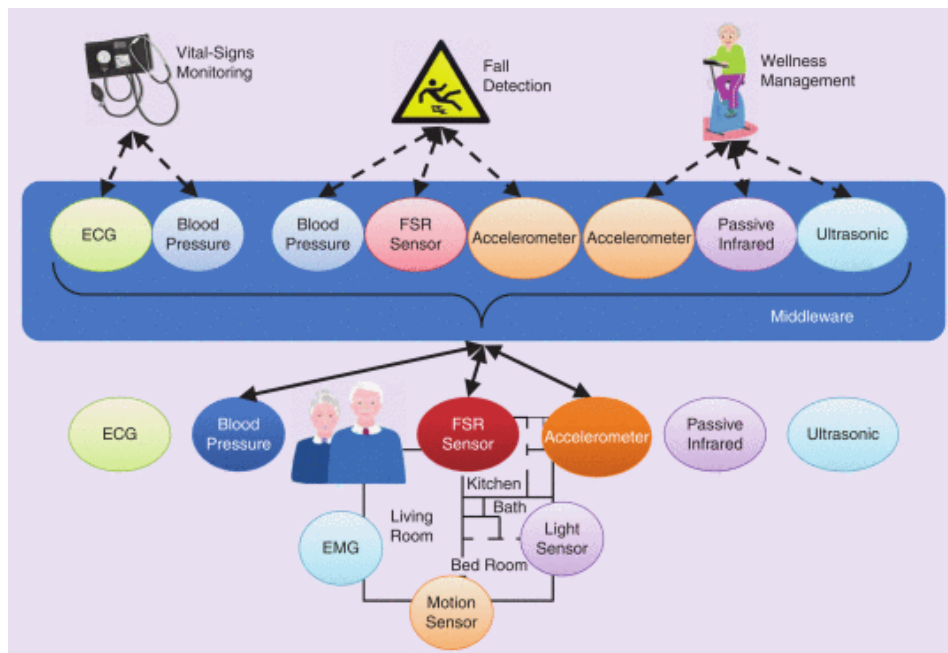
In many scenarios of practical interest, the data streams are generated by a variety of battery-operated standalone or embedded sensors (e.g., accelerometers on a smartphone), and the act of transmitting the sensor streams to a backend server for context extraction can impose a significant energy burden. Accordingly, a crucial technical challenge in the area of sensor-based pervasive health-care applications centers on the question of how one can efficiently and reliably convert streams of low-level sensor-generated data into high-level abstractions of context. Previous work in the broader field of sensor-driven context inferencing has largely assumed that the type and amount of low-level sensor data available to a specific application are invariant. This prior work has therefore focused on how to 1) automatically map low-level sensor data to appropriate abstractions of context states and 2) empirically establish whether the accuracy of inferred context is sufficient to enable automated adaptation [4].

In this article, we take a somewhat contrarian view and ask the question: How can we support the varying context requirements of multiple emerging context-dependent health applications while simultaneously trying to minimize the energy overhead of the sensor data collection process? In contrast, our previous work dealt with a single

context-dependent health application [12]. Our work is influenced by the observation that the landscape of remote health/wellness monitoring applications is changing from the earlier stove-piped model (where each application was customized for an explicit set of sensor devices) to a more fungible, standards-based model, where the underlying sensors are viewed as common, shareable resources that are simultaneously utilized by multiple applications.

- Smart assisted-living environments are gradually being equipped with a variety of different networked sensors (e.g., cameras, motion sensors, or light sensors) capable of programmatic data retrieval and control.
- Sensor-based health monitoring applications are growing, both in number and in the variety of medical contexts being monitored. In large part, the explosion of apps on the Apple AppStore and Google Googleplay are responsible for these recent phenomena—prominent examples of health-care-related applications include *Stress Check*, *Stress Doctor*, *Instant Heart Rate* (<http://www.azumio.com/>), *SmartRunner* (<http://www.smartrunner.com/pages/>), etc.

As an illustration, consider a remote context monitoring scenario (shown in Figure 1) in a smart assisted-living environment in which an elderly person resides. The smart home may be equipped with many sensors [light, humidity, electrocardiogram (ECG) electromyography, etc.], some of which may be body-worn while others may be embedded in the environment. A variety of applications and stakeholders (e.g., fall monitoring by a caregiver, wellness activity monitoring by a doctor, or vital sign monitoring by a nurse) need to access this low-level sensed information to abstract high level context (both physiological and activity) about the resident. An important observation is that a specific application's context can be satisfied by different possible combinations of sensor data types. For example, the fall-detection application may utilize data either from multiple video cameras, from a set of body-worn accelerometer and wall-mounted motion sensors, from a set of audio sensors, or from some arbitrary combination of these.



**Figure 1.** Multiapplication multicontext inferencing in a sensor-rich pervasive health-care environment.

The preceding example motivates the need for a matchmaking software infrastructure that mediates between the context-driven health and wellness applications and the set of available sensors in a way that minimizes the energy overhead, while still ensuring that the applications' needs for high-quality context inferences are met. To enable such a dynamic and automated association between application requirements and the available sensor resources in any environment, we make the following two key contributions in this article.

- First, we suggest the use of an explicit functional model to relate the accuracy of any inferred context to a measure of uncertainty about the true values of the sensor data.
- Then, we develop and evaluate an optimization-based heuristic that uses the model to dynamically select both a set of sensors and the parameters of the sensors to satisfy the context requirements of multiple context-aware applications, while minimizing the energy overhead of sensor-data transmission.

### A Formal Model for Context Inference

Our goal is to determine the automated adaptation of sensors so as to reduce the energy overheads associated with data transmission from the sensors without compromising the context requirements of any of the health and wellness applications. In achieving this objective, the accuracy or fidelity requirements associated with the context requirement are highly application dependent; for example, the fall-monitoring application may find an accuracy of 90% acceptable (i.e., it misses one out of ten cases of falls/stumbles), and the vital-signs-monitoring application may require a much higher accuracy of 99.999%, while the wellness application may be satisfied with a much lower fidelity of 50% in detecting the amount walked during the day (i.e., it is okay to under- or overcount the amount of time spent walking by  $\approx 50\%$ ). Accordingly, we must first establish a formal functional model that relates the underlying accuracy/fidelity of the sensor data to the accuracy of the specific inferred context.

Given that a context metric is inferred from the combination of values from multiple low-level sensors, we define the quality of inference (QoINF) as the error probability in estimating a context state, given the imprecision in the values of the contributing sensors. Concretely, we compute QoINF based on the average estimation error of the context; alternative definitions of accuracy (such as the percentage of false positives or false negatives) are equally reasonable and do not affect the remaining description of our model. Two key observations drive our use of QoINF.

1. While different combinations of sensor types may be used to infer the same high-level context at different levels of accuracy, it is almost universally true that the accuracy of the inferred context increases with an increase in the number and type of sensors utilized in the inferencing process. As a simple example, a combination of data from a body-worn accelerometer and ceiling-mounted motion sensors provides a more accurate estimation of whether a person is immobile after a fall, compared to deductions based solely on one sensor or the other.
2. The quality of the inferred context is not just a function of the set of chosen sensors but also of the permitted inaccuracy in the data values associated with each individual sensor. For example, the quality of the estimation of the heart activity context will be less accurate if the blood pressure sensor's tolerance range is  $\pm 20\%$  (indicating that the true reading may be up to 20% higher or lower than the reported value) in comparison to a tolerance range of  $\pm 5\%$ .

Mathematically, we can then say that the quality of inference function, denoted as QoINF, for any given context will be a function of  $i$  (the set of sensors used in the context inferencing process) and the  $q_i$  values (called the tolerance range) associated with each sensor  $s_i$ . Conceptually, the job of our matchmaking algorithms is to find,

given a specific QoINF function, the set  $i$  and the associated  $q_i$  values (for those selected sensors) that minimize the communication energy overhead.

### Quality of Inference for a Single Sensor

To simultaneously model the context accuracy and communication overheads associated with different values of  $q_i$  for a single sensor, we assume that each sensor utilizes the widely adopted event-driven reporting strategy, where it transmits a new sample only when its sensed value deviates from the previously transmitted sample by  $\pm q_i$ . In effect, this means that, at any instant, the context inferencing process is not aware of the sensor's true current value but knows that this value will be within  $\pm q_i$  of the last value transmitted by the sensor. Of course, a larger tolerance range results in a reduction in a sensor's reporting rate (frequency) and thus dramatically lowers its communication energy overheads [1], [2].

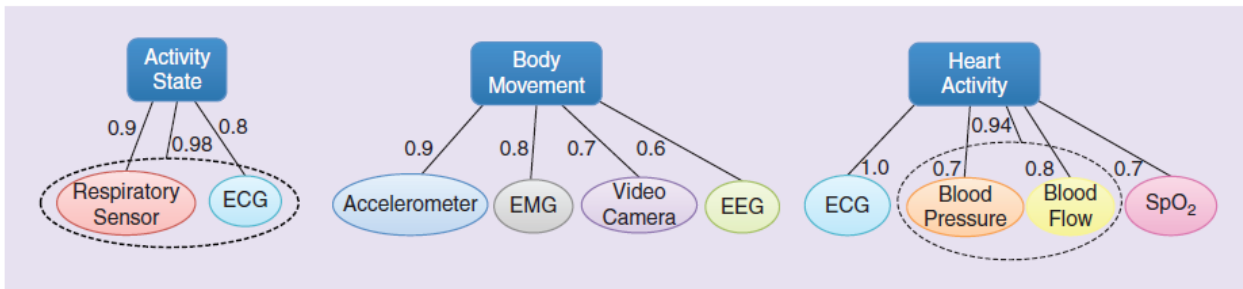
While many functional forms of the QoINF function are possible, we initially advocate and explore an inverse exponential functional model, where the accuracy of context inference or QoINF (for a specific application) for a specific sensor  $s_i$  and its associated  $q_i$  value are related via the model

$$\text{qoinf}(i) = 1 - \frac{1}{\nu_i} \exp\left(\frac{-1}{\eta_i q_i}\right), \quad (1)$$

where  $\eta_i, \nu_i$  are simply scalar constants. The choice of this inverse-exponential model is both mathematically motivated and empirically validated: not only does this functional model make our eventual goal of multicontext matchmaking tractable, it is also consistent with experimental results we have conducted using a variety of sensors (such as light, accelerometer, and motion sensors).

### Context Inference with Multiple Sensors and Applications

Having established the formal relationship between a single sensor and a single context attribute, we now consider our target scenario: multiple applications, each requiring different context inferences, potentially utilizing data from multiple available sensors. To precisely elucidate our approach, we assume an underlying set  $S$  of sensors. Determining the value of some context metric  $C$  may be viewed as a multidimensional mapping that uses the values sensed by some subset  $\theta$  of the available sensors (formally,  $\theta \subseteq S$ ) and maps them to one of the values associated with the context metric. To understand this relationship better, consider the case illustrated in Figure 2, which depicts nine different sensors that may be used to support smart health-care applications. An application that senses heart activity may choose some subset of these sensors to assess its context; for example, heart activity can be assessed by the combination of a blood-pressure and a blood-flow sensor. A domain-specific inference function uses these two low-level values and outputs a measure of heart activity.



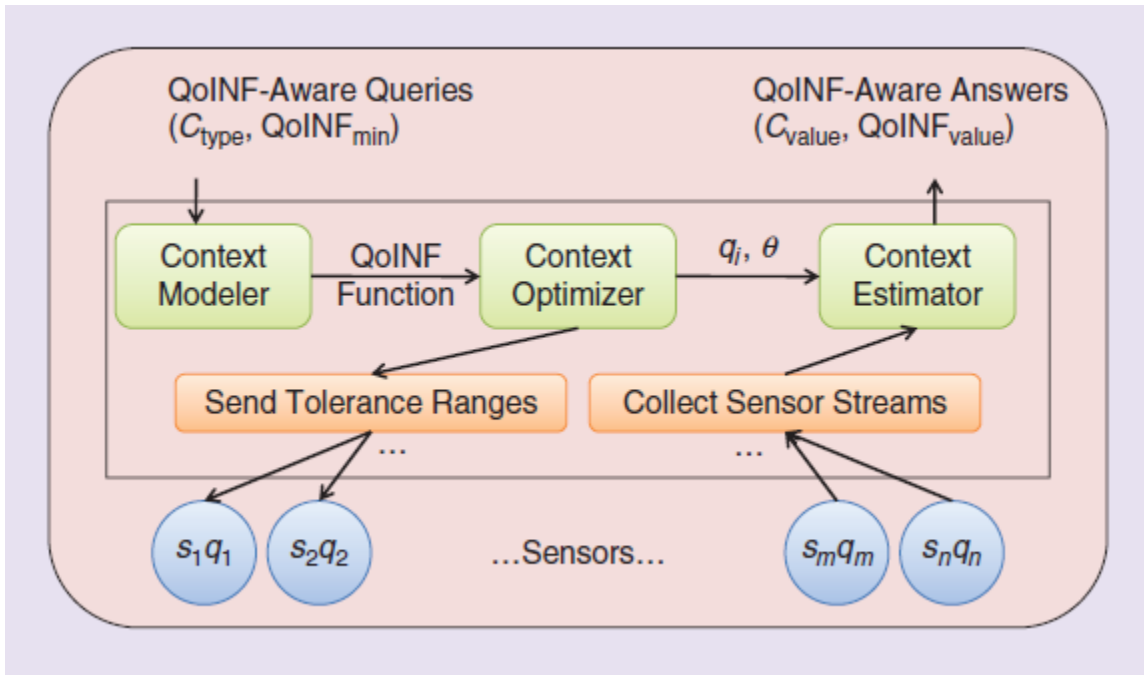
**Figure 2.** The impact of different sensor subsets on QoINF (without considering tolerance ranges).

To capture the reality that the same context may be inferred to varying degrees of accuracy using different sensor subsets, we associate a function that represents the accuracy of a certain subset of sensors with respect to a given context metric. That is,  $QoINF_c(\theta)$  gives the expected accuracy of inferring a context metric  $C$  using the sensors in the subset  $\theta$ . Figure 2 (where we implicitly assume that each of the sensors has a predefined tolerance range of 0.10) further illustrates this notion of multiple sensors and the QoINF values associated with different context variables. For example, the context measure *activity state* of an individual may be computed with an inferencing

accuracy of 0.90 (i.e., with a 10% error rate) using a respiratory sensor but only with 0.80 accuracy using a low-quality ECG sensor. However, by combining the data available from both sensors, we can achieve an inferencing accuracy of 0.98. Of course, this mapping itself will be a function of the tolerance ranges associated with each sensor. For example, if the tolerance range for the respiratory sensor degrades to 0.20 and the ECG sensor to 0.15, it is likely that the inferencing accuracy based on the combination of these two sensors will drop from 0.98 to 0.90. We describe a precise approach for expressing such composite QoINF functional models in the “Choosing a QoINF Function for Multiple Sensors” section.

### A Quality-Aware Context Architecture

Based on the preceding observations, we now present the high-level functional components of a QoINF-aware context-determination service, i.e., the matchmaking functionality (Figure 3). External applications subscribe to specific context measures and indicate minimally acceptable QoINF values. The context optimizer determines the best (least-cost) combination of sensors and their tolerance ranges that can meet the specified QoINF requirement. The transmitted sensor data are received by the context estimator, which continuously updates the application on the value inferred for the requested context measure(s).



**Figure 3.** An architecture for QoINF-aware context determination.

The rest of this article focuses on the logic of the context optimizer. We describe how we can determine the subset of sensors and their associated tolerance ranges that best satisfy the varying context requirements of multiple subscribing applications at the minimum cost. While many other measures of cost can be considered, we have explicitly focused on minimizing the sum of the transmission costs associated with each individual sensor (as wireless transmissions cost is one of the most significant energy burdens in sensor-based contextual applications). From past work [2],  $cost_i(q_i)$  (the average transmission energy overhead associated with sensor  $s_i$ ) is proportional to both the number of wireless hops ( $h_i$ ) utilized to transport the samples to the context estimator and the tolerance range  $q_i$ .

$$\text{cost}_i(q_i) \propto \frac{h_i}{q_i^2}.$$

### Choosing a QoINF Function for Multiple Sensors

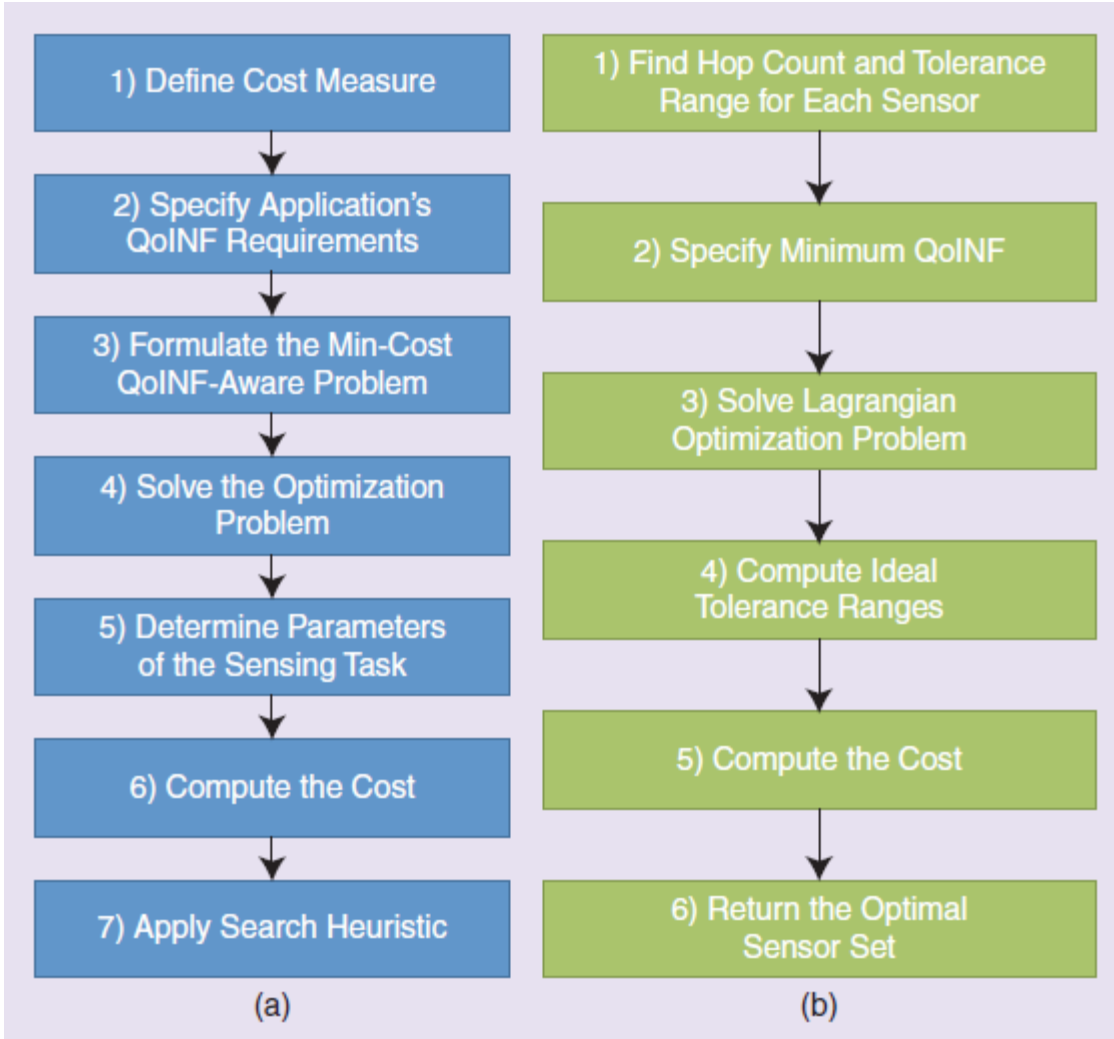
A QoINF function explicitly relates the quality of a context measure to the sensors (and their tolerance ranges) that contribute the actual data. Similar work has used decision fusion rules based on counting policy using a Poisson sensor distribution model [6] or by exploiting statistical dependencies (and independencies) of sensors [3]. If the QoINF function was completely arbitrary, the context optimizer would have the mathematically intractable task of performing an exhaustive search of all possible combinations of sensors and tolerance ranges. For a mathematically tractable approach (which is also supported well by our empirical results), we assume that the estimation error for each sensor is statistically independent of the others [11]. We can then define the QoINF value for a particular combination of sensors  $\theta$  (with the  $i$ th sensor having its own tolerance range  $q_i$ ) by

$$\text{QoINF}(\theta) = 1 - \prod_{i=1}^{|\theta|} \{1 - \text{qoINF}(i)\}, \quad (2)$$

where QoINF( $i$ ) is defined in (1). This definition satisfies all the following observations about valid QoINF measures: 1) its value is within (0,1) and 2) QoINF is nondecreasing in the size of  $\theta$  (i.e., incorporating data from an additional sensor cannot degrade the inference quality) and degrades with increasing  $q_i$ .

### Context Optimization: Selecting Sensor Settings

We now focus on explaining our second contribution, i.e., describing a process by which the context optimizer can determine the best set of sensors and their tolerance ranges. Figure 4 shows two complementary views of the internal details of the context optimizer. We first examine the basic problem: that of selecting the appropriate set of sensors and their settings, given a single context to estimate. We will then look at the more complex problem of simultaneously estimating multiple contexts.



**Figure 4.** Context optimization in a QoINF-aware architecture. (a) A generic view and (b) A parametric view.

### Single Context Optimization

Given a single context measure, the goal is to choose a subset  $\theta$  of sensors (and their tolerance ranges) to infer that context measure with a QoINF value that is at least equal to the application-specified minimum required fidelity at a minimum communication overhead. If the subset,  $\theta$ , of sensors is predefined, then determining the best tolerance ranges ( $q_i$  values) is a straightforward Lagrangian optimization problem. Accordingly, the challenge here is to determine, in the first place, which  $\theta$  to use. Clearly, one solution is to iterate through all possible combinations of available sensors. However, as sensors become increasingly ubiquitous in our targeted smart-assisted living environments, such an approach is excessively computationally expensive. A heuristic search can drastically reduce the computational cost by performing an intelligent exploration of the possibilities.

Our proposed heuristic is based on the observation that the additional cost in adding another sensor to the set  $\theta$  is dependent on the sensor's hop count from the context estimator and the sensor's sensitivity factors [the  $\eta$  and  $\nu$  terms in (1)]. Specifically, the algorithm favors sensors with lower hop counts (indicating a small update cost) and lower sensitivity factors (indicating a smaller degradation in QoINF with increasing tolerance ranges) [12]. The heuristic algorithm first sorts the available sensors based on their hop counts and sensitivity factors. It then incrementally considers larger sets of sensors, starting with the singleton set of the first sensor in



the list. The algorithm computes the tolerance ranges (for each individual member of the set) needed to ensure that the application-specified QoINF bound is satisfied and then computes the transmission cost associated with using those sensors with the corresponding tolerance ranges. If the QoINF requirement is not achievable with the considered set, the cost is set to  $\infty$ . The algorithm then compares this cost to the cost calculated in the previous round. If the cost has decreased, the algorithm continues its iterative exploration by growing  $\theta$ . If the cost has increased, the set computed in the previous round (and its associated tolerance ranges) is assumed to be the preferred solution [11].

### **Multicontext Optimization**

To address our eventual vision of a smart matchmaking service that lets numerous health-care-related applications and services make the best possible concurrent use of an underlying substrate of multimodal sensors, we must extend the algorithm to consider the optimization of multiple distinct contexts [14]. As a tangible illustration of this scenario, consider again a smart-home assisted-living deployment scenario depicted in Figure 1, with several sensors: [blood pressure (BP), ECG, passive infrared sensor (PIR), force-sensitive resistor (FSR), accelerometer, ultrasonic, electromyography (EMG), motion, light, etc.]. Some of these (i.e., motion, light, PIR, FSR, and ultrasonic) are embedded in the environment, and some (i.e., BP, ECG, accelerometer, and EMG) are worn on the body. Multiple applications, like vital-signs monitoring, fall monitoring, and wellness management, execute simultaneously using these sensors and require different context attributes at different levels of accuracy. For example, the fall-monitoring application may require a person's movement context to be inferred using BP, FSR, and accelerometer sensors, while for the wellness-management application, context describing a person's sleeping state with required accuracy can be achieved jointly by accelerometer, PIR, and ultrasonic sensors. In this simple example, all of the contexts required by different applications can be satisfied by using only the BP, FSR, and accelerometer sensors (with the required accuracy and imposed tolerance ranges); the other sensors (ECG, PIR, and ultrasonic) may be then turned off to conserve energy.

The preceding scenario can be expressed as a multiattribute optimization problem, whose goal is to achieve the required QoINF of multiple applications, while simultaneously minimizing the total communication overhead [12]. The extended heuristic algorithm for solving the multicontext problem considers the added dimension of the problem; specifically, the set  $\theta$  that is best for a particular context metric in isolation may no longer be ideal when considering contexts jointly. The heuristic algorithm still favors sensors with lower hop counts and lower sensitivity factors, but a sensor's sensitivity factors are dependent on the particular context being inferred. As a result, if we have  $L$  different contexts to jointly estimate, we have  $L$  sorted lists of the available sensors. Our goal is to satisfy all  $L$  contexts at the same time; our algorithm considers them sequentially. When only the first context ( $C_1$ ) is considered, its sorted list is used, and  $\theta$  is constructed exactly as in the single context case. When the algorithm moves on to the second context ( $C_2$ ), it first determines whether the existing  $\theta$  is sufficient for estimating  $C_2$ . If not, the algorithm adds new sensors using  $C_2$ 's sorted list. As it does so, it also tests whether any sensors that were added to support  $C_1$  have become redundant; if so, they are removed. The algorithm continues this process incrementally until it has considered all  $L$  contexts.

### **A Range-Based Sensor Selection for Multiple Contexts**

Here, we discuss an enhanced version of the previous heuristic algorithm that, for each additional context, tries to compare the total cost from the following two approaches: 1) using the current set of sensors and determining if a modification of the tolerance ranges of this current set is enough to satisfy the QoINF requirement of the additional context metric or 2) adding an additional sensor to the set of sensors and seeing what tolerance ranges this modified set must have to satisfy all the QoINF requirements of the contexts considered thus far. After computing the costs of each approach, this second heuristic selects the one that both satisfies the QoINF requirements of all of the considered contexts and has the lowest cost. This is in contrast to the approach in the previous algorithm, where the comparison was made only between adding a new sensor and the cost incurred by the current set of sensors (with their tolerance ranges unmodified). In other words, the previous approach did not

explore the option that one could satisfy the QoINF of the additional contexts, without altering the set of activated sensors, simply by tightening the tolerance ranges of the current set of selected sensors.

We have thus far assumed that, for a given context, the user is only in one context state at a time, i.e., either the user is in the sitting state, in the walking state, or in the running state. There are, however, other scenarios like watching television (TV) and speaking on the phone, which may happen concurrently. Such concurrent context states can also be determined using our model. As shown in our model, the minimum QoINF value and sensitivity factors for these multiple context states will be fundamentally different. For example, consider that we have one acoustic sensor for detecting the watching TV context state and one microphone sensor for recognizing the speaking on the phone context state. The operating analytics (tolerance range, etc.) of these two sensors can be computed by our proposed model while still maintaining the underlying objective of sharing sensor data streams to improve the accuracy and minimize the network cost.

## Evaluation

To illustrate the promise of this formal model-based approach, we experimented with a laboratory-based deployment in which individuals were monitored with body-worn sensors taking readings from a motion sensor (an accelerometer), a light sensor, and a temperature sensor. We have performed experiments with SunSPOT ([www.sunspotworld.com](http://www.sunspotworld.com)) and Shimmer sensors (<http://www.shimmer-research.com/>). Specifically, we have used a three-axis accelerometer, a light, and an embedded external gyro sensor on the SunSPOT platform and a three-axis accelerometer and gyro sensor on the Shimmer platform. This initial deployment gives important insights in the nature of context inference and the use of awareness of quality to direct the acquisition tasks [11], [12]. Our experimental data and results can be summarized via the following key observations.

- A clear relationship between QoINF and tolerance range exists, but this relationship is neither linear nor continuous; for some data types, the quality of (context) inference possible using the data type can drop precipitously with just a small change in tolerance range.
- The expected relationship between cost and tolerance range exists: raising the tolerance range decreases the cost. Taken with the previous observation, it is possible to exploit the tradeoff between quality and cost by tinkering with the tolerance ranges, and this tinkering is specific to particular data types. Figure 5 shows this tradeoff for the motion sensors we used in our experimental deployment.
- Using multiple sensor types to jointly infer a single context metric provides a clear benefit, and our basic and extended heuristic algorithms take advantage of this benefit of joint sensing.

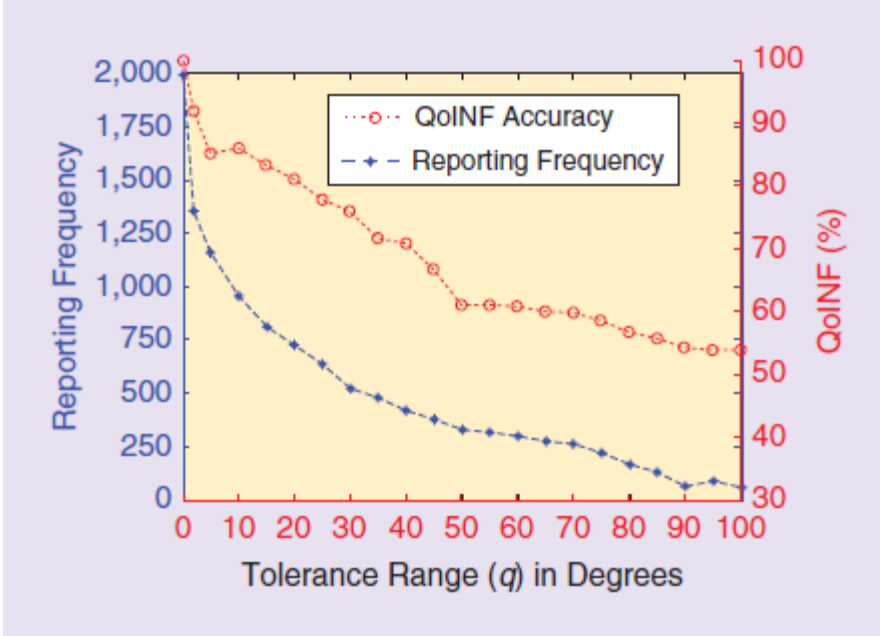
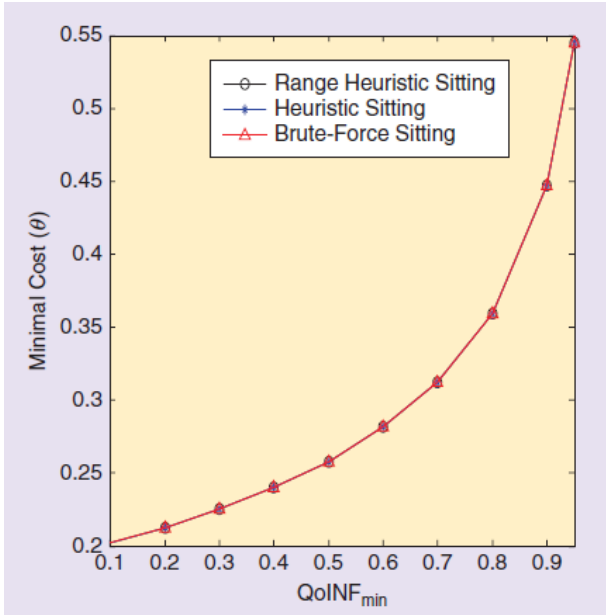


Figure 5. Communication overhead and accuracy tradeoffs.

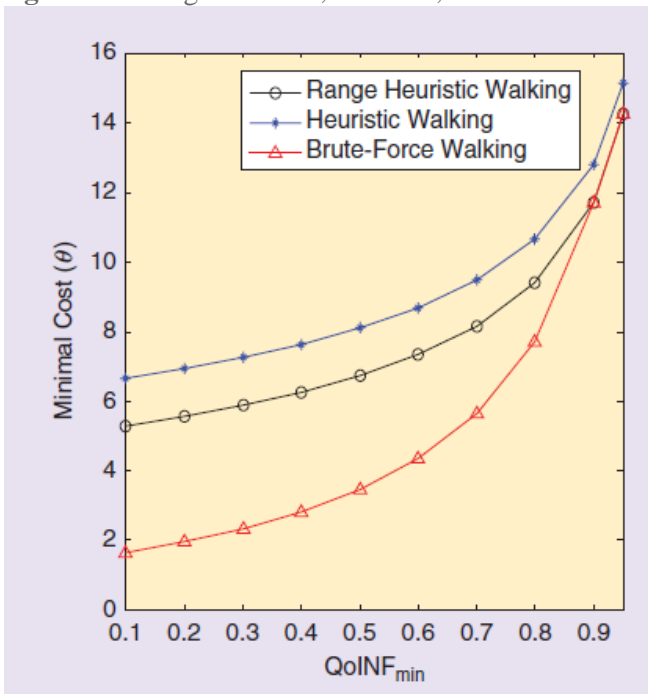
### A Performance of the Range-Heuristic

Our range-based heuristic can achieve application-specified quality and reduce network resource usage substantially. We compare our range-based heuristic algorithm with the naïve heuristic and brute-force search. Based on the derived sensitivity factors, we sort all of the sensors and generate the following sorted lists:  $K_1 = \{\text{Shimmer Accel, SunSPOT Accel, Shimmer Gyro}\}$  for context sitting;  $K_2 = \{\text{SunSPOT Accel, Shimmer Gyro, Shimmer Accel}\}$  for context walking; and  $K_3 = \{\text{Shimmer Gyro, Shimmer Accel, SunSPOT Accel}\}$  for context running. We use each approach to compute the optimal sensor set  $\tilde{\theta}$  and associated tolerance ranges  $Q(\tilde{\theta})$  that minimize the  $\widehat{COST}(\theta)$  for a target QoINF. We also use the range-heuristic to compute the  $q$  values for a target  $QoINF_{min}$  and then use those  $q$  values to determine the achievable QoINF.

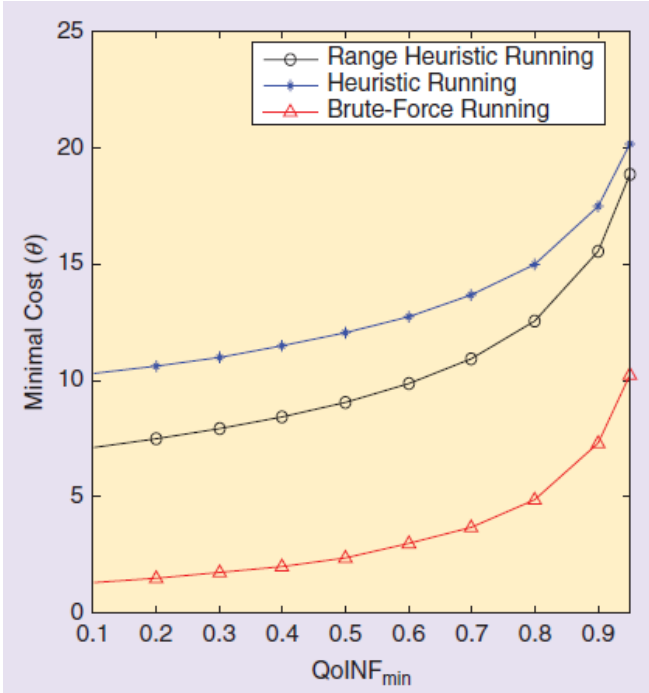
Figure 6 plots the minimal cost associated with the three search methods to determine the optimal subset of sensors and their tolerance ranges for the first context state considered, sitting in our case. In this example, the range-based heuristic and heuristic perform exactly as the brute force in finding the optimal sensor subset with minimum cost. Figure 7 compares the performance of these three algorithms for the context walking. The range-based heuristic performs better than the heuristic, and it performs close to brute force. Similarly, Figure 8 plots the performance for the running context, where again the range-based heuristic algorithm outperforms the naïve heuristic. Due to the simple set theoretic addition of sensors from one context to another (without examining the existing sensor set's satisfiability for the new context) in the heuristic algorithm, we observe that first just the Shimmer accelerometer has been selected for the sitting context; then for walking, both the Shimmer and SunSPOT accelerometers have been selected; and then for running, all three available sensors have been chosen. In the range-based heuristic, only the Shimmer accelerometer is selected for all the contexts at the minimal cost by tightening the tolerance range.



**Figure 6.** A range heuristic, heuristic, and brute-force minimal cost comparison for sitting.



**Figure 7.** A range heuristic, heuristic, and brute-force minimal cost comparison for walking.



**Figure 8.** A range heuristic, heuristic, and brute-force minimal cost comparison for running.

We also evaluate our range-based heuristic's ability to attain the application's desired QoINF. First, we calculate the tolerance ranges for the chosen optimal subset of sensors at minimal cost. Then with those specified tolerance ranges and the determined sensor set, we run our emulation on the already collected data traces to determine the empirically achieved accuracy of the algorithm. Figure 9 plots the QoINF achieved by the range-based heuristic algorithm for the context running. The range-based heuristic performs well at no more than 10% lower than the target QoINF. Nevertheless, we do notice that our range-based heuristic does not perform well in achieving target QoINF accuracy for the other two context states. We believe this is a result of the large approximation in our curve-fitting approach. This incurs errors in determining the sensitivity factors and therefore introduces a larger deviation in the  $q$  values, which ultimately affects the attainable QoINF accuracy of the range-heuristic algorithm with respect to the target QoINF metric. Adding more sensors to the selection process (as is likely in future pervasive computing scenarios) would be expected to help limit this negative impact.

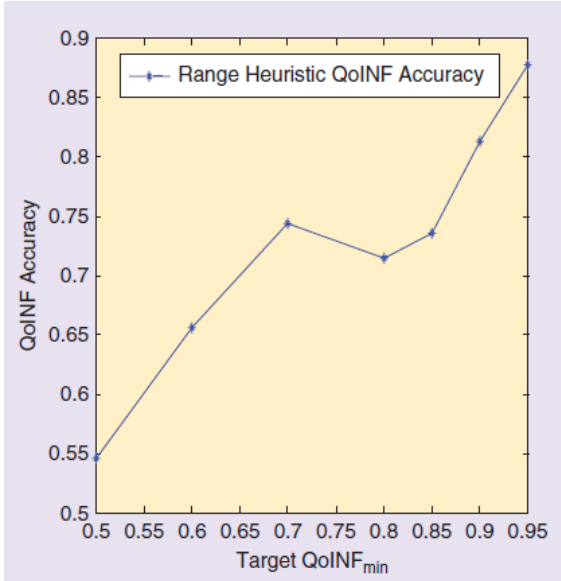


Figure 9. A range-based heuristic on achieving target QoINF for running.

## Insights and Challenges

Our initial work with this framework and its implementation provides enough evidence that our suggested approach of a) building formal functional models to characterize the relationship between context attributes and individual sensors and b) applying joint optimization of multiple contexts over a common substrate of sensors can provide significant savings in energy overheads for representative health and wellness applications. Accordingly, we believe that the technical community should explore this approach further. Our experience with the design and development of this framework has also left us with several insights and open Questions.

- What is the right QoINF function for a given context measure?** One of the main challenges in the application of our framework is establishing appropriate QoINF functions for context variables. Much of the work on utility-based context models faces the practical difficulty of computing useful utility functions [4]. We have used our inverse-exponential model and employed regression techniques on training data to derive the parameters for this model [12]. In reality, the functional relationship may be not only different (for instance, we already know that the  $q_0 \text{ inf}()$  function can be discontinuous) but also deployment specific (e.g., the correlation between a specific user's movements and motion sensor data may vary significantly based on individual behavioral characteristics or the layout of an assisted-living facility), and a separate training phase may be impractical. In such situations, we need to explore a more continuous, adaptive learning framework, where the system dynamically learns the relationship between different sensor parameters and the true user context, perhaps obtained from explicit user feedback or implicit user actions (e.g., [4]).
- How does one distinguish and combine between tolerance ranges and sensor errors?** In our model, the tolerance range is not an intrinsic characteristic of a sensor, but it is determined by the context optimizer: e.g., if  $q_i = \pm 10$  and the last reported value is 120, the true value of the sensor must lie in the interval (110, 130). Sensing errors (e.g., errors in sampling and calibration) are, on the other hand, intrinsic to a sensor and not application specific. For instance, if a sensor has an error of  $\pm 2$ , a reading of 120 could correspond to a ground truth of (118, 122). One way to view the relationship between these two variables is to note that, given  $q$  and  $e$  and a last reported value of  $v$ , the ground truth of the sensed attribute should lie between  $(v - q - e, v + q + e)$ . For our approach to work with sensors from different manufacturers and with different error characteristics, the context optimizer must be able to automatically derive and combine these two independent parameters. One practical approach to this issue may be to

have different sensors automatically publish their error ranges in a standard format [e.g., using the SensorML format (<http://www.opengeospatial.org/standards/sensorml>)] so that our framework can automatically incorporate these values. However, as it is well known that sensors will deviate from these nominal values over time, we need more research to establish how such deviations can be automatically detected under our  $q_i$ -based reporting approach.

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- **How do we extend our QoINF-based model to consider concurrent and correlated context?** In our formulation thus far, we have implicitly assumed that a context metric takes on only a single value at a time (e.g., a wellness management application assumes that the user is in only one of [sitting, walking, running] states at any instant) and that the different context attributes are mutually uncorrelated (e.g., the determination of a person's walking context is uncorrelated to her agitated with high BP context). In practice, if activity is defined to include both watching TV and talking on the phone, it is possible for an individual to be engaged simultaneously in both. Similarly, there will be statistical dependencies across contexts; for example, it is unlikely for a person to be agitated with high BP to be also simultaneously in the sleeping state. A more advanced framework is needed (perhaps employing semantic reasoning over contexts [13] or a hierarchical context inference model [9], [10]) to automatically detect such correlations and concurrency constraints and exploit them in selecting and tasking available sensors.

## Related Work

The tradeoff between communication overhead (cost) and the quality of fused data has been studied with respect to the effect of the tolerance ranges on the relative frequency of sink-initiated fetching (data pull) versus source-initiated refreshes (data push) [7]. The focus, however, has been on snapshot queries and not long-running subscription queries [8]. Temporal correlations across successive samples have also been exploited to reduce communication overhead of snapshot queries [1]; this approach used training data to parameterize a jointly normal density function. The collective adaptive precision setting algorithm [2] is designed for long-running aggregation queries (such as  $\{min, max\}$ ) and computes the optimal set of tolerance ranges for a given set of sensors that minimizes communication overhead. Unlike such work, which focused purely on structured-query-language-like aggregation queries over a preordained set of sensors, our goal is not only to support generalized context queries but also to simultaneously find the best subset of available sensors and their associated tolerance ranges. An energy management framework for wireless sensor networks that simultaneously considers QoINF requirements with energy constraints was presented in [5] that views the consumption of energy versus QoINF gains game theoretically and can decide to provide lower QoINF if the cost of data acquisition is too high; in contrast, we focus on health-care-related environments, where the QoINF requirement is considered to be inviolable.

## Conclusions

We motivate the need for a formal framework for energy-efficient determination of physiological context in pervasive health-care deployments, specifically using the scenario of remotely monitored assisted living. To this end, we introduce a formal framework for reasoning about the inherent tradeoffs between quality of context and the cost of acquiring it, followed by the use of this formalization to derive two heuristic algorithms for computing the context inference supporting structure. The key idea is to express the accuracy of context inference through a QoINF function that captures the dependence of context estimation accuracy on both the set of sensors selected to support context acquisition and their specified parameters of sensing. Such explicit recognition of the quality of sensed context within applications is an essential component of future context-aware ubiquitous health-care applications and software infrastructures.

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