Application-aware integration of data collection and power management in wireless sensor networks

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Abstract

Sensors are typically deployed to gather data about the physical world and its artifacts for a variety of purposes that range from environment monitoring, control, to data analysis. Since sensors are resource constrained, often sensor data is collected into sensor databases that reside at (more powerful) servers. A natural tradeoff exists between resources (bandwidth, energy) consumed and the quality of data collected at the server. Blindly transmitting sensor updates at a fixed periodicity to the server results in a suboptimal solution due to the differences in stability of sensor values and due to the varying application needs that impose different quality requirements across sensors. In order to adapt to these variations while at the same time optimizing the energy consumption of sensors, this paper proposes three different models and corresponding data collection protocols. We analyze all three models with a Markov state machine formulation, and either derive closed forms for the operation point of the data collection application or suggest algorithms for estimating this operating point to achieve a minimal energy consumption. We observe that the operating point depends on environmental characteristics and application quality requirements, which the proposed algorithms aim to accommodate. Our experimental results show significant energy savings compared to the naive approach to data collection.

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Keywords: Energy efficiency; Wireless sensor networks; Data collection; Power management

1. Introduction

With the advances in computational, communication, and sensing capabilities, large scale sensor-based distributed environments are becoming a reality. Sensor-enriched communication and information infrastructures have the potential to revolutionize almost every aspect of human life. An integral component of such an infrastructure is a data management system that allows seamless access to data dispersed across a hierarchy of storage, communication, and processing units—from sensor devices where data originates to large databases where the data generated is stored and/or analyzed.

Designing a scalable data management solution to drive distributed sensor applications poses many significant challenges. Given the limited computational, communication, and storage resources at the sensors, a traditional distributed database approach in which sensors function as nodes in a distributed system might not be a feasible option. In order to facilitate complex query processing and analysis, data might need to be migrated to repositories that reside at more powerful servers. An alternative solution, where sensor data is continuously collected at a logically centralized database, might also be infeasible. Since sensor readings may change very frequently and continuously, such environments are highly dynamic. Blindly transmitting the sensor updates to the server will impose severe network and storage overheads. Furthermore, since communication constitutes a major source of power drain [2] in battery-operated sensors, it would incur a very high energy cost.

The problem of effective data collection in highly dynamic environments has recently been studied in [20,24,34]. The key observation is that a large number of sensor applications can tolerate a certain degree of error in data. Data imprecision, of course, impacts application quality. For example, in target tracking using sensor networks, error in sensor intensity

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readings may result in error in localizing the object. Similarly, the result of a query for average temperature in a given region may be imprecise due to data error. The communication overhead between the data producers and the server can be alleviated by exploiting the applications’ error tolerance. Motivated by Olston et al. [24], in this paper, we explore data collection protocols for sensor environments that exploit the natural tradeoff between application quality and energy consumption at the sensors. Modern sensors try to be power aware, shutting down components (e.g., radio) when they are not needed in order to conserve energy. We consider a series of sensor models that progressively expose increasing number of power saving states. For each of the sensor models considered, we develop quality-aware data collection protocols that enable quality requirements of the queries to be satisfied while minimizing the resource (energy) consumption.

The rest of this paper is organized as follows. We formulate the quality-aware data collection problem for sensor environments in Section 2. Various sensor models and corresponding data collection protocols to minimize energy consumption are studied in Section 3. Adaptive sensor state management is discussed in Section 4. We analyze the performance in Section 5, discuss related work in Section 6 and conclude in Section 7.

2. Problem formulation

In this section, we describe system and query models used in this paper and develop a formal characterization of the sensor data collection problem.

2.1. System and query model

Our system consists of a set of $n$ sensors and one server (residing at a resource sufficient node) that maintains a database. For simplicity, we will assume that each sensor can communicate directly to the server. Detailed discussion on this assumption can be found at the end of Section 3. Each incoming query $Q_i$ is associated with an accuracy constraint $A_i$, indicating its tolerance to error in answer precision (we will explain the accuracy constraint and query answer accuracy in the next subsection). Furthermore, a query has a latency bound $D$ which requires that each query be answered within $D$ time units.

Each sensor node has a processor with limited memory, an embedded sensing circuitry, an analog-to-digital converter, and radio circuitry. A micro-operating system controls each component. We only consider different radio modes and assume all the other components are always turned on. We consider three sensor states: active (a), listening (l) and sleeping (s). While the sensor is in the active mode, the transmitter and receiver radios are on. While the sensor is in the listening state, the receiver radio is on. When a radio is in the idle mode, it is capable of detecting an incoming packet, but not in the process of receiving a packet, so we also classify this mode as the listening state since Tx is off and Rx is on. When the sensor goes to the sleeping state, its radio is turned off completely. Even in the sleeping state, changes in sensor values can still be detected, since we assume the sensor and processor are always on.

2.2. Data collection framework

Previous work [3,18,24,25] has shown that an effective approach to exploit the tradeoff between application quality and data imprecision is for the server to maintain an approximate value of the data whose divergence from the true value is guaranteed to be bounded by an error at any time. We next present the data collection framework similar to [24]. Let $S = \{s_1, \ldots, s_n\}$ be the set of sensors. Each sensor hosts its exact value that may change frequently. For each $s_i \in S$, let $v_i$ denote the value stored at sensor $s_i$. The approximation of $v_i$ is represented by a range $r_i$ with lower bound $l_i$ and upper bound $u_i : r_i = [l_i, u_i]$, which is stored in the database at the server. A query for the value of sensor $s_i$ is answered in the format of a range with a lower and an upper bound, so the answer accuracy is defined by the range size $u_i - l_i$. The accuracy constraint $A_i$ of query $Q_i$ specifies the maximum acceptable width of the result.

Fig. 1 illustrates the data collection process. Whenever the sensor value $v_i$ changes to $v'_i$, sensor $s_i$ checks whether $r_i$ is still a valid approximation for the new value. If $v_i$ falls outside $r_i$, a new approximation of $v'_i$ is sent to the server to update the database (this process is called source-initiated update). Otherwise, there is no need to transmit the update to the server, hence reducing communication overhead. Queries are executed over the cached ranges at the server. If the error tolerance of the query is larger than the data error, i.e., $A_i \geq u_i - l_i$, the query is processed without any communication with the sensor. Otherwise, the approximation offered by the database is insufficient, the server may request the exact value from remote sensor. The sensor responds with current exact value and a new approximation to be used by subsequent queries. This process is called consumer-initiated request and update.

2.3. Problem statement

Given $m$ user queries, our objective is to minimize sensor energy consumption in the process of answering all $m$ queries. Since a sensor consumes energy even when it is not transmitting or receiving data, besides reducing the communication overhead between a sensor and the server, we also need to minimize the time a sensor is either active or listening even when it is not transmitting updates to the server. Assume that the probabilities of source- and consumer-initiated updates at each time instant are $P_{su}$ and $P_{cu}$. Formally, we would like to

\[
\begin{align*}
\text{minimize} \quad & \bar{E} = E_{su} \cdot P_{su} + E_{cu} \cdot P_{cu} + E_{extra} \\
\text{subject to} \quad & a_i \leq A_i, \quad 0 \leq i < m, \\
& t_i \leq D, \quad 0 \leq i < m,
\end{align*}
\]

where $a_i$ is the answer accuracy for query $i$ and $t_i$ is the query response time. Also note that, $E_{su}$ is the energy required to send
an update to the server, and $E_{cu}$ is the energy required to both receive the request for the data and for transmitting the sensor value to the server. Note that $E_{su}$ and $E_{cu}$ are not constant. They depend upon the state at which the sensor was when the source-initiated update and consumer-initiated update occurred. Consider, for example, a sensor that is in the sleeping state. If the sensor value changes and exceeds the range associated for its value at the server, it must first transition to the active state followed by transmitting the value to the server. Thus, the total energy spent would be the sum of energy spent to transition from the sleep state to the active state and the energy spent to transmit the update to the server. In contrast, if the value divergence occurs when the sensor is in the active state, the energy consumption would be only for transmitting the update to the server. $E_{extra}$ is the amount of energy consumed while not receiving or transmitting any data. This is not a constant either, and it depends upon the state a sensor is in while the sensor is free.

To achieve the objective of minimizing the energy consumption at the sensor, we need to address the following issues:

- **How to maintain the database**: An optimal range needs to be maintained and adjusted for each sensor so that it reduces sensor energy consumption while still being able to meet query accuracy constraints. If the range is large, accuracy constraints of many queries will be violated resulting in expensive probes; likewise, if the range is small, sensor update would needlessly be transmitted to the server too frequently. Both cases will consume a large amount of energy. While the time to transmit an update to the server and the time to receive a request from the server is fixed in the collection process, the number of requests and updates is affected by the range size, hence the total energy consumption is dependent upon the choice of range size. We address how to set the range such that the energy consumption is minimized in Section 3.

- **How to manage sensor state**: We need to determine sensor state transition strategies. Sensors consume power not only when sending and receiving data, but also when idling at the active and listening states. To save energy, a sensor needs to power down into a lower energy state. Powering down a sensor requires additional cost to power up when a request that needs to be processed arrives. Furthermore, it could result in increased latency for queries. In Section 4, we address optimal state transition that determines the length of sensor idling and sleeping to minimize overall energy consumption.

### 3. Energy efficient data precision adjustment

In this section, we deal with how to setup the approximate range (for a sensor) in order to minimize the energy consumption due to communication between sensors and the server. The energy cost due to communication depends upon the number of source- and consumer-initiated updates which, in turn, depends upon the range size adaptation, patterns of the changes in sensor values, and query workload characteristics. Before presenting our solutions, we briefly review the approach described in [24] where the authors consider range adaptation to minimize the communication overhead between data producers and the server. Our approach builds upon some of their results.

Assuming that the communication cost incurred during a source- and consumer-initiated update is $C_{su}$ and $C_{cu}$, respectively, the expected cost per unit time is $C = P_{su} \cdot C_{su} + P_{cu} \cdot C_{cu}$. The authors established that $P_{su} = \frac{k_1}{r}$ and $P_{cu} = K_2 \cdot r$, where $r$ is the range size, and $K_1$ and $K_2$ are model parameters that depend on the characteristics of source updates and queries. ¹

Therefore, $C = \frac{k_1}{r} \cdot C_{su} + K_2 \cdot r \cdot C_{cu}$, which is minimized when

$$r = \sqrt{\frac{\rho}{K_2}}$$

where $\rho = 2 \cdot \frac{C_{cu}}{C_{su}}$. At this optimal point, it can be shown that the ratio of probability of consumer-initiated updates to the probability of source-initiated updates $\frac{P_{cu}}{P_{su}}$ is equal to $\rho$, which is a constant.

The algorithm exploits this observation and attempts to change the range $r$ such that the ratio of probability of consumer-initiated update to the probability of source-initiated update can be maintained to be the constant $\rho$. For example, if $\rho = 1$, the algorithm attempts to ensure that the probability of consumer-initiated updates is equal to the probability of source-initiated updates. In case $\rho < 1$, it is desirable for source-initiated updates to be more frequent than consumer-initiated updates. Thus the range is decreased on every consumer initiated update but only increased with probability $\rho$.

¹This justification is done under a simplified model, in which the changes in data values follow a random walk model in one dimension, the queries access the data periodically. Although this model is simplified, it is useful for deriving formulas and demonstrating the principles behind our algorithm. As we show empirically in other query workloads and precision constraints that the model is still valid.
switch (update-type) {
  case source-initiated update:
    with probability \min\{\rho, 1\}, set \(r' = \frac{r(1 + \theta)}{1 + \theta}; \) break;
  case consumer-initiated update:
    with probability \(\min\{\frac{1}{\rho}, 1\}\), set \(r' = \frac{r}{1 + \theta}; \) break;
}

return \(r'\);

Fig. 2. Range size adjustment algorithm proposed in [24].

We consider a series of sensor models based on power saving sensor states identified in the previous section. These models progressively consider more sensor states and become more complicated. We start with the always-active (AA) model where sensors are always in the active state. As explained before, this model serves as a baseline to study the energy savings that result in utilizing sensor states that consume less energy.

### 3.1. Always-active (AA) model

In this model, sensors are always active. The total energy consumption normalized over time duration \(T\) (i.e., power consumption) is shown as

\[
E_{\text{aa}} = PC_a \left( P_{\text{su}} T_{tx} \right) + PC_a \left( P_{\text{cu}} T_{rx} \right) + PC_a \left[1 - P_{\text{su}} T_{rx} - P_{\text{cu}} (T_{rx} + T_{tx})\right] \quad (\text{idling})
\]

As expected, it shows that the normalized energy consumption is equal to the power consumption at the active state. Therefore, irrespective of how the range is set, energy consumption is constant. This model serves as a baseline to study the energy savings that result in utilizing sensor states that consume less energy.

### 3.2. Active–listening (AL) model

In this model (illustrated in Fig. 3), the sensor consists of two states: active and listening. Initially, the sensor is in the listening mode. The sensor shifts to the active state if either the sensor value diverges from the range used to represent the sensor value at the server, or if it receives a request for its current value from the server. When a sensor is in the active state, it processes all its pending requests and waits for \(T_a\) time units before switching to the listening mode. We assume \(T_a\) is a multiple of time unit and \(T_a \geq 1\). The optimal value of \(T_a\) that minimizes energy consumption depends on the application workload and sensor value change patterns. We defer further discussion on how \(T_a\) can be set in order to minimize power consumption to Section 4. For the time being, we assume that \(T_a\) has been optimally set. With \(T_a\) fixed, we consider the problem of optimally determining the range \(r\) for the sensor that minimizes the energy consumption.

The sensor energy consumption under this model (Eq. (2)) consists of three parts:

- energy consumed by source-initiated updates. This depends on the sensor state when the source-initiated update is due: if the sensor is listening, there is a power-up energy and also transmission energy;
- energy consumed by consumer-initiated updates. In addition to the energy spent on receiving consumer-initiated requests

| Table 1 |
| Notations used in the models |

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<td>Interval size</td>
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<tr>
<td>(P_{\text{su}})</td>
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<td>(P_{\text{cu}})</td>
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<tr>
<td>(P_i)</td>
<td>Probability of a sensor being in state (i = a, l, s)</td>
</tr>
<tr>
<td>(T_{tx})</td>
<td>Time it takes to send a consumer- or source-initiated update</td>
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<td>(T_{rx})</td>
<td>Transition time from state (i = a, l, s)</td>
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upon first source-initiated update or consumer-initiated update

listening

active

Ta time units after processing last source or consumer-initiated update

Fig. 3. The active–listening (AL) model.

and transmitting the updates, power-up energy is needed if sensor is listening; and

- energy consumed by the sensor idling in different state. Besides receiving consumer-initiated requests, transmitting source/consumer-initiated updates and transition from listening to active, the sensor also consumes energy by staying in either active or listening state.

$$E_{al} = [P_l(E_{la} + PC_a Tr_x) + P_a(PC_a Tr_x)]P_{su}$$

(a) for source-initiated updates)

$$+ [P_l(PC_1 Tr_x + E_{la} + PC_4 Tr_x)$$

$$+ P_a(PC_a(T_{rx} + Tr_x))P_{cu}$$

(b) for consumer-initiated updates)

$$+ [1 - (P_l(T_{la} + Tr_x) + P_a Tr_x)P_{su}$$

$$- (P_l(T_{rx} + Tr_x + t_{rx}) + P_a(T_{rx} + t_{tx}))P_{cu}]$$

$$\cdot (PC_a + PC_1)P_l$$

(c) for idling). (2)

The energy consumption depends upon the probabilities $P_a$ and $P_l$ of the sensor being in the active and listening state. We next show how these probabilities can be expressed in terms of the probability of source-and consumer-initiated updates. If $T_a = 0$, the sensor state transition matrix capturing the state transition probabilities is as follows:

$$P = \begin{pmatrix}
    \text{listening} & \text{active} \\
    1 - P_{la} & P_{la} = P_{su} + P_{cu} \\
    1 - P_{au} & P_{au} = P_{su} + P_{cu}
\end{pmatrix}.$$ (3)

The long-term probability that the system will be in each state can be obtained by computing the steady state vector of the Markov Chain. Therefore, we get $P_l = 1 - P_{su} - P_{cu}$ and $P_a = P_{su} + P_{cu}$.

As mentioned before, $P_{su} = K_1$ and $P_{cu} = K_2 \cdot r$ [24]. To find the minimum $E_{al}$, we can find the root of the derivative $dE_{al}/dt$, and we get $r^* = \sqrt{\frac{2K_1}{K_2}}$. At this optimal point, $\frac{P_{su}}{P_{tu}} = \frac{K_1}{K_2} \cdot r^*$.

We next consider the case when $T_a > 0$ ($T_a$ is an integer and $T_a \geq 1$). In this case the sensor state transition matrix is as follows:

$$P = \begin{pmatrix}
    \text{listening} & \text{active} \\
    1 - P_{la} & P_{la} = P_{su} + P_{cu} \\
    1 - P_{au} & 1 - P_{au}
\end{pmatrix}.$$ (4)

where $P_{al} = (P_{su} + P_{cu}) \left(\frac{1}{T_a(P_{su} + P_{cu})} - 1\right)$ by assuming that source- and consumer-initiated updates are uniformly distributed. Since $x \leq [x] < x + 1$, $[x] = x + \alpha$, $0 \leq \alpha < 1$, we can re-write $P_{al}$ as follows: $P_{al} = \frac{1}{T_a} - (1 - \alpha)(P_{su} + P_{cu})$, $0 < \alpha \leq 1$. Similar to the calculation of long term state probability when $T_a = 0$, we obtain $P_l = \frac{1 - \alpha T_a}{1 + (1 - \alpha)T_a(P_{su} + P_{cu})}$ and $P_a = \frac{(P_{su} + P_{cu})T_a}{1 + (1 - \alpha)T_a(P_{su} + P_{cu})}$. We observe that, to minimize $E_{al}$, the optimal $r^*$ is $\sqrt{\frac{2K_1}{K_2}}$. The optimal point occurs when $\frac{P_{su}}{P_{tu}} = 2$.

The above analysis shows that for the AL model, independent of the value of $T_a$, the energy consumption is minimized when $\frac{P_{su}}{P_{tu}}$ is a constant (equal to 2). Since the data collection protocol proposed in [24] maintains the ratio of the probabilities to be a constant, it can be used in conjunction with the AL model to minimize energy.

3.3. AS model

In the AS model (described in Fig. 4) the sensor toggles between the sleeping and active modes.

Initially, the sensor is in the sleep state. Similar to the AL model, sensor shifts to the active state if the sensor value diverges from the range used to represent the sensor value at the server. Since a sensor in the sleeping state cannot receive requests from the server, it periodically wakes up on a time-out (i.e., if it has been sleeping uninterrupted for $T_a$ time units). Such a time-out-based transition is necessary in order to meet the quality requirements of queries that would have resulted in the consumer-initiated update at the server. The sensor, on switching to the active state sends its current value to the server. Note that this update can be used by the server to answer those queries that would have resulted in consumer-initiated requests while the sensor was in the sleep state. The sensor remains in the active state while there are requests for its value. After it has handled all the requests, it switches to the sleeping state after waiting for $T_a$ time units without handling any requests. We next discuss the energy consumption for the AS model.

In the AS model, total energy consumption (Eq. (5)) consists of the following parts:

- energy consumed by source-initiated updates. Besides the energy spent in transmitting source-initiated updates, there

\[ \text{energy consumed by source-initiated updates} = \frac{K_1}{K_2} \cdot r^3 \]

\[ \text{energy consumed by consumer-initiated updates} = \frac{K_1}{K_2} \cdot r_0^3 \]

\[ \text{energy consumed by idling} = \frac{K_1}{K_2} \cdot r^4 \]

\[ \text{energy consumed by state transition} = \frac{K_1}{K_2} \cdot r^5 \]
is energy involved in transition from sleeping to active if the sensor is sleeping when the source-initiated update is due;
• energy consumed by transition from the sleeping state to the active state and the associated value updates when a sensor wakes up due to time-out;
• energy consumed by consumer-initiated updates; and
• energy consumed while sleeping or being active without receiving or transmitting.

\[ E_{as} = \left[ \begin{array}{c} (E_{sa} + PC_a T_{tx}) P_s + PC_a T_{tx} P_a \left( T_{tx} P_s + P_a \right) \left( P_a - P_{su} P_{cu} \right) \left( P_{cu} - P_{su} \right) \left( P_{cu} - P_{su} \right) \right] \]

\[ = \left( P_{sa} - P_{su} P_{s} \right) \left( E_{sa} + PC_a T_{tx} \right) + [PC_a(T_{tx} + T_{s})] P_a P_{cu} \]

\[ + \left( PC_a P_a + P_{cu} P_s \right) \left[ 1 - (T_{s} + T_{tx}) P_s + (T_{s} + T_{tx}) P_a \right] \left( P_{sa} - P_{su} P_{s} \right) \left( T_{s} + T_{tx} \right) \left( T_{s} + T_{tx} \right) \left( P_{cu} - P_{su} \right) \left( P_{cu} - P_{su} \right) \]

We next derive the optimal setting of the range \( r \) for the sensor that minimizes the energy consumption under the assumption that the \( T_a \) has already been set. As stated before, the optimal setting of \( T_a \) will be derived in Section 4.

If \( T_a = 0 \), the sensor switches to the sleeping state as soon as there are no requests waiting. Therefore, \( P_{sa} = P_{su} \left( \frac{1}{T_a - P_{su}} \right) = \frac{1}{T_a} + \alpha P_{su} (0 \leq \alpha < 1) \) and \( P_{as} = P_{su} + P_{cu} \). The sensor state transition matrix is as follows:

\[ P = \begin{pmatrix} \text{sleeping} & \text{active} \\ \text{active} & \text{sleeping} \end{pmatrix} \]

Long term state probabilities are as follows:

\[ P_s = \frac{1}{T_s} - \beta (P_{su} + P_{cu}) + \frac{1}{T_s} + \alpha P_{su} \]

\[ P_a = \frac{1}{T_s} + \beta (P_{su} + P_{cu}) + \frac{1}{T_s} + \alpha P_{su} \]

For both \( T_a = 0 \) and \( T_a > 0 \), by applying these probability formula into Eq. (5), the total energy consumption can be expressed as a ratio of two high order polynomials (order of 9) of range size \( r \) (see [14] for details). Since it is not possible to express the ratio \( P_{sa} \) to \( P_{su} \) in terms of other parameters, the basic strategy for range setting described in [24] cannot be used. Instead, we need to monitor parameters \( K_1, K_2, \alpha \) and \( \beta \) at runtime. For this purpose, the following information for the sliding window of last \( k \) updates is maintained: (1) the number of sensor state transitions (\( N_{sa} \) and \( N_{as} \)) of the last \( k \) updates; and (2) the number of source- or consumer-initiated updates (\( N_{su} \) or \( N_{cu} \)) of the last \( k \) updates. Using this information, the values of \( K_1, K_2, \alpha \) and \( \beta \) is estimated. For example, \( K_1 \) is set to be \( P_{sa} \cdot r^2 \), where \( P_{sa} \) is estimated as the number of source-initiated updates (\( N_{su} \)) divided by \( T \), where \( T \) is the time period of the current window. The parameter \( K_2 \) can be estimated similarly. Given these parameter values, we find the roots of \( \frac{dE_{as}}{dr} \) and compare the energy values at the roots to determine the value of \( r \) that minimizes the energy consumption \( E_{as} \). Since the computation is too complex to be performed at the resource-constrained sensors, it is done at the server. Note that since the value of \( \alpha \) and \( \beta \) depends upon the number of sensor state transitions during the window, the sensors determine the values of \( \alpha \) and \( \beta \) and piggyback these values for the last \( k \) updates with the \( k \)th update. At the same time the server monitors \( K_1 \) and...
K; upon receiving the kth update, the server computes the new optimal range which is transmitted to the sensor.

3.4. ALS model

In this model (illustrated in Fig. 5), the sensor is initially in the sleeping state. It switches to the active state when a source-initiated update occurs or when it has been sleeping for T_akt time units without interruption. When it is in the active state, it processes all the waiting requests. After it has been free in the active state for T_akt time units, it goes to the sleeping state. Once in the listening state, any source- or consumer-initiated update will trigger the sensor to go to the active state; otherwise, if it is idling for T_l time units, it goes to sleep.

The sensor energy consumption (Eq. (14)) consists of the following parts:

- energy consumed by source-initiated updates. Besides the energy spent in transmitting source-initiated updates, there is energy involved in transitions (from sleeping to active if the sensor is sleeping, or from listening to active if the sensor is listening) when the source-initiated update is due;
- energy consumed by transition from the sleeping state to the active state and the associated value updates when a sensor wakes up due to time-out;
- energy consumed by consumer-initiated updates. If the sensor is sleeping, incoming consumer-initiated updates are dropped, so only when sensor is listening or active, would a consumer-initiated request be responded and
- energy consumed while sleeping or being active without receiving or transmitting.

\[ E_{als} = (P_S E_{sa} + P_t E_{la} + P C_a T_{tx}) P_{cu} \]

((a) for source-initiated updates)
\[ + (P_{sa} - P_{su} P_y) (E_{sa} + P C_a T_{tx}) \]

((b) for time-triggered updates)
\[ + [P_l (P C_a T_{tx} + E_{la} + P C_a T_{tx})] P_{cu} \]

((c) for consumer-initiated updates)
\[ + (P C_a P_a + P C_a P_1 + P C_a P_3) \cdot \left[ 1 - (P_{sa} T_{sa} + P_{lu} T_{lu} + T_{tx}) P_{su} \right] \]
\[ - (P_{sa} - P_{su} P_y) (T_{sa} + T_{tx}) \]
\[ - ((P_l + P_y) (T_{tx} + T_{tx}) + P_l T_{lu}) P_{cu} \]

((d) for idling).

(14)

Similar to the AS model, we can derive the probabilities of switching between sensor states, from which the steady state probability (P_a, P_1 and P_3) can be obtained. Applying these into Eq. (14), the energy consumption can be expressed as a function of r. Similar to the AS model, the optimal range size can be set based on the parameters monitored at runtime. The detailed derivation, though conceptually simple, is quite complex, so we refer the interested readers to [14]. We can apply the same data collection approach as in the AS model.

3.5. Discussion

Our discussion so far assumes a simplistic setting of a single access point (server) that is within one-hop communication range of a set of sensors. In a real system, a server may correspond to an access point that serves as a data collection hub for a set of sensors. Various access points, taken together, may form the overall distributed sensor database. Alternatively, data from these access points may be collected into a centralized sensor data repository. Our solution can serve as a building block for a large scale distributed sensor system.

Previous work [9] has studied the pros and cons of one- and multi-hop communication in wireless sensor networks. The results show that using multi-hop communication is not always optimal in terms of energy consumption. In fact, for typical sensor nodes, the optimum transmission distance to save total energy of transmission and receiving is about 20 m. We believe that there do exist application scenarios such as monitoring of room temperature where the entire network diameter is less than 20 m. Therefore, in those environments, the best communication policy is not to employ multi-hop routing strategies at all; instead, direct transmission from each node to the server is the most energy-efficient communication scheme. Our approaches will work in those environments.

Nevertheless, we do agree that the assumption of one-hop communication limited the applicability of our approaches. To this end, we next discuss how the approaches can be adapted when applied to a two-hop sensor network. A two-hop sensor network can be realized by applying clustering-based communication strategies. For instance, LEACH [16] is such a protocol that groups sensors into enough number of clusters so that each cluster head is one-hop away from the server and each sensor is one-hop away from its cluster head. To balance energy consumption in the network, all the nodes take turns to
be cluster heads. Alternatively, a two-hop sensor network can be realized by using heterogeneous sensing devices and organizing the network into tiers such as in Tenet [13], which has become a widely accepted architecture in the sensor network community. Our data collection protocol and state transition management can be slightly modified to work in a two-hop network. Depending on the role of a sensor node, a different algorithm may be used. For a cluster head as in clustering-based scheme or a master node as in Tenet, we can apply the range size adjustment algorithm proposed in TRAPP [24], the basis of our work. For other nodes, we can apply the data collection protocol presented in the paper.

4. Adaptive sensor state transitions

In the various sensor models discussed above, transitions among states are triggered both by: (a) a sensor value diverging from its representation at the server and (b) time-outs. For example, in the AL and ALS model, a sensor in a sleep mode shifts to the active mode after \( T_s \) time units. Furthermore, transition from active/listening to listening/sleeping is also based on time-outs. In this section, we derive how the sensor sets these time-outs in order to maximize energy savings. We believe application layer provides better information about when the radio is not needed, therefore we apply information from upper layers (above the MAC-layer) to control radio power levels.

In the AS and ALS models, a sensor must set a sleeping time \( T_s \) after which it transitions to the active state and sends an update to the server. Since sleeping consumes the least energy, it is desirable tomaximize the time \( T_s \) for which the sensor can sleep. To make sure that all the queries are answered within latency bound \( D \). The worst case query response time for the AS model or the ALS model \( T_s + T_{sa} + T_{sx} + T_{tx} \) should not be greater than \( D \). Therefore, \( T_s \) is chosen to be \( T_s \leq D - (T_{sa} + T_{sx} + T_{tx}) \).

In AL, AS and ALS model, \( T_s \) needs to be determined. We now use the AS model to show how an optimal value of \( T_s \) can be derived. The development for the ALS model is similar in nature and interested readers are referred to [14] for details. Waking up a sensor in the sleeping state requires additional update to the server. Since sleeping consumes the least energy, the best energy reductions possible. Thus, a careful selection of the arrival rate, the sleeping period could be so short that powering the most energy efficient choice. Depending upon the request to sleep immediately after it finishes the requests at hand is energy and latency, so it is not obvious that putting the sensor in nature and interested readers are referred to [14] for details.

We assume that the length of the idle interval can be modeled by a fixed and known distribution whose density function is \( \pi(t) \). The expected energy consumption for a single silent period will be

\[
E = \int_0^{T_a} \pi(t)PC_\text{a}t \, dt + \int_{T_a}^{T_a+T_s} \pi(t)[PC_\text{a}T_a + PC_\text{s}(t - T_a) + E_{sa}] \, dt. \tag{15}
\]

If we assume that requests (either source- or consumer-initiated update requests) are uniformly distributed in interval \( (0, T_a + T_s) \) (since we know that at the end of \( T_i \), there must be a time-out update request), then \( \pi(t) = \frac{1}{T_a + T_s} \). In this case, the expected energy consumption for a single silent period will be

\[
E = \frac{PC_\text{a}T_a^2 + 2PC_\text{a}T_a + (PC_\text{a}T_a^2 + 2PC_\text{s}T_s)}{2T_a(T_a + T_s)}. \tag{16}
\]

Since \( T_s \geq 0 \) and \( E > 0 \), \( E \) is non-decreasing and is minimal when \( T_a = 0 \). This implies that the sensor should go to sleep immediately after it finishes all the requests at hand.

While \( T_a = 0 \) is optimal if request inter-arrival pattern follows uniform distribution, in practice, this assumption is rarely true, and the problem of finding \( \pi(t) \) remains. Our approach is to learn \( \pi(t) \) at runtime and adaptively select \( T_a \) accordingly. The basic idea is as follows: we choose a window size \( w \) in advance. The algorithm keeps track of the last \( w \) idle period lengths and summarizes this information in a histogram. Every \( k \) requests, the histogram is used to generate a new \( T_a \).

The set of all possible inter-arrival period lengths \( (0, T_a + T_s) \) is partitioned into \( n \) intervals, where \( n \) is the number of bins in the histogram. Let \( t_i \) be the left endpoint of the \( i \)th interval. The \( i \)th bin has a counter which indicates the number of idle periods among the last \( w \) idle periods whose length fall in the range \( [t_i, t_{i+1}) \). The bins are numbered from 0 to \( n - 1 \) and \( t_i = 0, t_n = T_a + T_s \).

The counter for bin \( i \) is denoted by \( c_i \). The threshold for changing states is selected among \( n \) possibilities: \( t_0, \ldots, t_{n-1} \). We estimate the distribution \( \pi \) by the distribution which generates an idle period of length \( t_i \) with probability \( c_i/w \) for all \( i \in \{0, \ldots, n-1\} \). \( \sum_{i=0}^{n-1} c_i = w \). Thus \( T_a \) is chosen to be the value \( t_m \) that minimizes the following energy consumption:

\[
\min_{i=1}^{m-1} \frac{c_i}{w}PC_\text{a}t_i + \sum_{i=m}^{n} \frac{c_i}{w} [PC_\text{a}t_m + PC_\text{s}(t_i - t_m) + E_{sa}]. \tag{16}
\]

Similar derivation can be done to obtain \( T_a \) for AL/ALS models and \( T_1 \) for the ALS model (see details in [14]). Since the frequency and accuracy requirement of user queries vary from sensor to sensor, optimal active time \( T_a \) also differs from one sensor to another. Fig. 6 shows the algorithm for computing \( T_a \), which returns the index \( m \) and indicates that \( T_a \) should be set to be \( t_m \).

Only a sensor itself is aware of its own state transitions, so the above algorithm should be run at each sensor node. Given resource constraints of a sensor, an efficient implementation of the algorithm is necessary. The time complexity of the algorithm every time \( T_a \) and \( T_1 \) need to be updated is \( O(n) \) and
When a node transmits, it sends a source- or consumer-initiated Berkeley[28]. The transmission time (sensor nodes/motes developed by the University of California-parameters were obtained from the specification of the wireless posed at the server which then returns their results. can directly communicate with the server. User queries are

5.1. The simulation environment

The simulated infrastructure consists of a server, a database and a number of sensors (100–500). We assume that the sensors can directly communicate with the server. User queries are posed at the server which then returns their results.

The sensors are characterized as follows. The sensor-related parameters were obtained from the specification of the wireless sensor nodes/motes developed by the University of California-Berkeley [28]. The transmission time (Ttx) and reception time (Trx) are derived based on transmission rate 20 kbps of a mote. When a node transmits, it sends a source- or consumer-initiated update which is a 32-bit sensor value; when a node receives, it receives a consumer-initiated request which is a one bit notification. Therefore, we have Ttx = 1.60 ms and Trx = 0.05 ms. Each sensor holds one exact numeric value, and the database holds all the interval approximations. Sensor values are picked randomly and uniformly from the range [−150, 150]; they persist a random walk in one dimension: every second, the values either increases or decreases by an amount sampled uniformly from [0.5, 1.5].

User queries arrival times at the server are Poisson distributed with mean inter-arrival time set at 2s. Each query is accompanied by an accuracy constraint specifying the maximum acceptable width of the result. The accuracy constraints are generated based on parameters Aavg = 20 (average accuracy constraint) and Avar = 1 (accuracy constraint variation): they are sampled from a uniform distribution between Amin = Aavg · (1 − Avar) and Amax = Aavg · (1 + Avar).

5.2. Experimental results

Our performance study first evaluates the proposed sensor models in terms of sensor energy consumption and query response time. We then study the impact of Ttx and Trx values, as well as range size adjustment on the system performance. In our system, the two random variables are the changing sensor values and arriving user queries. We analyze the system’s behavior by varying the pattern of sensor value changes and query accuracy constraints.

Fig. 7 shows sensor energy consumption and query response time of the four proposed sensor models (AA, AL, AS and ALS). Not surprisingly, the energy consumption of the AA model is the highest, and its query response time is the lowest. This is the model where no energy is saved; sensors are always active, thus any consumer-initiated update requests can be detected immediately and then processed. As shown in Table 2, listening state consumes similar amount of power to active state, thus the AL model does not decrease energy consumption to a great extent. However, most of the time, the sensor is in the listening state when most requests arrive. It switches to the active state so that it can actually send out the updates. This power-up process takes time, which explains why query response time under the AL model is higher than the AA model. Models that incorporate sleeping state reduce energy consumption significantly. However, this comes at the price of higher query response time, since it takes more time for a sensor to switch from the sleeping state to the active state than from the listening state to the active state. Communication cost comparison of these four models show that our energy saving strategies also reduce communication cost slightly. This is because multiple queries waiting at the server can be answered using the database ranges refreshed by the next source-initiated update, avoiding the need for the sensor to transmit an update for each consumer-initiated request. Given that decreasing sensor energy consumption is our objective, the AS model outperforms the other models significantly due to its low energy cost. We, therefore, restrict the remainder of the performance study to the AS model.

Fig. 8 demonstrates the impact of Ts value selection on sensor energy consumption and query response time. When Ts is very small, the sensor powers up from the sleeping state to the active state very often consuming a large amount of energy. However, this benefits queries waiting at the server by shortening their waiting time. As Ts gets larger, the power consumption...
Table 2
Parameters used in the simulation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PC_a$</td>
<td>14.88 mW</td>
<td>$E_{al}$</td>
<td>0.025 μJ</td>
</tr>
<tr>
<td>$PC_l$</td>
<td>12.50 mW</td>
<td>$E_{la}$</td>
<td>0.014 μJ</td>
</tr>
<tr>
<td>$PC_s$</td>
<td>0.016 mW</td>
<td>$E_{sa}$</td>
<td>0.119 μJ</td>
</tr>
<tr>
<td>$T_{sl}$</td>
<td>4 μs</td>
<td>$T_{tx}$</td>
<td>0.05 ms</td>
</tr>
<tr>
<td>$T_{la}$</td>
<td>12 μs</td>
<td>$T_{tx}$</td>
<td>1.60 ms</td>
</tr>
<tr>
<td>$T_{sa}$</td>
<td>16 μs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

decreases and query response time increases. After $T_a$ reaches a certain point (100 ms in this case), the energy consumption levels out. This is because the likelihood of sensor switching because of time-out is very low: the energy consumed by source-initiated updates dominates; for the same set of queries and same sensor value change patterns, the energy consumption is similar.

Fig. 9 compares system performance under fixed $T_a$ with system performance using adaptive $T_a$. Since $T_a = 0$ was shown to be optimal when request arrival follows uniform distribution, we compare the adaptive approach to the approach that fixes $T_a$ to be 0. The results show that adaptive $T_a$ saves energy by half and also decreases query response time. When requests are bursty, it saves energy and shortens query waiting time by remaining active for a certain time period. Adapting $T_a$ to user query patterns and sensor value changes is much better than fixing its value.

Fig. 10 depicts the impact of range size where $T_a$ is adaptive to system conditions. We consider four different cases: (a) $r = 0$: this means the database stores single instantaneous values instead of intervals, (b) set $r$ to be the average accuracy constraint: on an average, queries can be satisfied by stored values, (c) adaptive $r$ as shown in our approaches: the optimal $r$ is found periodically to minimize the energy consumption, and (d) a large $r$: when $r$ is 0, all queries can be answered by just retrieving values from the database, so query response time is minimized; but each change in sensor value needs to be reported to the server, which consumes a large amount of energy. When $r$ is set to be very large, most source value changes will not exceed current range, so the likelihood of source-initiated updates is low. However, the coarse data representation is not sufficient for most of the queries, hence a number of consumer-initiated updates will occur. As a result, the average query response time is very high. Fig. 10 shows that our adaptive approach significantly outperforms other approaches.

Fig. 11 shows how the system behaves as sensor values change frequency varies where both $T_a$ and range sizes are adaptive to system conditions. When the sensor value changes very frequently, the likelihood of its value falling outside of the current range is high, leading to frequent source-initiated updates. This triggers the sensor to send out updates, and in some cases with the added cost of powering up from sleeping mode; both updates and power-up consume energy. Subsequently, energy consumption is very high. Because the server receives updates constantly, most queries can be answered promptly, and average response time is low. As sensor value changes less frequently, the energy consumption decreases. After it reaches a certain point, the energy consumption evens out. This is because when not enough source-initiated updates occur, the sensor wakes up after $T_a$ time units and sends an update, which dominates energy consumption.

Fig. 12 indicates the impact of query accuracy constraints where both $T_a$ and range sizes are adaptive to system conditions. The horizontal axis is the average accuracy constraint. When most queries need very accurate data, there will be many consumer initiated updates, therefore, both energy consumption and query response time are high. As accuracy constraints...
are relaxed, increasing number of queries can be answered by just returning the current values in the database, therefore sensor energy consumption becomes smaller and query response time is decreasing. After a certain point, the likelihood of getting consumer-initiated updates becomes very small, and then source-initiated updates and time-out updates consume most of the energy. For this reason, the curve levels off after that point.

5.3. Performance summary

Performance studies indicate that the AS model consumes the least amount of sensor energy; our proposed strategies of intelligent sensor state transition reduce energy consumption to a great extent; optimized range size adjustment works effectively with corresponding sensor models and saves more energy than static range or storing exact values.

6. Related work

In this section, we compare our work to related research in energy efficient protocols for sensor networks, quality aware data collection, sensor databases and data streaming.

6.1. Energy efficient protocols for sensor networks

Energy efficiency is one of the major concerns in sensor networks. To prolong system lifetime of sensor networks, various approaches have been devised to exploit low duty-cycle
operation (e.g., transition into a sleeping mode). In ASCENT [8], the decision of when a node should go into the sleep state is based on the number of active neighbors and per-link data loss rate. The PEAS [33] protocol avoids the overhead of keeping neighbor state by letting each node probe its surrounding nodes to maintain a desired working node density. STEM [29] trades power savings for path setup latency by using a separate radio operating at a lower duty cycle to detect incoming packets in order to manage sensor network topology. LEACH [16] and PEGASIS [21] aim to balance energy consumption among sensor nodes by rotating cluster heads so that the lifetime of the sensor network can be maximized. More recently, maximizing the lifetime of a two-tiered sensor network is addressed [26], where resource-constrained sensor nodes are deployed around resource-sufficient base stations and at least one application node exists within a sensor cluster. The lifetime is maximized by arranging the locations of base stations and strategically relaying between application nodes. The approaches described above focus on exploiting the cooperation among sensor nodes for better energy conservation. In contrast, our energy saving approaches proposed in this paper take into consideration application-level information. We explore how application’s tolerance of information imprecision and data delivery latency can be used to ensure that applications receive the information at their desired levels of accuracy without consuming significant amount of sensor energy. Considering application level information to balance the tradeoff between energy consumption and application quality is also explored in the context of grid [17].

6.2. Quality aware data collection

Balancing the tradeoff between quality and cost has been considered for resource-sufficient information sources, where the major concern is communication overhead. In the context of moving object databases [31], the location of a moving object is predicted based on its velocity vector; decisions of whether or not to update the database is made based on the difference between the cost of information imprecision and the cost of message passing. For more general settings where queries are imposed upon fast changing data, strategies were proposed for answering aggregate queries and maintaining the database at a
reasonable accuracy level [24, 25]. Furthermore, quality aware data collection under time constraints is studied [15] where a real-time collection framework, scheduling algorithm and a cost effective database maintenance strategy are proposed and validated. To apply the concept of quality awareness into sensor environments, an optimal online algorithm is proposed for creating piecewise-constant approximation of data to guarantee the quality of sensor data archival applications [20]. This paper aims to support quality awareness for point queries issued on top of dynamically changing sensor data. Point queries differ from data archival applications in that they are associated with implicit or explicit expectation of query response time. In addition, we specifically focused on minimizing energy consumed in the process of answering the queries.

In-network processing has been investigated to balance the tradeoff between energy consumption and quality of aggregate data [12, 30]. This paper focuses on exploiting application specified accuracy requirements for more efficient data collection coupled with power management. Similar idea of using application semantics to drive power management has also been explored for real-time sensor applications [11], spatiotemporal queries [5] and rare event detection [7].

6.3. Sensor databases

Research on sensor databases such as COUGAR [6], TinyDB [23], Aurora [1] and Quasar [19] aims to accommodate the special characteristics of sensors into databases. COUGAR describes a data model and long-running query semantics for sensor database systems where stored data are represented as relations and sensor data are represented as time series. The interaction of in-network aggregation with wireless routing protocol for distributed query processing in sensor networks is also investigated in [32]. TinyDB is a query processing system for extracting information from a network of TinyOS sensors. It provides a simple, SQL-like interface to specify the data you want to extract, along with additional parameters, like the rate at which data should be refreshed. Given a query specifying your data interests, TinyDB collects that data from motes in the environment, filters it, aggregates it, and routes it out to a PC. TinyDB does this via power-efficient in-network processing algorithms. Aurora aims to build a single infrastructure that can efficiently and seamlessly meet the various application requirements (e.g., timeliness) in the presence of huge volumes of continuous data streams and data uncertainty. Specifically, it focuses on the real-time data processing issues, such as QoS- and memory-aware operator scheduling, semantic load shedding for coping with transient spikes in incoming data rates, as well as hybrid data storage organizations that would seamlessly and efficiently combine pull- and push-based data processing. Our project Quasar [19] differs from these projects in that it uses the notion of application error tolerance to enhance overall system performance while guaranteeing desired levels of application quality in sensor environments. Our long term goal is to integrate various ideas at the sensor, middleware and application levels into a unified system which will be easily customized to individual sensing applications, but will be generic and modular enough to be useful to a large class of such applications. As part of the ongoing research in Quasar [19], the work presented in this paper explores how application quality tolerance can be used to reduce the energy consumption for query processing in sensor environments. This approach can be viewed as complementing in-network processing. An interesting future work is to combine the in-network query processing with quality-based adaptation to minimize energy consumption.

6.4. Data streaming

Data streaming has been a vibrant research field in recent years (e.g., OpenCQ [22, 27], Niagara [10], STREAM [4]). A whole gamut of issues have been addressed, such as system architectures, concepts/semantics of continuous queries, QoS specifications for fresh information delivery, system scalability etc. Our work targets a similar context where data is fast changing and update intensive, but the data generators are resource-limited sensor nodes. This constraint of sensors changed the objective of the problem to be minimization of sensor energy consumption.

7. Conclusions

A key concern of our work is to minimize sensor energy consumption without degrading application quality in distributed sensor environments. In this paper we have shown, using both theoretical analysis and experimental results, how the error tolerance of applications can be exploited to reduce energy consumption while at the same time meeting both accuracy and latency constraints of applications. We have also indicated that, with more complicated sensor models (such as the AS and ALS models), while saving more energy, both sensors and the server have to participate in parameter monitoring and adaptation. Furthermore, we observed that it saves more sensor energy to adaptively determine the duration that the sensor stays in the active state based on source- and consumer-initiated update patterns.

The work presented here focused on collecting data that supports single-item queries. As sensor applications must run in increasingly distributed environments, aggregate queries are often needed. With the same goal of minimizing sensor energy consumption and ensuring application quality, we are in the process of dealing with aggregate continuous queries by taking into account: (1) the spatial and temporal locality of sensor values, and (2) the server’s unawareness about sensor states.

In this paper, sensor data is stored in the database in the format of a range with a lower bound and an upper bound, which has been widely explored in caching to reduce communication overhead [24]. More descriptive representation such as probability density functions can be applied to better capture the changes in sensor values. This is part of our ongoing work.
Finally, sensor networks are subject to higher fault rates than traditional networks: connectivity between nodes can be lost due to environmental noise and obstacles; nodes may die due to power depletion, environmental changes or malicious destruction. Providing resilient data collection will require further work that takes into account resource-limited nature of sensor nodes, imprecision of sensor data and the high fault rate of sensor networks.

The eventual goal of our work is to develop effective tools for context information collection in highly dynamic and distributed environments. With the advances of MEMS and wireless networking technologies, sensors are promising to be deployed in a large scale to capture various information from the surroundings. Context-sensitive middleware services will heavily rely on the data obtained from sensors, therefore the work presented in this paper is part of the fundamental support. Middleware techniques for achieving the competing goals of accuracy and energy efficiency such as those described in this paper are key to delivering the right information to the right user at the right time.

References


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