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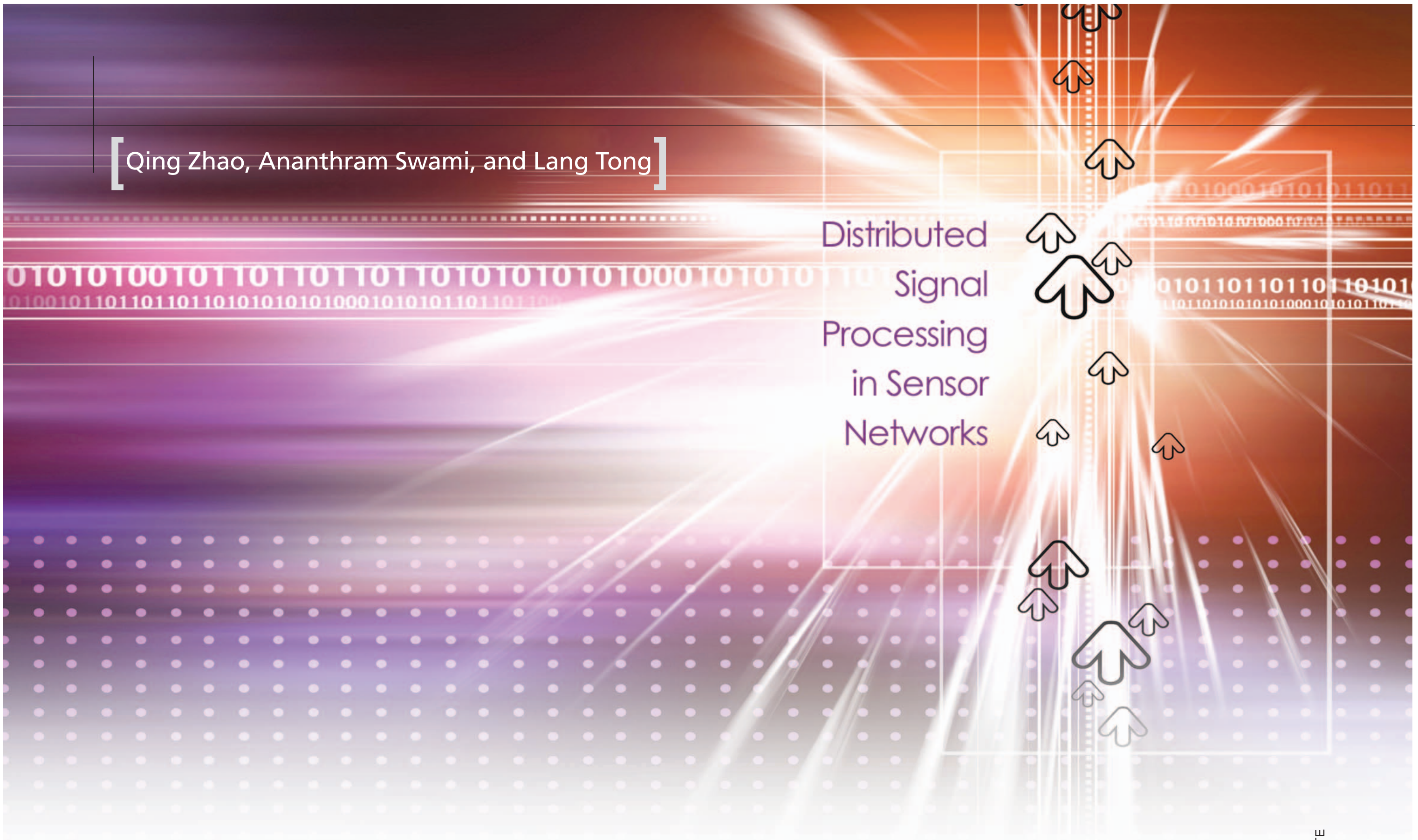


The Interplay Between Signal Processing and Networking in Sensor Networks

[A perspective on large-scale networks for military applications]

In this article, we provide a signal processing perspective on large-scale sensor networks. We focus on two characteristics of sensor networks: application specificity and energy constraint. The former requires that network protocols be designed for the application at hand, which is often signal processing in nature, and measured by application-specific metrics. The latter calls for novel distributed signal processing techniques to provide accurate and timely network state information that can be exploited by network protocols to ensure energy efficiency. The underlying theme is about how a principled integration of signal processing and networking can lead to an efficient and fair use of limited resources. We hope to demonstrate that capturing and exploiting dependencies between signal processing and networking offer design choices resulting in improved network performance.

 1053-5888/06/$20.00©2006IEEE

We start with challenges brought forth by military applications envisioned for sensor networks. We then extract from these challenges several typical design issues in which signal processing and networking intertwine. By presenting these issues along with their potential solutions in two complementary categories, signal processing for networking and networking for signal processing applications, we hope to illuminate the interaction between signal processing and networking. Two specific examples, one from each category, are then provided using medium access control (MAC) as a case study. We show that the optimal MAC under an energy constraint requires integration with the physical layer and the separation of MAC from the application layer leads to an irrecoverable performance loss in detection and estimation. This article is then concluded with a few words on potential unintended consequences of an integrated design for sensor networks.

CHALLENGES IN SENSOR NETWORKS FOR MILITARY APPLICATIONS

Future tactical military communications will involve the deployment of large-scale sensor networks in which hundreds to thousands of microsensors, inexpensive and lightweight devices with integrated sensing, computing, communications, and possibly actuation capabilities, will work together to achieve a common mission-specific objective [1]. The nodes may be heterogeneous with varying resources, capabilities, and mobility (e.g., fixed unmanned ground sensors and robotic sensors). The network must operate under severe constraints on energy and bandwidth, over challenging interference-rich radio channels, and with dynamic changes in topology and connectivity. The quality of service (QoS) requirements will be diverse, ranging from time-critical data to support telemedicine, robotics, and fire control to background data.

The tradeoffs between local or distributed data processing and transmission of raw data to a fusion center must be examined under the constraints of energy, bandwidth, and latency. The relevant metric should be application specific, e.g., the accuracy of target detection and target tracking, the accuracy of estimating the density of a chemical spill [2]–[4], the timeliness in detecting the spread of an epidemic, the accuracy of classification, or the quality and utility of the delivered information. The metric may only loosely capture the information needs in a tactical scenario (e.g., quantification of the commander's intent is not easy). Sensor nodes are typically duty cycled to save energy and prolong lifetime; this in turn impacts MAC/routing issues particularly when the sleep patterns are not coordinated or prescheduled. Given that the sensors communicate to the fusion center over a wireless link and given the vision of a large-scale multihop ad hoc network, the characteristics of the radio channel and the MAC and routing protocols will also impact this tradeoff study.

A glance at current and past U.S. Department of Defense programs is informative in tracing the evolution of sensor network applications. Detection, classification, and tracking of targets are classic applications of sensor networks, both in the civilian and military sectors. There is a long history of wired sensor networks where power and bandwidth were not seriously constrained. Examples include AWACS, networked radar systems, ocean bed acoustic sensor networks for submarine detection and tracking, and the DARPA Distributed Sensor Networks program [1].

The U.S. Army's Disposable Sensors program envisages a distributed sensing system based on a heterogeneous mixture of inexpensive seismic, acoustic, RF, chem/bio, magnetic, and infrared sensors, consisting of as many as 10^4–10^7 sensors [5]. Thus understanding scaling issues and developing scalable algorithms and protocols is critical. Battlefield environmental monitoring such as sensing biological, radioactive, nuclear, chemical, and explosive materials is becoming increasingly important in asymmetric warfare scenarios as well as from public health and safety perspectives in peacetime. The sensing environment may be harsh and unamenable to predeployment of wired networks, or the network may have to operate in hostile territory. As such, there is an increasing push to develop disposable sensors.

The vision of the DARPA Networked Embedded Systems Technology (NEST) program is to enable "fine-grain" networked fusion of a distributed system of 100–100,000 simple computing nodes. Such sensors may provide cues to wake up resource-consuming imagers. Sensors may be manually emplaced or dispersed from cannons or moving ground/aerial vehicles. Severe constraints on energy, computing, and communications capabilities dominate this problem. As the scale of the distributed network increases, networking and networked signal processing become critical.

Such a massively deployed network could provide a replacement to landmines [6]. In a self-healing minefield, the network continuously monitors itself; when nodes die, other nodes may move to maintain sensing coverage. Self-configuration and reconfiguration to maintain coverage and connectivity is an important problem, and the communication overheads for these cannot be ignored in an energy-constrained network. There are tradeoffs in the overhead to acquire channel information and the advantages to be gained in exploiting such (usually imprecise and incomplete) information. There is a clear interplay between sensing, signal processing, communications, and actuation in such a network. A typical landmine replacement sensor is about 12 cm in diameter, 6 cm high, with 10% of the volume being devoted to batteries. Such a sensor can store about 18 Wh or 65 J/K of energy (nine Li-ion batteries). With antennas close to the ground, it takes about 1 mJ to reliably transmit 100 b across 100 m over a Rayleigh fading channel with an attenuation factor of four. Given that energy is also consumed in sensing, RF monitoring, and low-level circuitry in sleep mode, scalable energy management protocols, energy-efficient processing, and communications become critical.

Robotic sensors, micro-unmanned autonomous vehicles, or sensors with some ability to move have long been envisioned for applications such as in disaster recovery and urban rescue operations. Since mobility itself can consume a large amount of energy, coordinating sensor movements and communications becomes a challenging task. Here, scaling may not be an issue, but the finite battery energy and the expected short lifetime of the network must be taken into account.

Application-specific sensor suites will also provide the basis for disposable battlefield intelligence systems for clearing and securing urban centers, the so-called military operations in urban terrain (MOUT). As an example, consider a sniper localization system [7] consisting of acoustic shockwave detectors and a multihop ad hoc network where time of arrival is used to localize the sniper. MAC (which sensor should report its data) clearly impacts the localization accuracy, and network-wide time synchronization must be ensured. Thus the application metric drives not only the parameters at the local sensors but also the MAC protocols. In a multihop network collecting time-sensitive information, latency is an important metric and should be addressed in routing protocols. In this class of applications, where neighboring sensors have correlated information, there is a clear tradeoff across compression at individual nodes, local data aggregation among neighboring nodes, the global performance metric, and the total energy expenditure.

From the preceding examples of sensor networks, we see that scaling issues and energy efficient signal processing are critical in maximizing the network lifetime. These examples illustrate the essential interplay between sensing, signal processing or computing, transmission, MAC and routing protocols in a wireless sensor network.

THE INTERPLAY BETWEEN SIGNAL PROCESSING AND NETWORKING

In this section, we hope to illustrate that a cross-layer approach that integrates signal processing and networking is crucial to meeting the challenges in sensor networks for military applications. We focus on the interplay between signal processing and networking by highlighting several design issues central to sensor networks.

SIGNAL PROCESSING FOR NETWORKING

EXPLOITING PHYSICAL LAYER PARAMETERS IN NETWORK PROTOCOL DESIGN

Under the layered architecture, network protocols are designed with minimum input from the physical layer. To an upper-layer protocol, the physical layer is a black box in which nodes are indistinguishable. Starting to gain recognition in the signal processing and the networking communities is the viewpoint that a tight coupling between physical and upper layers leads to a greater level of adaptivity to the wide-range of variations in wireless channels. A number of physical layer parameters have found their role in MAC and routing. Among these parameters, channel state and residual energy are perhaps the most relevant to the energy efficiency of sensor networks.

Using channel state information (CSI) in transmission and networking is the fundamental idea behind opportunistic strategies. Sparkled by the work of Knopp and Humblet [8], a number of opportunistic MAC protocols [9]–[13] and channel-adaptive routing schemes [14]–[17] have been proposed. While exploiting CSI for different objectives subject to various constraints, these protocols bear the same signature: prioritizing nodes according to their channel states to take advantage of the diversity of wireless channels.

It has been widely recognized that the residual energy information (REI) of individual nodes plays a crucial role in network lifetime. Various sensor placement schemes [18], [19], routing, and transmission protocols [20]–[28] that utilize REI have been proposed. The role of REI is to balance the energy consumption across the network by prioritizing nodes with more residual energy for energy-consuming tasks such as transmission. We will show that both CSI and REI are critical to maximizing network lifetime. Given that the node with the best channel may not have the most residual energy, the fundamental question is how to achieve the optimal tradeoff between CSI and REI in the protocol design.

While recognizing the benefit of exploiting CSI and REI, we cannot ignore the cost associated with obtaining this information. A protocol requiring global information on channel state and residual energy may encounter an unacceptable level of overhead in large-scale networks [29]. It is thus desirable to design distributed protocols using only local CSI and REI to better address the tradeoff between the benefit and the cost. Energy-efficient signal processing techniques for acquiring CSI and REI clearly affect this tradeoff, providing another example of signal processing for networking as examined below.

NETWORK STATE ESTIMATION FOR ADAPTIVE NETWORKING

Sensor networks, especially those deployed for military applications, have to operate in a wide range of time-varying conditions: sensor locations are unpredictable prior to deployment; network energy profile and sensor population change over time; network topology varies due to duty cycling, battery depletion, and friendly interference and hostile jamming; traffic assumes various heterogeneous patterns and QoS requirements due to events that are random in time and space. Adaptability is fundamental to the efficient use of limited resources. An enabling component of adaptive networking is sophisticated signal processing that provides accurate and timely network state estimation. Here network state can be any physical parameter that is of interest to network design, including sensor location, channel state, and residual energy profile as well as network topology and traffic characteristics.

Sensor synchronization and localization are crucial to many network operations such as duty cycling, scheduling, collaborative transmission, and geographic routing. The unique characteristics and design constraints of sensor networks have cast synchronization and localization in a new context and stimulated increasing interests from the signal processing community in revisiting these two classic problems. A detailed survey on this topic can be found in [30]. In [86], sensor self-localization is cast as a problem of inference in graphical models, where power conservation and careful use of scarce communication resources can be effectively addressed.

As pointed out earlier, lifetime-maximizing protocols require knowledge of the network residual energy profile. This information, as well as the population/density of functioning sensors, is also important for network maintenance. For example, the knowledge of the number of operating sensors as a function of geographical location facilitates the decision on whether and where to deploy new sensors. It is thus crucial to track the network energy profile and the sensor population. Ignoring the stringent energy constraint, the large network size, and the harsh wireless multiaccess medium leads to a trivial solution where every sensor is scheduled to report its energy level periodically. A desired solution is to piggyback the residual energy information on data packets to avoid extra transmissions solely for the purpose of network monitoring. This approach, however, provides only an energy profile sampled in space and time. The sampling pattern is determined by the network application (for example, the spatial and temporal distributions of the random events being detected by the network) and the MAC and routing protocols used in data collections. How to infer the energy profile from the collected data samples is thus a complex signal processing problem and is coupled with the upper layer protocols. Detailed discussions on this problem and several scalable estimation algorithms for energy profile monitoring can be found in [31]–[33].

Sensor networks may exhibit a wide range of variations in traffic load and traffic pattern, from quiescent sensing state to emergency response. It is highly desirable to have traffic-adaptive MAC and routing that are reconfigurable based on the network operating conditions [34]. For example, at times when an emergency arises resulting in a rush of data toward certain parts of the network, routing protocols should be proactive, maintaining network connection to ensure rapid and energy-efficient data delivery. When the network is in a quiescent sensing state, routing protocols should be reactive, establishing links and connections only when necessary. A fundamental challenge in achieving this traffic-adaptive networking is to develop signal processing techniques for traffic estimation and change detection. Such signal processing techniques should be distributed to ensure scalability and avoid extra data flows. Classic techniques in change detection [35] and nonparametric estimation [36]–[38] may find new exciting applications in sensor networks as demonstrated in [39] and [40].

NETWORKING FOR SIGNAL PROCESSING APPLICATIONS

Sensor networks are application specific, and a wide range of applications being considered (*e.g.,* detection, estimation, monitoring, classification, and tracking) rely on signal processing tools. Since the network as a whole is to perform certain signal processing tasks, the network should be designed not for individual nodes but to optimize the application-specific metric. We present here a brief survey of networking protocols designed specifically for enhancing signal processing performance.

PROTOCOL DESIGN FOR DETECTION AND PARAMETER ESTIMATION

Making statistical inference using distributed sensors has long been a subject of investigation (see the references in [87]). Earlier work in this area aimed at integrating data collected at different radar sites that are connected with bandwidth constrained but wired links. The sensor networks considered in recent years are different in two important aspects. First, the transmissions from sensors to the fusion center are wireless, mutually interfering, and possibly through multihop routing. Second, the number of sensors involved in sensing and communication can be large, and their deployment may be random.

Statistical inference over multiaccess channels has been considered recently. If sensors have locally quantized measurements, a sufficient statistic for statistical inference at the fusion center is the empirical measure or type (loosely, the histogram of quantized data) [41]; collecting data from individual sensors is in fact unnecessary. This observation has led to the so-called type-based multiple access (TBMA). TBMA provides a data-centric MAC protocol for detection [42], [43] and estimation [44], [45].

In sensor networks deployed for detection and estimation, routing, too, should be designed to optimize signal processing metrics. Consider solely the signal processing component. The more data the gateway node has, the better the performance, and the routes over which the data travel to the gateway node should not affect the performance. This argument, however, is only valid if there is no energy constraint, and the gateway node has the luxury to wait until data from all sensors arrive, and there are no other flow competing for or colliding with these routes. For battery-operated sensors, conserving energy is perhaps the most important design objective. Practical constraints dictate that only data from some nodes be collected, which leads to several interesting questions: how should the sensor network be sampled (taking into account the spatial-temporal correlation in the data)? how should the data be routed? what is the quality of the overall information at the gateway node? what is the corresponding consumption in energy, both locally, and over the network? Here, quality of information may simply be the accuracy of detection or estimation, but timeliness of the information adds an interesting twist.

The key step is to link detection and estimation performance with a certain type of link metric in such a way that classic routing protocols can be used to optimize the detection and estimation performance. For the problem of detecting one dimensional Gauss-Markov process, a link metric in the form of mutual information is defined in [46], which leads to the optimal route that maximizes the decay rate of detection error probability.

NETWORKING FOR SIGNAL FIELD RECONSTRUCTION

Signal field reconstruction is another important application of sensor networks. From a signal processing perspective, estimating a signal field from sensor measurements is the classic problem of signal reconstruction from possibly random samples, and the literature is extensive. There is, however, a communication and networking aspect of the problem unique to sensor networks. A network designer, on one hand, would like to reconstruct the signal field as accurately as possible, while on the other hand, must design the network using simple and energy-efficient protocols. Tradeoffs thus have to be made between reconstruction performance and energy consumption. Achieving the optimal tradeoff requires a cross-layer approach that connects MAC and network layer functions with application layer attributes such as the mean square error of the signal reconstruction.

A key issue in achieving the optimal tradeoff is to exploit the spatial and temporal correlation of sensor measurements during data collection so that a given reconstruction performance can be met with minimum transmissions from sensors. The problem becomes more complex in a heterogeneous network consisting of sensors with different modalities. There are three approaches to reducing spatial correlation: distributed source coding, data aggregation, and spatial sampling. The first approach, as considered in [47] and [48], brings an information-theoretic perspective to information retrieval in sensor networks. The second approach is commonly used under a multihop ad hoc architecture where data are aggregated at intermediate nodes along a multihop route to a gateway node [49]–[51]. It is thus strongly coupled with the design of routing protocols.

Under the approach of spatial sampling, the sampling pattern is crucial to providing QoS guarantee while maintaining energy efficiency. Taking the viewpoint that a particular MAC protocol will lead to a certain sampling pattern of the signal field, the authors of [52]–[55] examine the impact of MAC on signal field reconstruction. An interesting observation is that if the rate of sensor outage (due to duty cycling and battery depletion) exceeds a certain threshold, the optimal deterministic scheduling scheme may perform worse than random access. In [56] and [57], a distributed sensor scheduling scheme is proposed to ensure that a minimum number of sensors transmit while maintaining the reconstruction performance. In [58] and [59], a MAC scheme along with an application-specific sampling pattern is developed to satisfy a given QoS requirement with optimal energy efficiency. An in-depth discussion on spatial/temporal sampling and quantization in sensor networks can be found in [89].

AN INTEGRATED APPROACH TO MAC FOR OPTIMAL NETWORK LIFETIME

In this section, we focus on the implications of energy constraint on MAC design in sensor networks. We illustrate that to achieve an efficient use of limited energy resources, MAC design should be based upon a physical layer model that captures diversities among nodes. We show that protocols exploiting dependencies between the MAC and the physical layers offer significant improvement in energy efficiency.

LAW OF NETWORK LIFETIME

Energy-efficient design can be formulated as an unconstrained or a constrained optimization problem [60]. In the former, the design objective is to either maximize the number of transmitted information bits per unit energy cost or minimize the total energy consumption. An implicit assumption is that each node has an infinite amount of energy. On the other hand, the constrained formulation aims at maximizing the network lifetime under the assumption that each node is powered by a nonrechargeable battery with a finite amount of energy.

The performance measure of network lifetime is particularly relevant to sensor networks where battery-powered, dispensable sensors are deployed to collectively perform a certain task. For a communication network, which is generally designed to support individual users, network lifetime is subject to interpretation; a communication network may be considered dead by one user while continuing to provide required QoS for others. In contrast, a sensor network is not deployed for individual nodes, but for a specific collaborative task at the network level. The lifetime of a sensor network thus has an unambiguous definition: it is the average time span from the deployment to the instant when the network can no longer perform the task.

Much has been said about maximizing network lifetime. The lack of an accurate characterization of network lifetime as a function of key design parameters, however, presents a fundamental impediment to optimal protocol design. Given that the network lifetime depends on network architectures, specific applications, and various parameters across the entire protocol stack, existing techniques tend to rely on either a specific network setup [18], [61]–[68] or the use of upper bounds on lifetime [69]–[76]. As such, it is difficult to develop a general design principle.

There is a simple law that governs the network lifetime for all applications, under any network configuration. It is shown in [77] that the network lifetime $\mathcal{L}$ defined as the average time span from the deployment to the instant when the network is considered dead is given by

$$\mathcal{L} = \frac{\mathcal{E}_0 - \mathcal{E}_w}{\lambda \mathcal{E}_r}, \tag{1}$$

where $\mathcal{E}_0$ is the total initial energy over the network (not necessarily uniformly distributed among sensors), $\mathcal{E}_w$ the expected wasted energy (i.e., the total unused energy in the network when it expires), λ the average sensor reporting rate defined as the number of data collections per unit time, and $\mathcal{E}_r$ the expected reporting energy consumed by all sensors in a randomly chosen data collection. (For ease of presentation, we ignore energy consumption sources such as battery leakage and network maintenance. Incorporating them into the formula, however, is straightforward as shown in [77].)

TWO KEY PHYSICAL LAYER PARAMETERS AND A GENERAL DESIGN PRINCIPLE

The law of lifetime given in (1) provides a quantitative characterization of key components that affect network lifetime under a general network setting. Specifically, a lifetime-maximizing protocol should aim at reducing the average wasted energy $\mathcal{E}_w$ and the average reporting energy $\mathcal{E}_r$. To reduce $\mathcal{E}_w$, the protocol should exploit REI of individual sensors to achieve balanced energy consumption across the network. To reduce $\mathcal{E}_r$, the protocol should exploit CSI to prioritize sensors with better channels for transmission so that energy consumed in transmission is reduced. The law of lifetime thus allows us to identify these two key physical layer parameters that affect the network lifetime.

Since channel realizations are independent of the residual energies, the sensor with the best channel may not have the most residual energy. A lifetime-maximizing protocol needs to optimally trade off CSI and REI. A closer examination of the law of lifetime given in (1) reveals a general principle for balancing CSI and REI. Consider first $\mathcal{E}_r$ which can be obtained by averaging the expected reporting energy $\mathcal{E}_r(k)$ consumed in the kth data collection over the randomly chosen data collection index K as shown in [77]:

$$\mathcal{E}_r = \mathbb{E}_K[\mathcal{E}_r(K)],$$

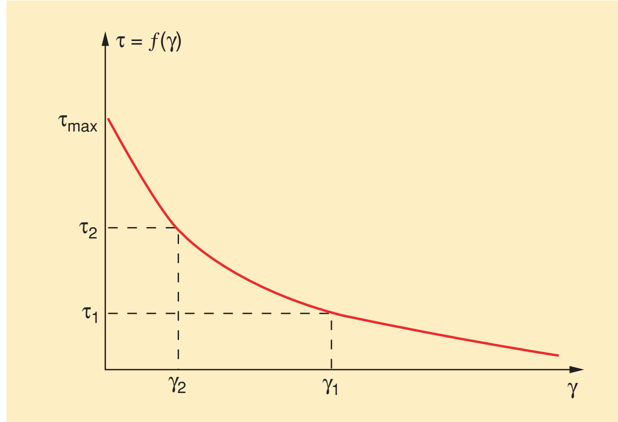
where $\mathbb{E}_K\{\cdot\}$ denotes the expectation over K. Note that the probability mass function $\Pr\{K = k\}$ is determined by the probability that the network lives to see the kth data collection, which decreases with k [77]. This observation leads to the conclusion that the energy consumed at the early stage of the network lifetime carries more weight. Thus, reducing the energy consumption $\mathcal{E}_r(k)$ in the kth data collection is crucial when k is small (i.e., when the network is young). On the other hand, the wasted energy $\mathcal{E}_w$ only depends on the sensor residual energies when the network dies. Hence, balancing energy consumption across sensors is only crucial when the network is approaching the end of its lifetime.

This discussion suggests that a lifetime-maximizing protocol should be adaptive with respect to the network age. Specifically, a protocol should be more opportunistic by favoring the sensor with the best channel (focusing on reducing $\mathcal{E}_r$) when the network is young and more conservative by favoring the sensor with the most residual energy (focusing on reducing $\mathcal{E}_w$) when the network is old. We see here an intuitive connection between extending network lifetime and retirement planning. When we are young, we can afford to be more aggressive, putting retirement savings to relatively more risky investments. As we age, we become more conservative. This general design principle applies to various upper layer protocols including MAC and routing.

A DISTRIBUTED ASYMPTOTICALLY OPTIMAL MAC PROTOCOL FOR LIFETIME MAXIMIZATION

We present here an example of applying the general design principle derived from the law of lifetime to MAC design. Consider a sensor network with N nodes. For simplicity, we assume that only one sensor is required to transmit its measurement to a mobile access point in each data collection. Sensor measurements are in the form of equal-sized packets. The channel between the mobile access point and a sensor follows a block fading model with the block length equal to the transmission time of one packet. The required reporting energy $E_r(c_i)$ of sensor i is a decreasing function of the fading gain c_i. In other words, the better the channel gain c_i, the smaller the required transmission energy $E_r(c_i)$. A sensor is considered dead when its battery depletes. The network expires when the number of dead sensors exceeds a certain percentage which is determined by the specific network application. The goal here is to dynamically choose one sensor for transmission in each data collection so that the network lifetime is maximized.

It has been shown in [29] that the above problem can be formulated as a stochastic shortest path Markov decision process and the lifetime-optimal MAC protocol is given by the optimal policy for this Markov decision process. The value of this optimal approach mainly lies in defining the limiting performance. Its practical value is limited due to the large implementation overhead resulting from centralized scheduling and obtaining global CSI and REI. It is thus desirable to have a distributed protocol that requires only local CSI and REI yet approaches the fundamental performance limit defined by the optimal solution using global information.



[FIG1] Opportunistic carrier sensing.

In [78] and [79], we formulate this problem by introducing the concept of energy-efficiency index γ_i which is a real-valued function of sensor i's channel state and residual energy: $\gamma_i = g(c_i, e_i)$. In each data collection, the sensor with the largest energy-efficiency index is scheduled for transmission. The problem of exploiting CSI and REI in MAC design is thus reduced to the design of the function g.

Furthermore, such a protocol can be implemented in a distributed fashion via the opportunistic carrier sensing scheme first proposed in [58]. The basic idea is to incorporate the local information (i.e., the energy-efficiency index) of each sensor into the backoff strategy of carrier sensing. At the beginning of each data collection, the mobile access point broadcasts a beacon signal to activates sensors. Each sensor estimates its channel gain using the beacon signal and calculates the predefined energy-efficiency index γ_i based on its own channel gain c_i and residual energy e_i. Every sensor then maps its own γ_i to a backoff time τ_i based on a predetermined common function $f(\gamma)$ and listens to the channel. Sensor i will transmit with its chosen backoff delay τ_i if and only if no one transmits before its backoff time expires. If $f(\gamma)$ is chosen to be a strictly decreasing function of the energy-efficiency index γ as shown in Figure 1, then this opportunistic carrier sensing scheme will ensure that the sensor with the largest energy-efficiency index seizes the channel. (When the propagation delay is negligible, $f(\gamma)$ can be any decreasing function. When the delay is significant, however, $f(\gamma)$ needs to be designed judiciously to maintain the performance of opportunistic carrier sensing. In [13], a backoff function $f(\gamma)$ is constructed and graceful performance degradation is demonstrated with respect to propagation delay.)

We now consider the design of the energy efficiency index γ. Following the general design principle, we have developed in [79] and [80] a dynamic MAC protocol that adaptively trades off CSI and REI according to the age of the network. Referred to as a dynamic protocol for lifetime maximization (DPLM), this MAC protocol selects the sensor whose channel gain demands the least fraction of its residual energy for transmission. The energy-efficiency index is defined as

$$\gamma_i = \frac{e_i}{E_r(c_i)}.$$

It turns out that this simple MAC scheme is asymptotically optimal. Specifically, the relative performance loss of DPLM as compared to the limiting performance achieved by centralized scheduling using global information diminishes with the initial energy $\mathcal{E}_0$. The dynamic nature of this protocol is also established in [79]. It is shown that the probability that DPLM selects the sensor with the best channel decreases while the probability of selecting the sensor with the most residual energy increases monotonically with the network age.

DATA CENTRIC MAC FOR SIGNAL DETECTION AND ESTIMATION

In this section, we give an example of networking protocol design for signal detection and estimation. Shown in Figure 2 is a distributed detection and estimation scheme over a multiaccess communication channel in which the ith sensor obtains a quantized measurement X_i drawn from a certain distribution. The classical detection and estimation problem is to make an inference about θ based on X_i. We now add one level of networking to this problem by assuming that sensors have to deliver their measurement X_i (in some energy-efficient form) to the fusion center through a noisy multiaccess channel. The fusion center can be a cluster head or a mobile access point roving around the sensor network. What makes this problem different from the classical distributed detection and estimation problem is the emphasis on the multiaccess channel. Consequently, the problem is one of cross-layer design that involves physical layer communications, MAC among sensors, and signal processing at the fusion center that aims to satisfy application layer specifications (e.g., miss detection and false alarm rates).

A LAYERED APPROACH TO DISTRIBUTED INFERENCE

If a classical layered approach is used to design the MAC, the objective then is to collect data from each sensor as rapidly and as reliable as possible and use the collected data for statistical inference. For example, one would encode and modulate the measurement X_i at the physical layer and use a MAC scheme (such as TDMA/CDMA/FDMA or a random access protocol such as CSMA) for transmission. At the fusion center, X_i are decoded (estimated), and the decoded X_is are used for estimating θ or making decision on hypotheses. Separating communication from detection and estimation has a number of fundamental weaknesses. The statistical inference made at the fusion center suffers from transmission errors due to channel fading and multiaccess interference. Furthermore, the strategy of transmission over user-orthogonalized channels does not scale with the size of the network under a fixed bandwidth constraint.

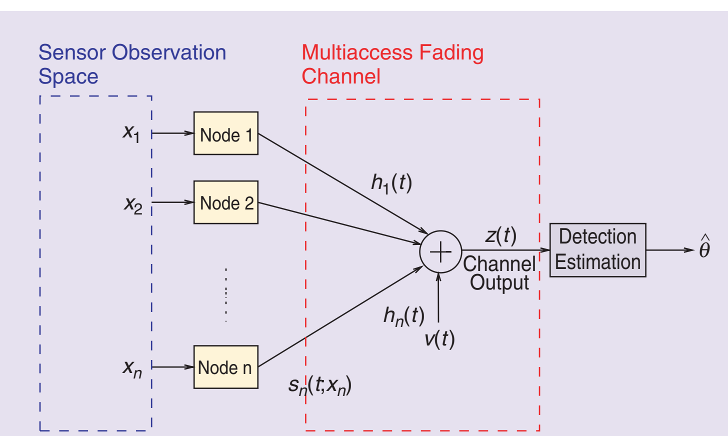
A CROSS-LAYER DESIGN FOR ESTIMATION OVER MULTIACCESS CHANNELS

Perhaps a holistic approach is warranted here, starting at the performance metric that will dictate the cross-layer design. Suppose that the fusion center has direct access to sensor measurements $\{X_i\}$, and each X_i is a discrete random variable drawn i.i.d. from probability mass function $\mathbf{p}_\theta = (p_\theta(1), \ldots, p_\theta(k))$, where k is the number of quantization levels. In this case a fundamental limit on estimation performance is given by the Cramér-Rao bound (CRB) [81]

$$\mathbb{E}\{(\hat{\theta} - \theta)^2\} \geq \frac{1}{nI(\theta)},$$

where $I(\theta) = \sum_{i=1}^{k}[(dp_\theta(i)/d\theta)^2/p_\theta(i)]$ is the Fisher information, and n is the number of samples collected at the fusion center. The CRB is not always achievable for finite n, but there is a class of estimators, including the maximum likelihood (ML) estimator, that achieves the CRB asymptotically as $n \to \infty$.

The fusion center does not have direct access to sensor data $\{X_i\}$, and it must make inference based on the received signal. The problem then becomes the joint design of a transmission scheme at the physical layer and an access scheme at the MAC layer. Specifically, upon receiving a measurement $X_i = x_i$, sensor i choose a particular waveform (modulation) $s_i(t; x_i)$ for transmission. (Notice that each sensor may have its own transmission waveform, allowing the modeling of classical multiaccess schemes such as TDMA, FDMA, and CDMA.) The fusion center receives a mixture of transmissions from all sensors



[FIG2] Distributed estimation over multiaccess fading channels.

$$z(t) = \sum_i y_i(t) + v(t), \quad y_i(t) = s_i(t; x_i) * h_i(t),$$

where $h_i(t)$ is the channel fading process and $v(t)$ the additive noise. It should be obvious that the design of signaling scheme $\{s_i(t; x)\}$ will affect the detection and estimation performance.

The problem of cross-layer design can then be formulated as the joint optimal design of $s_i(t; x_i)$ (subject to power and bandwidth constraints) at the sensor and the statistical inference algorithm at the fusion center to minimize inference error.

TYPE-BASED MULTIPLE ACCESS

A crucial observation is that the estimator does not need to know the raw data X_i to achieve the best performance; it needs only sufficient statistics. It is for this reason that the classical layered approach that focuses on retrieving data X_i is not appropriate for such application specific designs.

In estimating the unknown parameter θ, a sufficient statistic is the *type* or the empirical measure [41], [82]. Suppose that the measurement X_i assumes a value from a finite alphabet $\mathcal{X}$ of size k. The type of x is the k-dim probability vector $\tilde{\mathrm{p}} = (1/n)(N_1, \ldots, N_k)$, where N_j is the number of nodes that observe j.

What we need is a data-centric MAC that allocates network resources, not to individual sensor, but to data types. The so-called TBMA [44], [45] is an orthogonal transmission scheme that integrates transmission at the PHY layer with the application layer detection and estimation performance. Specifically, consider a set of orthonormal waveforms $\{u(t;1), \ldots, u(t;k)\}$, one for each possible measurement value. If the ith sensor has the measurement x, it transmits $s_i(t;x) = \sqrt{\mathcal{E}}u(t;x)$. The received signal at the access point is modeled as

$$z(t) = \sum_{i=1}^{n} \sqrt{\mathcal{E}} h_i(t) * u(t; x_i) + v(t). \tag{2}$$

Note that all nodes with the same measurement transmit the same waveform simultaneously.

The advantage of the above scheme is clear under the ideal conditions when all sensors are synchronized and there is no fading, *i.e.,* $h_i(t) = 1$. In this case (2) simplifies to

$$z(t) = \sum_{j=1}^{k} \sqrt{\mathcal{E}} N_j u(t; j) + v(t).$$

Suppose that the access point passes $z(t)$ through the bank of matched filters $\{u^*(-t;1), \cdots, u^*(-t;k)\}$ and samples their output at $t = 0$. In this case, signals corresponding to the same data measurement add coherently, and the received signal vector, scaled by $1/\sqrt{\mathcal{E}}n$, has the form

$$\begin{aligned} \mathrm{y} &= \frac{1}{n}(N_1, \ldots, N_k) + (v_1, \ldots, v_k) \\ &=: \tilde{\mathrm{p}} + \mathrm{v}, \tilde{\mathrm{v}} \sim \mathcal{N}\left(0, \frac{\sigma^2}{2\mathcal{E}n^2} I\right). \end{aligned}$$

It is apparent that the received signal vector y converges to the sufficient statistic $\tilde{\mathrm{p}}$ in distribution.

Unfortunately, the ML estimator based on $\mathrm{y} = (y_1, \ldots, y_n)$ is complicated, and the exact ML estimator is not tractable. In [45], an alternative estimator is proposed that is a weighted least squares matching of the empirical measure (type) with the likelihood function

$$\hat{\theta}_{\mathrm{TBMA}} = \arg\min_{\theta} \sum_{i=1}^{k} \frac{(p_\theta(i) - y_i)^2}{p_\theta(i)}. \tag{3}$$

The asymptotic optimality of synchronous TBMA, along with the asymptotic ML estimator (3) has been established in [45] that, for $X_i \overset{i.i.d.}{\sim} \mathrm{p}_\theta$, TBMA together with the estimator in (3) is asymptotically efficient, i.e.,

$$\begin{aligned} \hat{\theta}_{\mathrm{TBMA}} &\to \theta \quad \text{in probability,} \\ \sqrt{n}(\hat{\theta} - \theta) &\to \mathcal{N}\left(0, \frac{1}{I(\theta)}\right) \text{ in distribution,} \end{aligned}$$

where $I(\theta)$ is the Fisher information contained in x. This result shows that the asymptotic performance of TBMA is the same as if the access point had direct access to sensor measurements.

CROSS-LAYER DESIGN AND ROBUSTNESS

While cross-layer design can provide significant performance gain by removing barriers that partition the design space, care must be taken to guard against unintended consequences [83]; a jointly optimized scheme may be less robust against modeling errors.

As an example, consider the case when TBMA is not completely synchronized, and the wireless channel is subject to fading. It turns out that the gain of TBMA over TDMA (or any user-orthogonal schemes) is affected considerably by channel fading and synchronization. Consider specifically the case when the channel h_i is random with mean μ_h and variance σ_h^2. It can be shown that TBMA coupled with the asymptotic ML estimator has the following behavior

$$\begin{aligned} \hat{\theta} &\to \theta \quad \text{in probability,} \\ \sqrt{n}(\hat{\theta} - \theta) &\to \mathcal{N}\left(0, \frac{1 + \frac{\sigma_h^2}{\mu_h}}{I(\theta)}\right) \quad \text{in distribution.} \end{aligned}$$

In other words, in the presence of fading or synchronization errors, there is a loss in performance which depends on the mean μ_h and the variance σ_h^2 of the fading coefficients. For zero mean channels, the TBMA scheme fails. Are there other cross-layer schemes that are more robust and at the same time offer much improved performance and bandwidth efficiency? Likely there are (see [84] and [85] for one approach that involves multiple collections), and these are areas of research that require further attention.

CONCLUSIONS

In this article, we provided a signal processing perspective on different aspects of the sensor networking problem. It is our hope that by exploring and illuminating the connection and interplay between signal processing and networking, research efforts made by these two independently evolving communities can be joined together to advance the fundamental theory of sensor networks.

While we recognize the potential benefit of an integrated approach to sensor networks, we are also aware that an integrated design may lead to unintended consequences [83]. For example, security may be compromised by a cross-layer design: attackers may be able to exploit the cross-layer interactions, and the compartmentalized security provided by a layered design is lost [86]. Although not discussed in this article, authentication of data and sender is crucial in sensor networks. Security must be explicitly taken into account in the integrated design of sensor networks and should not be an add-on. Nevertheless, given that sensor networks are deployed for specific applications, many of which are signal processing in nature, the interplay of signal processing and networking in the context of sensor networks deserves attention and careful examination.

ACKNOWLEDGMENTS

This work was supported by the Army Research Laboratory CTA on Communication and Networks under Grant DAAD19-01-2-0011 and by the National Science Foundation under contract CNS-0435190.

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REFERENCES

[1] C. Chong and S. Kumar, "Sensor networks: Evolution, opportunities, and challenges," *Proc. IEEE*, vol. 91, pp. 1247–1256, Aug. 2003.

[2] J. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, pp. 102–114, Aug. 2002.

[3] S. Pattem, S. Poduri, and B. Krishnamachari, "Energy-quality tradeoffs for target tracking in wireless sensor networks," in *Proc. IPSN'03*, Palo Alto, California, Apr. 2003, pp. 32–46.

[4] T. Pham and H. Papadoulopoulos, "Distributed tracking in an ad-hoc sensor network," in *Proc. IEEE Statistical Signal Processing Workshop*, 2005.

[5] J. Lavery, "Distributed microsensing: Devices, networks and information processing," U.S. Army Res. Lab, Strategic Assessment Rep., No. A067024, 1999.

[6] W. Meriall, F. Newberg, K. Sohrabi, W. Kaiser, and G. Pottie, "Collaborative networking requirements for unattended ground sensor systems," in *Proc. IEEE Aerospace Conf.*, Mar. 2003, pp. 2153–2165.

[7] G. Simon, A. Ledeczi, and M. Maroti, "Sensor network-based countersniper system," in *Proc. SenSys*, Nov. 2004.

[8] R. Knopp and P. Humblet, "Information capacity and power control in single cell multi-user communications," in *Proc. Int. Conf. Communications,* Seattle, Washington, June 1995, pp. 331–335.

[9] R. Cheng, "Optimal transmit power management on a fading multiaccess channel," in *Proc. Information Theory Workshop*, Haifa, Israel, June 1996.

[10] D. Tse and S. Hanly, "Multiaccess fading channels: I polymatroid structure, optimal resource allocation and throughput capacities," *IEEE Trans. Inform. Theory*, vol. 44, pp. 2796–2815, Nov. 1998.

[11] X. Qin and R. Berry, "Exploiting multiuser diversity for medium access control in wireless networks," in *Proc. IEEE INFOCOM*, San Francisco, CA, 2003, pp. 1084–1094.

[12] P. Venkitasubramaniam, S. Adireddy, and L. Tong, "Sensor networks with mobile agents: Optimal random access and coding," *IEEE J. Select Areas Commun. (Special Issue on Sensor Networks)*, vol. 22, no. 6, pp. 1058–1068, Sep. 2004.

[13] Q. Zhao and L. Tong, "Opportunistic carrier sensing for energy efcient information retrieval in sensor networks," *EURASIP J. Wireless Commun. Networking*, no. 2, pp. 231–241, 2005.

[14] R. Dube, K. Wang, C. Rais, and S. Tripathi, "Signal stability based adaptive routing (SSA) for ad-hoc mobile networks," *IEEE Pers. Commun.*, vol. 4, pp. 36–45, Feb. 1997.

[15] Y. Kwok and V. Lau, "A novel channel-adaptive uplink access control protocol for nomadic computing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 13, no. 11, pp. 1150–1165, 2002.

[16] M.R. Souryal, B.R. Vojcic, and R.L. Pickholtz, "Information efciency of multihop packet radio networks with channel-adaptive routing," *IEEE J. Select. Areas. Commun.*, vol. 23, pp. 40–50, Jan. 2005.

[17] X.H. Lin, Y.K. Kwok, and V.K.N. Lau, "A quantitative comparison of ad hoc routing protocols with and without channel adaptation," *IEEE Trans. Mobile Computing*, vol. 4, pp. 111–128, Mar.–Apr. 2005.

[18] P. Cheng, C.-N. Chuah, and X. Liu, "Energy-aware node placement in wireless sensor network," in *Proc. IEEE Global Telecommunications Conf.*, Nov.–Dec. 2004, vol. 5, pp. 3210–3214.

[19] Y. Chen, C. Chuan, and Q. Zhao, "Sensor placement for maximizing lifetime per unit cost in wireless sensor networks," in *Proc. IEEE Military Communication Conf.*, Oct. 2005.

[20] J. Chang and L. Tassiulas, "Energy conserving routing in wireless ad-hoc networks," in *Proc. IEEE INFOCOM*, 2000, pp. 22–31.

[21] A. Shankar and Z. Liu, "Maximum lifetime routing in wireless ad-hoc networks," in *Proc. IEEE INFOCOM*, 2004, pp. 1089–1097.

[22] Q. Xie, C. Lea, M. Golin, and R. Fleischer, "Maximum residual energy routing with reverse energy cost," in *Proc. IEEE Globecom*, 2003, pp. 564–569.

[23] R. Kannan, L. Ray, R. Kalidindi, and S. Iyengar, "Max-min length-energy-constrained routing in wireless sensor networks," in *Proc. 1st European Workshop Wireless Sensor Networks*, Jan. 2004.

[24] O. Younis and S. Fahmy, "Distributed clustering in ad-hoc sensor networks: A hybrid, energy-efficient approach," in *Proc. IEEE INFOCOM*, 2004, pp. 629–640.

[25] Z. Ignjatovic, M. Perillo, W. Heinzelman, and M. Bocko, "An energy conservation method for wireless sensor networks employing a blue noise spatial sampling technique," in *Proc. 3rd Int. Symp. Information Processing Sensor Networks*, 2004, pp. 116–127.

[26] J. Chang and L. Tassiulas, "Maximum lifetime routing in wireless sensor networks," *IEEE/ACM Trans. Networking*, vol. 12, pp. 609–619, Aug. 2004.

[27] C. Cress, S. Yang, and M. Sudit, "Energy efficient data retrieval for networked multi-mode wireless sensors," in *Proc. 1st ACM Int. Workshop Performance Evaluation Wireless Ad-Hoc, Sensor, Ubiquitous Networks*, Venezia, Italy, Oct. 2004, pp. 119–120.

[28] V. Srinivasan, C.-F. Chiasserini, P.S. Nuggehalli, and R.R. Rao, "Optimal rate allocation for energy-efficient multipath routing in wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, vol. 3, pp. 891–899, May 2004.

[29] Y. Chen, Q. Zhao, V. Krishnamurthy, and D. Djonin, "Transmission scheduling for optimizing sensor network lifetime: A stochastic shortest path approach," submitted for publication.

[30] B.M. Sadler, "Fundamentals of energy-constrained sensor network systems," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 20, pp. 17–35, Aug. 2005.

[31] C. Budianu and L. Tong, "Good-turing estimation of the number of operating sensors : A large deviations analysis," in *Proc. ICASSP 2004*, May 2004, pp. 1029–1032.

[32] C. Budianu, S. Ben-David, and L. Tong, "Estimation of the number of operating sensors in large-scale sensor networks," *IEEE Trans. Signal Processing*, to be published.

[33] A. Leshem and L. Tong, "Estimating sensor population via probabilistic sequential polling," *IEEE Signal Processing Lett.*, 2005, vol. 12, no. 5, pp. 395–398, May 2005.

[34] Q. Zhao and L. Tong, "Energy-efficient adaptive routing for ad hoc networks with time-varying heterogeneous traffic," in *Proc. IEEE ICASSP*, Mar. 2005, pp. v/801–v/804.

[35] M. Basseville and I. Nikiforov, *Detection of Abrupt Changes: Theory and Application*. Englewood Cliffs, NJ: Prentice Hall, 1993.

[36] J.D. Gibbons and S. Chakraborti, *Nonparametric Statistical Inference*. New York: Marcel Dekker, 2003.

[37] M. Hollander and D.A. Wolfe, *Nonparametric Statistical Methods*. New York: Wiley, 1973.

[38] D.J. Sheskin, *Handbook of Parametric and Nonparametric Statistical Procedures*. London, U.K.: Chapman & Hall, 2004.

[39] S. Ben-David, T. He, and L. Tong, "Non-Parametric approach to change detection and estimation in large scale sensor networks," in *Proc. 2004 Conf. Information Sciences Systems*, Princeton, NJ, Mar. 2004.

[40] T. He, S. Ben-David, and L. Tong, "Nonparametric change detection and estimation in large scale sensor networks," *IEEE Trans. Signal Processing,* vol. 54, no. 4, pp. 1204–1217, Apr. 2006.

[41] T. Cover and J. Thomas, *Elements of Information Theory*. New York: Wiley, 1991.

[42] K. Liu and A. M. Sayed, "Optimal distributed detection strategies for wireless sensor networks," in *Proc. 42nd Annu. Allerton Conf. Communications, Control, Computing*, Oct. 2004.

[43] G. Mergen, V. Naware, and L. Tong, "Asymptotic detection performance of type-based multiple access in sensor networks," in *Proc. IEEE SPAWC*, New York, NY, June 2005, pp. 1018–1022.

[44] G. Mergen and L. Tong, "Estimation over deterministic multiaccess channels," in *Proc. 42nd Allerton Conf. Communications, Control, Computing,* Monticello, Illinois, 28 Sept.–1 Oct. 2004.

[45] G. Mergen and L. Tong, "Type-based estimation over multiaccess channels," *IEEE Trans. Signal Processing*, vol. 54, no. 2, pp. 613–626, Feb. 2006.

[46] Y. Sung, L. Tong, and A. Ephremides, "Route selection for detection of correlated random elds in large sensor networks," in *Proc. 39th Conf. Information, Science, Systems*, Mar. 2005.

[47] S. Pradhan, J. Kusuma, and K. Ramchandran, "Distributed compression in a dense microsensor networks," *IEEE Signal Processing Mag.*, vol. 19, no. 1, pp. 51–60, Mar. 2002.

[48] Z. Xiong, A. Liveris, and S. Cheng, "Distributed source coding for sensor networks," *IEEE Signal Processing Mag.*, vol. 21, no. 5, pp. 80–94, Sept. 2004.

[49] C. Intanagonwiwat, R. Govindan, and D. Esterin, "Directed diffusion: A scalable and robust paradigm for sensor networks," in *Proc. 6th ACM/Mobicom Conf.*, Boston, 2000, pp. 56–67.

[50] C. Intanagonwiwat, D. Esterin, R. Govindan, and J. Heidemann, "Impact of network density on data aggregation in wireless sensor networks," in *Proc. Int. Conf. Distributed Computing Systems (ICDCS)*, July 2002, pp. 457–458.

[51] A. Scaglione and S.D. Servetto, "On the interdependence of routing and data compression in multi-hop sensor networks," in *Proc. MOBICOM02,* Atlanta, Georgia, 23–26 Sept. 2002.

[52] M. Dong, L. Tong, and B.M. Sadler, "Impact of data retrieval pattern on homogeneous signal field reconstruction in dense sensor networks," *IEEE Trans. Signal Processing*, to be published.

[53] M. Dong, L. Tong, and B.M. Sadler, "Information retrieval and processing in sensor networks: Deterministic scheduling vs. random access," submitted for publication.

[54] M. Dong, L. Tong, and B.M. Sadler, "Effect of MAC design on source estimation in dense sensor networks," in *Proc. ICASSP 2004*, Montreal, Quebec, Canada, May 2004, pp. 853–856.

[55] M. Dong, L. Tong, and B. M. Sadler, "Source reconstruction via mobile agents in sensor networks: Throughput–distortion characteristics," in *Proc. MILCOM*, Boston, Oct. 2003, pp. 694–698.

[56] R. Iyer and L. Kleinrock, "QoS control for sensor networks," in *Proc. 2003 ICC*, May 2003, pp. 517–521.

[57] Z. Hu, J. Zhang, and L. Tong, "Dynamic activity management in many-to-one sensor networks," in *Proc. IEEE MILCOM*, Oct. 2005.

[58] Q. Zhao and L. Tong, "Quality-of-service specic information retrieval for densely deployed sensor network," in *Proc. IEEE Military Communications Int. Symp.*, Boston, Oct. 2003, pp. 591–596.

[59] Q. Zhao and L. Tong, "Energy-efficient information retrieval for correlated source reconstruction in sensor networks," *IEEE Trans. Wireless Commun.*, to be published.

[60] J. Wiesselthier, G. Nguyen, and A. Ephremides, "Energy-aware wireless networking with directional antennas: The case of session-based broadcasting and multicasting," *IEEE Trans. Mobile Computing*, vol. 1, no. 3, pp. 176–191, 2002.

[61] R.C.D. Ganesan and B. Beferull-Lozano, "Power-efficient sensor placement and transmission structure for data gathering under distortion constraints," in *Proc. Symp. Information Processing Sensor Networks (IPSN '04)*, Berkeley, California, 26–27 Apr. 2004.

[62] V.P. Mhatre, C. Rosenberg, D. Kofman, R. Mazumdar, and N. Shroff, "A minimum cost heterogeneous sensor network with a lifetime constraint," *IEEE Trans. Mobile Computing*, vol. 4, pp. 4–15, Jan.–Feb. 2005.

[63] I. Maric and R.D. Yates, "Cooperative multicast for maximum network lifetime," *IEEE J. Select. Areas. Commun.,* vol. 23, pp. 127–135, Jan. 2005.

[64] J. Park and S. Sahni, "Maximum lifetime broadcasting in wireless networks," in *Proc. 3rd ACS/IEEE Int. Conf. Computer Systems Applications*, 2005, p. 8.

[65] Z.M. Wang, S. Basagni, E. Melachrinoudis, and C. Petrioli, "Exploiting sink mobility for maximizing sensor networks lifetime," in *Proc. 38th Annu. Hawaii Int. Conf. System Sciences*, Jan. 2005.

[66] Y. Chen and S.H. Son, "A fault tolerant topology control in wireless sensor networks," in *Proc. 3rd ACS/IEEE Int. Conf. Computer Systems Applications*, 2005, p. 57.

[67] J. Zhu and S. Papavassiliou, "On the energy-efficient organization and the lifetime of multi-hop sensor networks," *IEEE Commun. Lett.*, vol. 7, pp. 537–539, Nov. 2003.

[68] E. Duarte-Melo and M. Liu, "Analysis of energy consumption and lifetime of heterogeneous wireless sensor networks," in *Proc. IEEE Globecom,* Taipei, Taiwan, Nov. 2002, pp. 21–25.

[69] A. Kansal, A. Ramamoorthy, M. Srivastava, and G. Pottie, "On sensor network lifetime and data distortion," in *Proc. IEEE Int. Symp. Information Theory*, Sept. 2005, pp. 6–10.

[70] S. Arnon, "Deriving an upper bound on the average operation time of a wireless sensor network," *IEEE Commun. Lett.*, vol. 9, pp. 154–156, Feb. 2005.

[71] F. Ordonez and B. Krishnamachari, "Optimal information extraction in energy-limited wireless sensor networks," *IEEE J. Select. Areas Commun.*, vol. 22, no. 6, pp. 1121–1129, 2004.

[72] H. Zhang and J. Hou, "On deriving the upper bound of lifetime for large sensor networks," in *Proc. MobiHoc*, 2004, pp. 121–132.

[73] Z. Hu and B. Li, "On the fundamental capacity and lifetime limits of energy-constrained wireless sensor networks." in *Proc. 10th IEEE Real-Time and Embedded Technology Applications Symp. (RTAS 2004)*, Toronto, Canada, 25–28 May 2004.

[74] D.M. Blough and P. Santi, "Investigating upper bounds on network lifetime extension for cell-based energy conservation techniques in stationary ad hoc networks," in *Proc. ACM MOBICOM'02*, Atlanta, Georgia, Sept. 2002.

[75] M. Bhardwaj, T. Garnett, and A. Chandrakasan, "Upper bounds on the lifetime of sensor networks," in *Proc. 2001 IEEE Int. Conf. Communications*, 2001, pp. 785–790.

[76] M. Bhardwaj and A. Chandrakasan, "Bounding the lifetime of sensor networks via optimal role assignments," in *Proc. INFOCOM 2002,* New York, June 2002, pp. 1587–1596.

[77] Y. Chen and Q. Zhao, "On the lifetime of wireless sensor networks," *IEEE Commun. Lett.*, vol. 9, pp. 976–978, Nov. 2005.

[78] Y. Chen and Q. Zhao, "Maximizing the lifetime of sensor network using local information on channel state and residual energy," in *Proc. 39th Conf. Information Science Systems*, Mar. 2005.

[79] Y. Chen and Q. Zhao, "Applying retirement-planning strategy to sensor networks: An integrated approach to energy-aware medium access," submitted for publication.

[80] Y. Chen and Q. Zhao, "Distributed transmission protocol for lifetime maximization in sensor network," in *Proc. 6th IEEE Int. Workshop Signal Processing Advances Wireless Communications*, June 2005, pp. 895–899.

[81] J. Shao, *Mathematical Statistics*. New York: Springer-Verlag, 1999.

[82] I. Csiszár, "The method of types," *IEEE Trans. Inform. Theory*, vol. 44, p. 2505, Oct. 1998.

[83] V. Kawadia and P.R. Kumar, "A cautionary perspective on cross-layer design," *IEEE Wireless Commun.*, vol. 12, pp. 3–11, Feb. 2005.

[84] A. Anandkumar and L. Tong, "Type-based random access for distributed detection and estimation over multiaccess fading channels," in *Proc. 40th Annu. Conf. Information Science Systems (CISS)*, Mar. 2006.

[85] A. Anandkumar and L. Tong, "A large deviation analysis of detection over multiaccess channels with random number of sensors," in *Proc. IEEE ICASSP*, May 2006.

[86] A. Wood and J. Stankovic, "Denial of service in sensor networks," *Computer*, pp. 54–62, Oct. 2002.

[87] M. Çetin, L. Chen, J.W. Fisher III, A.T. Ihler, R.L. Moses, M.J. Wainwright, and A.S. Willsky, "Distributed fusion in sensor networks," *IEEE Signal Processing Mag.*, vol. 23, no. 4, pp. 42–55, 2006.

[88] J.B. Predd, S.R. Kulkarni, and H.V. Poori, "Distributed learning for decentralized iInference in wireless sensor networks," *IEEE Signal Processing Mag.*, vol. 23, no. 4, pp. 56–69, 2006.

[89] M. Gastpar, M. Vetterli, and P.L. Dragotti, "Sensing reality and communicating bits: A dangerous liaison," *IEEE Signal Processing Mag.*, vol. 23, no. 4, pp. 70–83, 2006.

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