ON THE USE OF CHANNEL STATE FOR ENERGY EFFICIENT INFORMATION RETRIEVAL IN SENSOR NETWORKS

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ABSTRACT

We consider distributed information retrieval for sensors networks with cluster heads or mobile access points. The performance metric used in the design is energy efficiency defined as the ratio of the average number of bits reliably retrieved by the access point and the total amount of energy consumed. We demonstrate that opportunistic strategies that use channel state information may not be optimal when channel acquisition at individual sensors consumes substantial energy. We then propose a distributed opportunistic transmission protocol using a combination of carrier sensing and backoff strategy that incorporates channel state information of individual sensors. By selecting a set of sensors with the best channel states to transmit, the proposed protocol achieves the upper bound on energy efficiency when the signal propagation delay is negligible. This protocol provides a distributed solution to the general problem of finding maximum/minimum. It can also be extended to solve the problem of network lifetime maximization.

1. INTRODUCTION

A key component in the design of sensor networks is the process by which information is retrieved from sensors. In an ad hoc sensor network with cluster heads/gateway nodes, sensors send their packets to their cluster heads using certain transmission protocol [1] (see Fig 1). For sensor networks with mobile access [2], data are collected directly by the mobile access points. In both cases, a population of sensors (those in the same coverage area of an access point) share a common wireless channel. Thus, an information retrieval protocol that determines which sensors should transmit and the rates of transmissions needs to be designed for efficient channel utilization. In this paper, we are interested in distributed information retrieval which allows each sensor, by itself, to determine whether it should transmit and the rate of transmission. In the context of sensor networks, distributed strategy has many advantages over centralized approach: less overhead, more robust against node failures, and possibly more energy efficient.

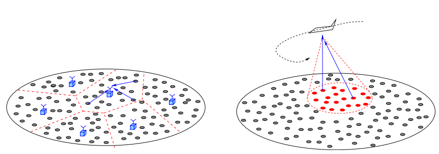

Fig. 1: Information retrieval in sensor networks.

1.1. Energy Efficient Opportunistic Transmission

By opportunistic transmission we mean that the information retrieval protocol utilizes the channel state information (CSI). Suppose that the channel states of a set of activated sensors have been obtained. An opportunistic transmission protocol chooses, according to certain criterion, a subset of activated sensors to transmit and determines their transmission rates. Knopp and Humblet [3] showed that, to maximize the sum-capacity under the average power constraint, the opportunistic transmission that allows a single user with the best channel to transmit is optimal.

The idea of opportunistic information retrieval, at the first glance, is appealing for sensor networks where energy consumption is of primary concern. If the channel realization of a sensor is favorable, the sensor can transmit at a lower power level for the same rate or at a higher rate using the same power. If the sensor has a poor channel, on the other hand, it is better that the sensor saves the energy by not transmitting (and not creating interference to others). What is missing in this line of argument, however, is the cost of obtaining channel states and the cost of opportunistic scheduling. If it takes a considerable amount of energy to estimate channel at each sensor and if determining the set of sensors with best channels requires additional communications among sensors, it is no longer obvious that an opportunistic information retrieval is more energy efficient than a strategy—for example, using a predetermined schedule—that does not require the channel state information.

It is necessary at this point to specify the performance metric used in the design of information retrieval protocols. For sensor networks, we use energy efficiency (bits/Joule) defined by the ratio of the expected total number of bits reliably received at the access point and the total energy consumed. Here we will include both the energy radiated at the transmitting antenna and the energy consumed in listening, computation, and channel acquisition (when an opportunistic strategy is used). For sensor networks, it has been widely recognized that energy consumptions beyond transmission can be substantial [1, 2, 4].

Using energy efficiency as the metric, we aim to address the following questions: if channel acquisition consumes energy, is opportunistic transmission strategy still optimal? What would be an energy efficient *distributed* opportunistic information retrieval? What network parameters affect the energy efficiency? Can these parameters be designed optimally?

1.2. Summary of Results

The contribution of this paper is twofold. First, we demonstrate that when the cost of channel acquisition is small as compared to the energy consumed in transmission, the opportunistic transmission is optimal. However, when the average number of activated sensors exceeds a certain threshold, the opportunistic strategy loses its optimality; its energy efficiency approaches to zero as the average number of activated sensors approaches to infinity.

Second, we propose opportunistic carrier sensing—a distributed protocol that achieves a performance upper bound assumed by the centralized opportunistic transmission. The key idea is to incorporate local CSI into the backoff strategy of carrier sensing. Specifically, a decreasing function is used to map the channel state to the backoff time. Each sensor, after measuring its channel, generates the backoff time based on this backoff function. When the propagation delay is negligible, the decreasing property of the backoff function ensures that the sensor with the best channel state seizes the channel. To minimize the performance loss caused by propagation delay, the backoff function is constructed to balance the energy consumed in carrier sensing and the energy wasted in collision. It should be emphasized that the distributed opportunistic protocol developed in this paper applies also to non-information theoretic metrics such as throughput and throughput per unit cost. The basic idea of this protocol, first proposed in [5, 6], also provides a distributed solution to the general problem of finding maximum/minimum. Furthermore, by taking into account the residual energy of each sensor, we extend the idea of opportunistic carrier sensing to solve the problem of network lifetime maximization.

2. THE NETWORK MODEL

Let M denote the number of active sensors that share the wireless channel to an access point[1]. We assume that M is a Poisson random variable with mean Λ. The physical channel between an active sensor and the access point is subject to flat Rayleigh fading with a block length of T seconds, which is also the length of transmission slots. The channel is thus constant within each slot and varies independently from slot to slot.

Consider the first slot where n nodes transmit simultaneously. The received signal $y(t)$ at the access point can be written as

$$y(t) = \sum_{i=1}^{n} h_i x_i(t) + v(t), \quad 0 \leq t \leq T, \tag{1}$$

where h_i is the channel fading process experienced by sensor i, $v(t)$ the white Gaussian noise with power spectrum density $N_0/2$, and $x_i(t)$ the transmitted signal with fixed power P_{out}. Define

$$\rho \triangleq \frac{P_{\text{out}}}{WN_0}, \quad \gamma_i \triangleq |h_i|^2 \sim \exp(\bar{\gamma}_i). \tag{2}$$

Under independent Rayleigh fading, γ_i is exponentially distributed with mean $\bar{\gamma}_i$. The average received SNR of sensor i is thus given by $\rho\bar{\gamma}_i$.

In each slot, energy consumed by active sensors may come from three operations: transmission, reception, and scheduling. In the distributed opportunistic transmission, active sensors estimate their channel states based on a beacon signal broadcast by the access point[2] and determine who should transmit and at what rate. The expected total cost E_c of scheduling transmissions based on the channel states of the active sensors is lower bounded by

$$E_c \geq \Lambda e_c, \tag{3}$$

where e_c is the amount of energy consumed by one sensor in estimating its channel state from the beacon signal. This lower bound holds for both centralized and distributed implementations of the opportunistic transmission. It is achieved when the active sensors, each with access only to its own channel state, can determine the set of transmitting sensors at no cost.

[1]We assume no interference among the signals received by different cluster heads. It thus suffices to consider information retrieval in one cluster.

[2]We assume reciprocity. The channel gain from a sensor to the access point is the same as that from the access point to the sensor.

3. OPPORTUNISTIC STRATEGY

In this section, we address the performance of the opportunistic transmission under the metric of energy efficiency. After specifying the underlying coding scheme, we obtain an upper bound on the performance of the opportunistic transmission and characterize the optimal number of transmitting sensors.

3.1. Sum Capacity and Coding Scheme

Given that the channel fading process h_i is independent among sensors, and strictly stationary and ergodic, the sum capacity achieved by an information retrieval protocol which enables n sensors in each slot is given by

$$R = W\mathbb{E}[\log(1 + \rho \sum_{i=1}^{n} \gamma_i)], \tag{4}$$

where W is the transmission bandwidth and the expectation is over the fading process γ_i (see (2)). The information rate is constant over time and each codeword sees a large number of channel realizations.

An alternative coding scheme is to use different transmission rates according to the channel states of the transmitting sensors. In this case, each codeword experiences only one channel realization, resulting in smaller coding delay. When the block length T is sufficiently large, the achievable sum-rate averaged over time can be approximated by (4). Note that using variable information rate in each slot requires the channel state information in both encoding and decoding. If more than one sensor is enabled for transmission, each transmitting sensor must know not only its own channel state, but also the channel states of other simultaneously transmitting sensors in order to determine the rate of transmission. In Section 4 we show that with the proposed opportunistic carrier sensing, each transmitting sensor obtains the channel states of other sensors at no extra cost. The proposed protocol is thus applicable to both coding schemes. Without loss of generality, we assume, for the rest of the paper, this alternative coding scheme which uses variable information rate. We point out that under this coding scheme, (4) is only an approximation to the achievable sum rate. A more rigorous formulation is to use error exponents.

3.2. n-TDMA

As a benchmark, we first give an expression of energy efficiency for a predetermined scheduling where n sensors are scheduled for transmission in each slot. At the beginning of each slot, n sensors wake up, measure their channel states, and transmit. Referred to as n-TDMA, this scheme with optimal n has the energy efficiency

$$\begin{aligned} S_{\text{TDMA}} &= \max_n \frac{WT\mathbb{E}[\log(1 + \rho \sum_{i=1}^{n} \gamma_i)]}{E_c + nTP_{\text{tx}}} \\ &\leq \max_n \frac{WT\mathbb{E}[\log(1 + \rho \sum_{i=1}^{n} \gamma_i)]}{ne_c + nTP_{\text{tx}}}, \end{aligned}$$

where expectation is over M and $\{\gamma_i\}_{i=1}^n$, and we have used the lower bound[3] on E_c given in (3). The above optimization can be obtained numerically.

[3]Note that when $n > 1$, these n transmitting sensors need to know each other's channel state to determine the rate of transmission. Thus, the cost E_c of scheduling may be larger than ne_c.

3.3. Opportunistic Transmission

3.3.1. A Performance Upper Bound

With the opportunistic strategy, n sensors with the best channels are enabled for transmission in each slot. Let $\gamma_M^{(i)}$ denote the ith best channel gain among M sensors. The energy efficiency of the opportunistic strategy with optimal n is

$$S_{\text{opt}} = \max_n \frac{WT\mathbb{E}[\log(1+\rho\sum_{i=1}^n \gamma_M^{(i)})]}{E_c + nTP_{\text{tx}}} \qquad (5)$$

$$\leq \max_n \frac{WT\mathbb{E}[\log(1+\rho\sum_{i=1}^n \gamma_M^{(i)})]}{\Lambda e_c + nTP_{\text{tx}}}, \qquad (6)$$

where expectation is over M and $\{\gamma_M^{(i)}\}_{i=1}^n$.

3.3.2. The Optimal Number of Transmitting Sensors

Since the performance upper bound given in (6) is achieved by the opportunistic carrier sensing proposed in Section 4, we can use this upper bound to study the optimal number n^* of transmitting sensors and the optimality of the opportunistic transmission.

It has been shown by Knopp and Humblet [3] that the optimal transmission scheme for maximizing sum capacity is to enable only one sensor—the one with the best channel—for transmission ($n^* = 1$). Under the metric of energy efficiency, however, the optimal number of transmitting sensors may be larger than 1.

Proposition 1 *For fixed slot length T, transmission power P_{tx}, and the channel acquisition cost e_c, the optimal number n^* of transmitting sensors for the opportunistic transmission is given by*

$$\begin{cases} n^* = 1 & \textit{if } \Lambda < \frac{TP_{tx}(2C_1 - C_2)}{e_c(C_2 - C_1)} \\ n^* > 1 & \textit{otherwise} \end{cases}, \qquad (7)$$

where $C_n = WT\mathbb{E}[\log(1+\rho\sum_{i=1}^n \gamma_M^{(i)})]$.

A proof of Proposition 1 can be found in [**?**]. The intuition behind Proposition 1 is that the cost in channel acquisition dominates when Λ exceeds certain threshold; allowing one more transmission improves the sum rate without inducing significant increase in energy consumption.

3.4. Tradeoff between Sum Capacity and Energy Consumption

Since the extreme value of i.i.d. samples increases with the sample size, it is easy to show that the sum capacity achieved by n sensors with the best channels increases with Λ. Unfortunately, larger Λ also leads to higher energy consumption in channel acquisition (see (3)). Proposition 2 shows that the gain in sum capacity does not always justify the cost in obtaining the channel states.

Proposition 2 *For fixed slot length T, transmission power P_{tx}, and the channel acquisition cost $e_c > 0$, we have*

$$\lim_{\Lambda\to\infty} S_{opt} = 0.$$

A direct consequence of Proposition 2 is that the opportunistic strategy loses its optimality when Λ exceeds a threshold; there exists $\Lambda_0 < \infty$ such that $S_{\text{opt}} < S_{\text{TDMA}}$ when $\Lambda > \Lambda_0$.

The proof (see [?]) of Proposition 2 is based on results in asymptotic extreme order statistics [7]. For Rayleigh fading considered in this paper, $\gamma_m^{(1)}$ is on the order of $\log m$ when m is large. Thus, the numerator of (6) increases with the rate of $\log\log\Lambda$ while the denominator increases linearly with Λ, resulting in diminishing energy efficiency. It is thus critical that the average number Λ of activated sensors be optimized. In [8], possible schemes of controlling Λ by the design of sensor duty cycle were studied.

Shown in Figure 2 are numerical results on the energy efficiency of the opportunistic transmission as compared to the predetermined scheduling. Since both the sum-rate and the energy consumption of n-TDMA are independent of Λ, the energy efficiency is constant over Λ. For the opportunistic strategy, the energy efficiency increases with Λ when Λ is relatively small. In this region, the energy consumption is dominated by transmission; the increase in the cost of channel acquisition does not significantly affect the total energy expenditure. The energy efficiency thus improves as the sum capacity increases with Λ. When Λ increases beyond 100 where the cost in channel acquisition contributes more than 10% of the total energy expenditure, the increase in energy consumption overrides the improvement in sum-rate; the energy efficiency starts to decrease. Eventually, the gain in sum capacity achieved by exploiting CSI can no longer justify the cost in obtaining CSI, and the opportunistic strategy is inferior to the predetermined scheduling.

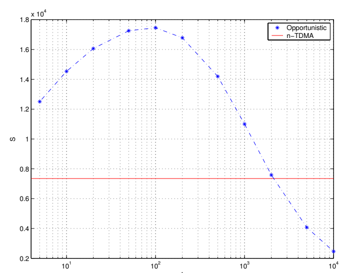

Fig. 2: Tradeoff between sum capacity and energy consumption ($W = 1$kHz, $\rho\bar{\gamma}_i = 3$dB, $T = 0.01$s, $P_{\text{tx}} = 0.181$w, $e_c = 1.8$nw).

4. OPPORTUNISTIC CARRIER SENSING

In this section, we present opportunistic carrier sensing, a distributed protocol that achieves the performance upper bound of the opportunistic strategy given in (6).

The key idea of opportunistic carrier sensing is to exploit channel state information in the backoff strategy of carrier sensing. Consider first $n^* = 1$, *i.e.,* in each slot, only the sensor with the best channel transmits. After each active sensor measures its channel gain γ_i using the beacon of the access point, it chooses a backoff τ based on a predetermined function $f(\gamma)$ which maps the channel state to a backoff time and then listens to the channel. A sensor will transmit with its chosen backoff delay if and only if no one transmits before its backoff time expires. If $f(\gamma)$ is chosen to be a strictly decreasing function of γ as shown in Figure 3, this opportunistic carrier sensing will ensure that only the sensor with the best channel transmits. Under the assumption of negligible propagation delay, $f(\gamma)$ can be any decreasing function with range $[0, \tau_{\max}]$, where $\tau_{\max}$ is the maximum backoff. Since $\tau_{\max}$ can be chosen as any positive number, the time required for each sensor listening to the channel can be arbitrarily short. Hence, energy consumed in each slot comes only from each sensor estimating its own channel state (the lower bound on E_c given in (3)) and the transmission by one sensor; opportunistic carrier sensing thus achieves the performance upper bound of the opportunistic strategy.

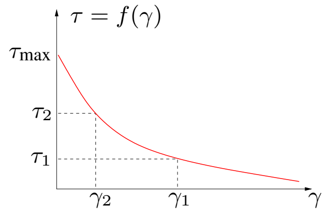

Fig. 3: CSI-based carrier sensing.

We now consider $n^* > 1$. If the energy detector of each sensor is sensitive enough to distinguish the number of simultaneous transmissions, the opportunistic carrier sensing protocol stated above can be directly applied - a sensor transmits with its chosen backoff if and only if the number of transmissions at that time instant is smaller than n^*. Note that by observing the time instant τ at which the number of simultaneous transmissions increases (energy level jumps) and mapping this time instant back to the channel gain using $\gamma = f^{-1}(\tau)$, a sensor obtains the channel states of other transmitting sensors and can thus determine its transmission rate. Note that the channel gain of a transmitting sensor is learned by measuring the backoff of the transmission, not the signal strength.

If, however, sensors can not obtain the number of simultaneous transmissions, we generalize the protocol as follows. We partition each slot into two segments: carrier sensing and information transmission (see Figure 4). During the carrier sensing period, sensors transmit, with backoff delay determined by $f(\gamma)$, a beacon signal with short duration. A sensor transmits a beacon if and only if the number of received beacon signals is smaller than n^*. By measuring the time instant at which each beacon signal is transmitted, those n^* sensors with the best channels can also obtain all n^* channel states from $f^{-1}(\tau)$ and thus encode their messages accordingly. Shown in Figure 4 is an example where $n^* = 2$. During the carrier sensing segment $[0, \tau_{\max}]$, two beacon signals are transmitted at τ_1 and τ_2 by two sensors with best channel gains. Based on τ_1, τ_2, and $f^{-1}(\tau)$, these two sensors obtain each other's channel state (see Figure 3). They then encode their messages for transmissions in the second segment of the slot. One possible encoding scheme, as shown in Figure 4, is based on the idea of successive decoding. The sensor with the higher channel gain γ_1 encodes its message at rate $W \log(1 + \rho\gamma_1)$ as if it was the only transmitting node. The other sensor with channel gain γ_2 encodes its message by treating the transmission from the sensor with channel γ_1 as noise. It transmits at rate $W \log(1 + \rho'\gamma_1)$ where

$$\rho' = \frac{P_{\text{out}}}{N_0 W + P_{\text{out}}\gamma_1}.$$

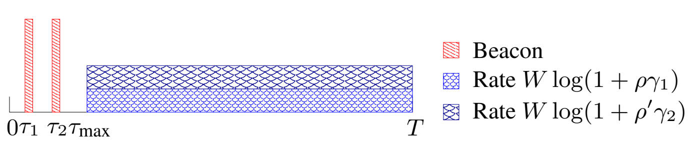

Fig. 4: CSI-based carrier sensing for $n^* = 2$.

So far we have assumed that the propagation delay among activated sensors is negligible. In this case, $f(\gamma)$ can be any decreasing function. When the delay is significant, however, $f(\gamma)$ needs to be designed judiciously to maintain the performance of the opportunistic carrier sensing. In [8], a backoff function $f(\gamma)$ is constructed and graceful performance degradation demonstrated with respect to propagation delay.

We point out that the idea of opportunistic carrier sensing provides a distributed solution to the general problem of finding maximum/minimum. By substituting the channel gain γ with, for example, the temperature measured by each sensor, the distance of each sensor to a particular location, or the residual energy of each sensor, we can retrieve information of interest (the highest/lowest temperature, the measurement closest/farthest to a location) from sensors of interests (those with the highest energy level or those with the best channel gain) in a distributed and energy efficient fashion.

5. NETWORK LIFETIME MAXIMIZATION

A different formulation for the energy-aware information retrieval in sensor networks is to maximize the network lifetime under a hard constraint on the initial energy at each sensor. In this case, not only the local information on the channel gain needs to be exploited, the residual energy at each sensor should also be considered in transmission scheduling. Let $e_i(t)$ denote the residual energy of sensor i at time t. The transmitting sensor at time t should be determined based on $g(\gamma_i(t), e_i(t))$, *i.e.,* the sensor with the maximum value of $g(\gamma_i(t), e_i(t))$ will be scheduled for transmission where the function $g(\cdot)$ is chosen to maximize the network lifetime. By using $g(\gamma_i(t), e_i(t))$ (instead of $\gamma_i(t)$) as the argument in the backoff function $f(\cdot)$ as given in Figure 3, the opportunistic carrier sensing can be easily extended to a protocol that maximizes network lifetime. The problem is thus reduced to the choice of $g(\gamma_i(t), e_i(t))$. Assume that the sensors transmit at a fixed data rate and adjust the transmission power according to the channel gain. One possible choice of $g(\gamma_i(t), e_i(t))$ is

$$g(\gamma_i(t), e_i(t)) = \frac{e_i(t)}{E_{tx}(\gamma_i(t))}, \tag{8}$$

where $E_{tx}(\gamma_i(t))$ is the energy consumed in transmitting one packet which is a monotonically decreasing function of $\gamma_i(t)$. As shown in [9, 10], significant gain in network lifetime can be achieved over the scheme that utilizes solely the channel state information.

6. REFERENCES

[1] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. on Wireless Communications*, vol. 1, pp. 660–670, Oct. 2002.

[2] L. Tong, Q. Zhao, and S. Adireddy, "Sensor Networks with Mobile Agents," in *Proc. 2003 Intl. Symp. Military Communications*, (Boston, MA), Oct. 2003.

[3] R. Knopp and P. Humblet, "Information capacity and power control in single cell multi-user communications," in *Proc. Intl Conf. Comm.*, (Seattle, WA), pp. 331–335, June 1995.

[4] E. Shih, S. Cho, N. Ickes, R. Min, A. Sinha, A. Wang, and A. Chandrakasan, "Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks," in *Proc. of 2001 ACM MOBICOM*, (Rome, Italy), pp. 272–286, July 2001.

[5] Q. Zhao and L. Tong, "Quality-of-Service Specific Information Retrieval for Densely Deployed Sensor Network," in *Proc. 2003 Military Communications Intl Symp.*, (Boston, MA), Oct. 2003.

[6] Q. Zhao and L. Tong, "QoS Specific Medium Access Control for Wireless Sensor Network with Fading," in *Proc. of Eighth International Workshop on Signal Processing for Space Communications*, (Catania, Italy), Sept. 2003.

[7] T. Ferguson, *A Course in Large Sample Theory*. London, UK: Chapman & Hall, 1996.

[8] Q. Zhao and L. Tong, "Distributed Opportunistic Transmission for wireless sensor networks," in *Proc. of 2004 ICASSP*, May 2004.

[9] Y. Chen and Q. Zhao, "Maximizing the Lifetime of Sensor Network Using Local Information on Channel State and Residual Energy." submitted to the 39th Conference on Information Science and Systems, Jan 2005.

[10] Y. Chen and Q. Zhao, "Distributed Transmission Protocol for Lifetime Maximization in Sensor Network." to appear in Proc. of IEEE SPAWC, June 2005.