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DISTRIBUTED SIGNAL PROCESSING IN WIRELESS SENSOR NETWORKS

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While distributed sensor signal processing goes back a long way, a recent development is the implementation of wireless links for sensor communication. Typically, distributed nodes in a wireless sensor network (WSN) are battery powered and the whole network has access to only a finite portion of the spectrum. This leads to both power and bandwidth constrained wireless communication between sensing nodes and the fusion nodes. Securing reliable communication over a wireless channel is a challenging task due to physical properties of the wireless medium. Hence, channel-induced errors need to be taken into account in order to achieve optimal data fusion/detection in distributed wireless sensor systems. In recent years, many authors have investigated various aspects of distributed processing in resource-constrained wireless sensor networks. In this chapter, we provide a tutorial exposition of those recent contributions.[1]

6.1 THE PROBLEM OF DISTRIBUTED DETECTION AND DATA FUSION

Gathering and processing of information through a large number of networked sensors has potential applications in a number of areas, including environmental monitoring (e.g., traffic, habitat, security), industrial sensing (e.g., nuclear power plants), infrastructure integrity monitoring (e.g., health monitoring of bridges, power grid), homeland security (e.g., remote surveillance of ports and airports), and military applications (e.g., target tracking) [1–7]. Availability of microsensors with miniature batteries, processors with built-in computation, and wireless connectivity capabilities has made such a paradigm a reality. Sensor nodes (because a sensor has computation and communication capabilities apart from sensing, it is termed a *sensor node*) can be deployed almost anywhere: on the ground and in the air, inside buildings, on vehicles, and under water. In some applications, they can even be worn by humans. Realizing the full potential of sensor networks, however, presents a number of challenges, including the limitations posed by finite battery life, limited processing capability due to power constraints, and limitations posed by unreliable wireless link quality.

Typically, each individual distributed node in a wireless sensor network (WSN) can sense in multiple modalities, but has limited communication and computation capabilities. There are two issues related to reliable information gathering: (1) efficient methods for exchanging information between nodes and (2) collaborative processing of useful information about the environment being monitored. A successful design of a sensor network involves addressing layers of design issues: computational capability of a sensor node, network architecture, and routing of information between nodes [1,2,4,8]. All these issues must be resolved so that reliable information is gathered in an efficient and affordable manner while extending the whole network lifetime.

In this chapter, we restrict our attention to the problem of distributed detection and data fusion in wireless sensor networks [9,10]. This problem primarily touches on the computational aspects of a sensor node, the exchange of information between nodes (link layer issues, as termed in communications terminology), and the routing architecture. Information processing in any application can be broadly classified into two categories, namely, detection and estimation [11–13]. In a detection problem, one is interested in knowing whether a particular phenomenon of interest (POI), say the presence of a biological spill or the presence of a particular object or an individual in a specified location, is present. The answer to such a query is binary in nature, yes or no. Myriad sensors gather and process information about the POI, before passing them on to a fusion center where a final answer to the query is arrived at [9,10,14–17]. As in any situation with uncertain and incomplete information, the final answer arrived at could be different from the true situation of the POI. An acceptably reliable operation is achieved by guaranteeing that the number of incorrect decisions made over a period of time remains below an acceptable number. In an estimation problem, on the other

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hand, one would like to know the characteristics of a POI, e.g., a precise location of a target or the strength of a biological spill, etc. Moreover, one may want to know the characteristics of a POI as a function of time or space, e.g., the spatial distribution of a biological spill over a region of interest or the movement of a target in a region as a function of time (e.g., target tracking) [2,18–20]. Reliable performance is assured by specifying the estimated value to be within a fraction of the true value. In a wireless sensor network, the communication between two nodes is typically unreliable due to channel fading/shadowing, transmission bandwidth limitations, and transmitter and receiver processing power constraints. The quality of sensed data, the quality of processed data at a node, and the quality of information passed between nodes all play important roles in the overall performance of a sensor network. A number of papers have addressed the interplay between these issues within the context of distributed detection [14–16][21–26] and estimation [18,19,27–32].

This chapter is organized as follows: In Section 6.2, we briefly outline various architectures that have been considered for data fusion in sensor networks. This is followed by a discussion of recent results in distributed detection data fusion in wireless sensor networks in Section 6.3. Note that the emphasis of Section 6.3 is on recent work that has addressed strictly resource-constrained large wireless sensor networks. Thus, results on large system analysis and performance in fading channels will be the primary focus of our discussion. However, we will also briefly outline recent advances in distributed estimation in wireless sensor networks. Next, in Section 6.4 we detail recently established performance results for distributed detection and data fusion systems with analog-relay amplifier local processing. Here we consider large system analysis for both sensor system optimization techniques based on large system performance measures. Section 6.6 provides a summary of the chapter.

6.2 FUSION ARCHITECTURES

Consider the generic wireless sensor network architecture shown in Figure 6.1. The sensors monitor the environment to provide inference regarding a POI. Here $Z_1, Z_2, \cdots, Z_n$ represent the observations at sensor nodes $1, 2, \cdots, n$, respectively. Unless otherwise stated, it is assumed that each sensor observation is statistically independent of others, conditioned on the true state of nature of the environment (some studies have addressed correlation among sensor data and these will be discussed in the sequel). The locally processed (e.g., quantized) data sent from these nodes are represented as $U_1, U_2, \cdots, U_n$, where $U_k = \delta_k(Y_k)$ with $\delta_k(.)$ being the local processing (decision) rule at node k. For example, if node k quantizes its observation Y_k to D_k number of levels, $U_k \in [1, 2, \cdots, D_k]$. Using a particular modulation and coding scheme, the node k transmits its data U_k to a *central* node, called the cluster head or the access point (AP) (see Figure 6.2).

Depending on the application under consideration, different fusion architectures are possible in these wireless sensor networks. Most of them stem from the architectures that were originally considered in decentralized detection problems and from the architectures present in mobile ad hoc networks [17]. Broadly speaking, there are three types of fusion architectures in decentralized detection/estimation, namely the parallel, the serial, and the tree structure [14]. In the parallel configuration, all the sensors pass their locally processed data (i.e., quantized, compressed, or amplified data) to a central site called the fusion center, where a final inference regarding the POI is made. In the serial configuration, sensors communicate in a tandem fashion, with sensor S_1 sending

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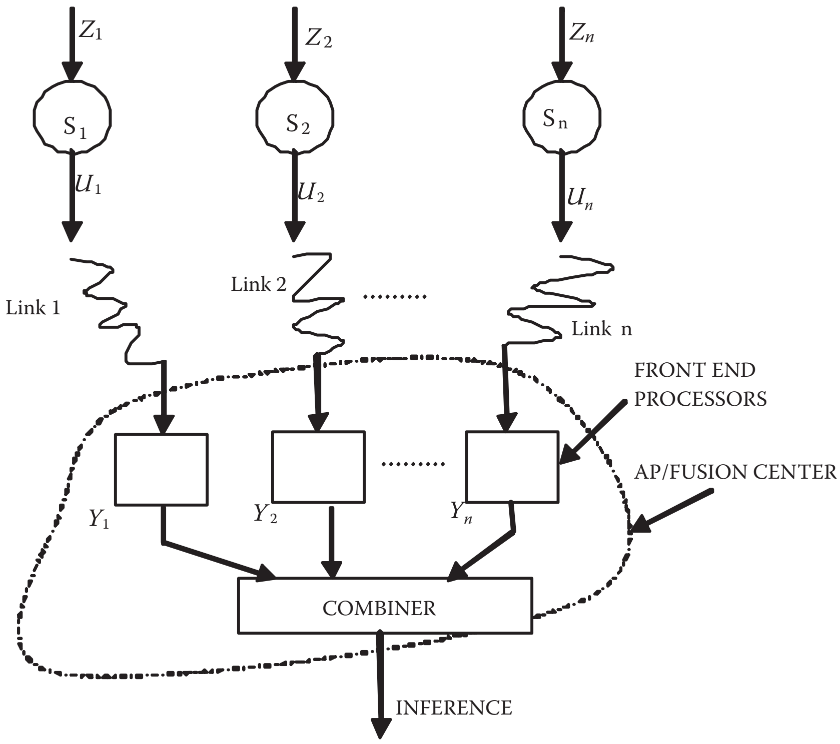

Figure 6.1 Parallel Data Fusion Model in Sensor Network

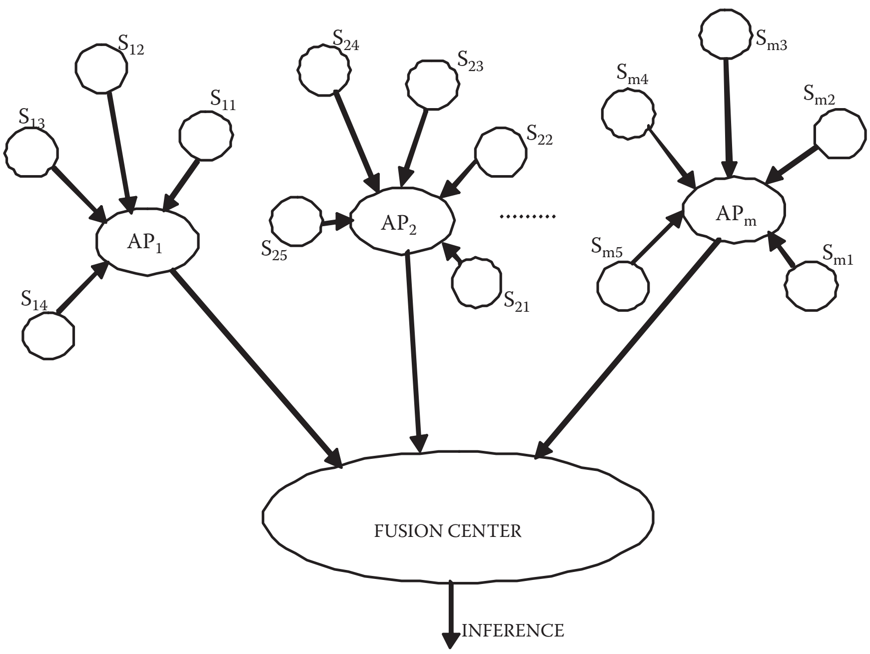

Figure 6.2 Sensor Network Topology

its quantized (locally processed) data to sensor S_2, which in turn sends a quantized data, which is derived based on its own data and the data from S_1, to the next sensor S_3 in the tandem chain. Data progression along the chain continues until the last sensor is reached, where the final inference is made [33–35]. In general, for decentralized detection, the performance of the serial configuration is inferior to that of the parallel configuration [14]. The tree structure is similar to the architecture used in ad hoc networks, where data from neighboring nodes is transmitted to a *central* node (or the AP) as in Figure 6.2. Several such AP neighborhoods might be monitoring the environment with regard to a POI. These APs then transmit their quantized data to the next level of cluster head nodes in the hierarchy. If more than one such second level cluster head node exists, then these will in turn transmit its data to a third level cluster head node. Data progression continues until a final cluster node, called the fusion center, is reached.

In wireless sensor networks, a typical architecture is similar to the tree structure described above. In a number of applications, the architecture will have only two levels, with the first level APs (i.e., distributed sensing nodes) sending their data to the fusion center for the final assessment. Of course, because data is wirelessly transmitted from a node to an AP, this connection could be established through intermediate nodes, which is then called a multihop transmission. Another possibility is for two or more nodes to transmit data cooperatively to an AP, which is called cooperative relaying [36]. Cooperative relaying seems to provide a definitive advantage in performance, especially when the direct link between a node and an AP experiences severe signal degradation. Pertinent questions in many of these wireless sensor networks include, how to designate APs among a large number of sensor nodes distributed in a given geographical area, how to identify neighborhood nodes that form the cluster around an AP, and how to route information to an AP or from APs to the fusion center? Optimal solutions to these questions become more difficult when one considers energy constraints on nodes as well as any possible mobility of nodes with time. A flurry of research is being done to answer these questions in recent years, but a comprehensive consideration of these results is beyond the scope of this chapter. In the next two sections, we consider primarily the quality of the data as received at an AP from a node and the quality of the final inference arrived at the fusion center. A bulk of the discussion deals with the detection problem, although some results from distributed estimation research are also provided briefly at the end of Section 6.3.3.

6.3 RECENT ADVANCES IN DISTRIBUTED DETECTION/ESTIMATION IN RESOURCE-CONSTRAINED WIRELESS SENSOR NETWORKS

Up until recently, most work on decentralized detection/estimation assumed that the senor data was transmitted to the fusion center error free [14,15]. In a WSN, however, this assumption of perfect transmission fails as data is sent over a typically unreliable channel [4,37]. To account for such channel-induced error, some recent studies have addressed the performance of decentralized detection and fusion schemes in resource-constrained WSNs. Due to the assumption of a large number of sensors in a WSN, a number of these studies has specifically dealt with the asymptotic (infinite number of sensors) performance issues [16,21,24,38–43].

To be specific, let us consider the architecture shown in Figure 6.1. The sensors monitor the environment to determine the presence or the absence of a POI based on local observations $Z_1, Z_2, \cdots, Z_n$. We may assume that the local processing at distributed nodes is a form of quantization such that the data sent from distributed nodes to the fusion center is $U_1, U_2, \cdots, U_n$, where $U_k = \delta_k(Y_k) \in [1, 2, \cdots, D_k]$. In general, this local processing at distributed nodes could either be continuous or discrete mappings, in the sense that U_ks could either be analog or discrete (quantized) valued. The node k sends its quantized data U_k to the AP using a particular modulation and a coding scheme.

Until recently, it has been common to assume the existence of parallel and noninterfering communication links between each sensor node and the AP. However, in the context of wireless sensor networks it is more realistic to assume that there could be bandwidth or power constraints on these links. Partial or complete interference among transmitted signals from different sensors could also be an interesting topic to consider, especially because of savings in bandwidth or power. A receiver at the AP processes the signal received from node k and puts out the output Y_k. Due to channel degradation such as fading and additive white Gaussian noise, Y_k can be considered as a corrupted version of U_k. Using all of the data, $\{Y_k\}_{k=1}^{n}$, the AP then makes a final decision regarding the presence or the absence of a POI.

6.3.1 Detection in Large Systems

Assuming a total capacity constraint $\sum_{k=1}^{n} \log_2(D_k) \leq R$ on the communication channel, the allocation of optimal numbers of bits to each sensor was considered in [21]. For the problem of detecting deterministic signals in additive Gaussian noise, it was shown in [21] that having a set of identical binary sensors is asymptotically optimal, as the number of observations per sensor goes to infinity. Thus, the gain offered by having more sensors exceeds the benefits of getting detailed information from each sensor. It must be mentioned that this result was obtained with the restriction that each $\log_2(D_k)$ was an integer, i.e., no fractional bit was allowed, and that each $\log_2(D_k)$ was rounded off to the nearest higher integer. Previously large decentralized system performance has been considered in [16], with the emphasis on optimal processing at the sensors and at the fusion center. However, in [16], the links between the sensors and the fusion center were assumed to be error free.

With a joint power constraint on the channels between sensors and the AP, and assuming additive white Gaussian noise (AWGN), it was shown using a large deviation theory, that having identical sensor nodes, i.e., each node having the same transmission scheme, is asymptotically (as the total transmit power is allowed to go to infinity or equivalently, as the number of sensors, each with finite power, is allowed to go to infinity) optimal [38]. With reference to Figure 6.1 terminology, in this work, $Y_k = U_k + W_k$, where W_k represents the AWGN. For any reasonable coding (local processing) scheme (δ_k, $k = 1, 2, \cdots, n$) and a fusion rule, which is a function of (Y_k, $k = 1, 2, \cdots, n$), the Bayes error probability goes to zero as the total energy is allowed to go to infinity. Having established the optimality of identical sensor nodes, an appropriate measure of efficiency is the normalized Chernoff information [38]:

$$S = -\frac{1}{f(\delta)} \min_{\lambda\in[0,1]} \left(\log \mathbb{E}_0 \left\{e^{\lambda Z_k}\right\}\right), \tag{6.1}$$

where $\mathbb{E}_0\{.\}$ denotes the expectation with respect to the induced variable $U_k = \delta(Y_k)$, under the no POI hypothesis (null hypothesis), H_0 and $f(\delta)$ denote the expected power spent at a node. In [38], the measure S was computed for two transmission schemes, namely, binary sensor nodes and analog sensor nodes. A binary sensor node employs a binary mapping and sends U_k, where $U_k = m$ if Y_k exceeds a threshold and $U_k = -m$ if Y_k falls below the threshold (in [38] the threshold was taken as 0 for the case of a specific observation model for Z_k). In the case of analog sensor nodes, as will be discussed in detail in the next section, $U_k = gY_k$, where g is the amplification gain of the sensor node [36,39,44]. A plot of normalized Chernoff information S against the observation SNR (i.e., the signal-to-noise ratio of the observation Z_k at the sensor) showed that there exists a threshold SNR below which the analog sensor nodes perform better than their binary counterparts. Indeed, the authors observed that for some detection applications, wireless sensor nodes with continuous transmission mappings may outperform sensor nodes with finite-valued transmission mappings. They also pointed out that for the Neyman–Pearson criterion of signal detection, the normalized relative entropy measure (Kullback–Leibler distance) plays a role analogous to that of the Chernoff measure for Bayes error criterion.

The problem of decentralized detection in a sensor network subjected to a total average power constraint and all nodes sharing a common bandwidth was considered in [24]. The bandwidth constraint was taken into account by assuming nonorthogonal communication between sensors and the data fusion center via direct-sequence codedivision multiple access (DS-CDMA) spreading. In the case of large sensor systems and random spreading, the asymptotic decentralized detection performance was derived assuming independent and identically distributed sensor observations via random matrix theory. The results showed that, even under both power and bandwidth constraints, it is better to combine many not-so-good local decisions rather than relying on one (or a few) very-good local decisions. Using large deviation analysis similar to that in [38], the question of allocating two bits per sensor versus one bit per sensor was addressed in [45]. A general conclusion is that a higher SNR at a sensor would dictate a larger number of bits per sensor for achieving higher Chernoff information at the fusion center.

The impact of specific binary modulation schemes on the overall performance of fusion rules were examined in [41] and [42], by modeling each link between a sensor and the fusion center as an independent and identically distributed slow Rayleigh-fading AWGN channel. While [41] addressed only the performance of counting rules (fusion center counts the number of decisions received in favor of the presence of a POI and compares it to a threshold) at the fusion center, performances of other combiners were addressed in [42]. For three standard modulation techniques (binary phase shift keying (BPSK), on/off keying (OOK), and frequency shift keying (FSK)) this study considered (1) the impact of the sensor-fusion center link on the quality of the decision received at the fusion center and (2) the minimum required sensor decision quality, given the availability of a minimum sensor-to-fusion center link SNR, in order that the asymptotic (large number of sensors) error in the counting rule classification goes to zero. With a proper choice of threshold for noncoherent OOK detection, it was shown that an asymptotic performance comparable to that of FSK, while achieving some energy savings, is possible. Asymptotic error exponents of the probability of false alarm and the probability of miss at the fusion center were derived in [42] for the following cases: BPSK modulation and (1) maximal ratio combining (MRC), (2) equal gain combining (EGC), and (3) decision fusion (DF) and BFSK modulation and (1) square law combining and (2) decision fusion. In the case of BPSK, the EGC performs the best for low and moderate SNR, with DF achieving the next best performance. The DF scheme performs the best for large SNR values, whereas the MRC performs the best for very low SNR values. Similar relative performance results were obtained earlier for the case of a finite number of sensors (see discussion below and [37]). In the case of BFSK, square law combining was shown to outperform DF, except for large SNR values.

6.3.2 Detection Performance in Fading Channels

An analysis of the performance of different fusion rules in the presence of Rayleigh has been carried out in [37]. In this work, the sensor nodes are assumed to transmit their binary decisions ($U_k \in \pm 1$) over parallel noninterfering, but slow Raleigh fading channels to the fusion center. The BPSK modulation with coherent detection was assumed. Assuming that the fusion center has the knowledge of channel state information (CSI), the authors derived the optimal likelihood ratio test (LRT) at the fusion center. For large SNR, the LRT was shown to approach the Chair–Varshney rule [10], which is based on individual decisions made from the matched filter outputs of each link. Note that the Chair–Varshney rule requires the knowledge of sensor quality information, i.e., individual (local) sensor probability of false alarm and the probability of detection. For identical sensors, i.e., all having the same decision quality, they also showed that the LRT approaches the MRC as the average SNR of the fading link approaches zero.

They also pointed out another interesting result: In traditional combining there is one source and many diversity paths, whereas the MRC maximizes the SNR among all linear combiners, it does not exhibit any such optimality in distributed sensor networks, where a consensus of decisions of all the sensors does not occur with probability one. Interestingly, except for very small SNR, both EGC and the Chair–Varshney rule outperform MRC. The EGC also performs better than the Chair–Varshney rule, except for large SNR values. Similar to this analysis, an exercise of finding different statistics for the fusion of censored decisions was carried out in [46]. Although the authors termed this as censoring, it is essentially an OOK modulation for transmitting the U_ks. Certainly, OOK allows for noncoherent detection, thereby eliminating any need for phase track of an individual link. Assuming complete CSI and sensor information quality, the authors derived the LRT, which is a function of the energy detector outputs of the individual links. For very small SNR and independent and identically distributed (iid) sensors, the LRT becomes a weighted energy detector, with weights being proportional to the individual channel gains. Censoring strategy with resource constraints (expected cost arising from transmission and measurement at each sensor) was considered in [47]. It was found that the randomization over the choice of measurement and when to transmit achieves the best performance (in Bayesian, Neyman–Pearson, and Ali–Silvey sense).

The effect of link quality on the performance of a counting rule has been investigated in [41,48]. Assuming iid sensor observations and a specific quality of sensor decision, [48] showed how the fusion false alarm probability could change several orders of magnitude as the link error rate changes from low to high. For a counting rule at the fusion center and a slow fading channel, [48] established the correctness of using an average bit error rate for a link, averaged with respect to the fading distribution. The effect of correlation on the performance of a wireless sensor detection system subjected to a total transmission power constraint was studied in [44]. Assuming that the sensors are placed as a linear array, such that the correlation coefficient between any two sensors is exponentially decreasing with distance separation, they studied the fusion performance with analog-relay amplifier local processing at the sensors. It is found that the optimal number of sensor nodes in the system increases as the correlation coefficient decreases. In general, systems with many low-power nodes appear to perform better in the case of a deterministic signal detection, regardless of the specific correlation coefficient. In contrast, the effect of correlation on the detection of a stochastic (random) signal in a total power constrained sensor network was investigated in [39]. An important observation was that the average fusion probability of error does not improve monotonically with the number of sensors, unlike in the case of deterministic signal detection reported earlier in [44,47]. In particular, [39] showed that there is an optimal number of sensors that minimizes the probability of fusion error, which depends on both the local observation SNR as well as channel SNR (we will discuss these results in detail in Section 6.4 below).

6.3.3 Estimation with Distributed Sensors

In this section, we briefly discuss some important results in distributed estimation in sensor networks. In estimation problems, the nodes periodically transmit their processed information to the fusion center where the estimation of a POI takes place (see Figure 6.1). Early work in this area dealt with target tracking based on distributed data [49]. Essentially, the problem boiled down to aggregating different Kalman filter estimates that were obtained at several sensors. Performance analysis of parameter estimation with distributed sensors was carried out in [50]. A specific design of a decentralized estimation system was considered in [50]. The local processors at the sensor nodes were taken to be quantizers and the aim was to minimize a certain distortion function. Necessary conditions for the optimum system based on Bayes distortion measure and Fisher information were derived. The numerical results in [50] also compared the resulting quantizers obtained by different distortion criteria. Another early work considered the estimation of an unknown constant, using distributed estimators [51]. For estimating a constant parameter in Laplace noise density at each sensor, it was assumed that the sample medians of a set of iid observations at each sensor were obtained. These local median estimates were then combined in some fashion at the fusion center. The results obtained reveal that the mean of local medians exhibits a slightly smaller mean-squared error (MSE) than the median of local medians. It is noteworthy that in all these early papers, the links between sensors and the fusion center were assumed to be error free.

Some recent work has considered distributed estimation of a constant parameter within the context of bandwidth constrained sensor networks [52,53]. In this setup, each sensor observes a corrupted version of the parameter and quantizes its data. The analysis in [53] applies only to the case of the observation noise at a sensor being over a bounded interval. Bandwidth constraint is indirectly met by allowing approximately 1/2 of the sensors to send one bit quantized data, 1/4 of the sensors to send two bits quantized data, and so on. In [53] both the quantization rule at a sensor (all sensors employ identical quantizers) and the fusion rule were completely distribution free, thereby making the scheme highly suitable for ad hoc networks. Moreover, the authors showed that the MSE of the proposed distributed quantizer is almost within a factor of four of the Cramer–Rao lower bound of the centralized counterpart. Subsequently, [54] has shown that the MSE of any universal decentralized estimator is lower bounded by 1/16-th of the MSE of the scheme in [53]. For the case of distributed estimation of a constant parameter in Gaussian noise, results in [52] showed that a class of maximum likelihood (ML) estimators requires sending just one bit from each sensor, when the dynamic range of the parameter is small or comparable to the noise standard deviation. Moreover, such a scheme yields a fused estimator whose variance is close to that of the sample mean estimator based on all (unquantized) sensor samples. When the dynamic range is comparable or larger than the noise standard deviation, there exists an optimum quantization scheme that achieves the best possible variance for a given bandwidth constraint.

Another interesting result in distributed estimation is the use of dithering to reduce MSE [55]. In [55], the authors showed that the addition of independent random noise to sensor observations before quantization helps to reduce the MSE of the estimate at the fusion center. In the past, such dithering is known to be beneficial in the quantization of speech signals.

The theory and methodology of estimating inhomogeneous, two-dimensional fields using wireless sensor networks have been addressed in [56]. The sensors make noisy measurements of the field, and the goal is to obtain an accurate estimate of the field at some desired location (typically remote from the sensor network). Key questions are the accuracy attainable in estimation and the energy consumption for communication. This paper also presented a practical strategy for estimation and communication. So far, all analysis in estimation has assumed that the links between sensors and the fusion center are error free. The impact of link errors on the overall estimation accuracy needs to be investigated.

6.4 RECENT RESULTS ON ANALOG DATA FUSION IN WIRELESS SENSOR NETWORKS

Having provided a summary of recent advances in distributed detection/estimation under resource constraints for wireless sensor networks, in this section we will consider some of those results in detail. Specifically, we consider large wireless sensor networks with so-called analog-relay amplifier local processing schemes. We will look at some large system analysis based fusion performance and sensor system optimization results for resource-constrained wireless sensor networks.

Let us consider a binary hypothesis testing problem in an n-node wireless sensor network connected to a data fusion center via distributed parallel architecture [14,17]. Denote by H_0 and H_1 the null and alternative hypotheses, respectively, having corresponding prior probabilities $P(H_0) = \pi_0$ and $P(H_1) = \pi_1 = 1 - \pi_0$. Note that, unless otherwise stated, we will assume equal priors so that $\pi_0 = \pi_1 = 1/2$. To be specific, the observed POI is a Gaussian signal denoted by $X_k \sim \mathcal{N}(m, \sigma_x^2)$ corrupted by AWGN. The k-th local sensor observation Z_k, for $k = 1, \cdots n$, can be written as

$$\begin{aligned} H_0: &\quad Z_k = V_k \\ H_1: &\quad Z_k = X_k + V_k \end{aligned} \tag{6.2}$$

where observation noise $V_k \sim \mathcal{N}(0, \sigma_v^2)$ is a zero-mean Gaussian with a collection of noise samples $\mathbf{V} = [V_1, V_2, \cdots, V_n]^T \sim \mathcal{N}(\mathbf{0}, \Sigma_v)$. Each sensor locally processes its observations to generate a local decision $U_k = \delta_k(Z_k)$ which is sent to the fusion center. Denote by $\mathbf{Y}(U_1(Z_1), U_2(Z_2), \cdots, U_n(Z_n))$ the received signal at the fusion center. The fusion center makes a final decision U_0 based on the decision rule $U_0 = \delta_0(\mathbf{Y})$. The problem at hand is to choose $\delta_0(\mathbf{Y}), \delta_1(Z_1), \delta_2(Z_2), \cdots, \delta_n(Z_n)$ to optimize a given performance metric (e.g., Bayesian or Neyman–Pearson criterion). If local observations are independently conditioned on the true hypothesis, then all local decision rules simplify to a set of likelihood ratio (LR) based tests but with possibly coupled thresholds [9]. While this assumption is commonly found in most work on distributed detection, in the context of dense wireless sensor networks it may not be justified. Once the conditional independence assumption is dropped, the optimality of simple threshold tests may be lost and the analysis could get unwieldy.

In this section, we exclusively consider a simple but important continuous local mapping called the amplify-and-relay processing, according to which the local observations are amplified before retransmission to the fusion center [44]:

$$U_k = g_k Z_k, \quad \text{for} \quad k = 1, \cdots n, \tag{6.3}$$

where $g_k > 0$ is the analog-relay amplifier gain at the k-th node. Interestingly, as mentioned in the previous section, it has been shown in [38] that below a certain threshold SNR value, such continuous local mappings may outperform binary (or discrete valued) local mappings for certain detection problems. This makes analog-relay local processing a good candidate for emerging low-power, wireless sensor networks.

In modeling dense distributed wireless sensor networks it is more appropriate to consider nonorthogonal sensor-to-fusion center communication over noisy channels. Thus, let the k-th sensor node be assigned a signaling waveform (code) $\mathbf{s}_k$ normalized such that $\mathbf{s}_k^T\mathbf{s}_k = 1$, for $k = 1, \cdots, n$. We assume that the number of degrees of freedom (DoF) in the signaling waveform to be N (for example, the number of chips per symbol in DS-CDMA signaling) so that $\mathbf{s}_k$ is a length N vector. The message U_k of the k-th sensor is transmitted to the fusion center over a noisy, bandlimited wireless channel by modulating onto the signaling waveform $\mathbf{s}_k$. Hence, k-th sensor's transmitted signal is given by $\mathbf{s}_k U_k = g_k \mathbf{s}_k Z_k$. Throughout this section we assume an AWGN channel with double-sided spectral density σ_w^2 and ignores the effects of fading for simplicity. Assuming synchronized sensor transmissions, the signal received at the fusion center is a superposition of signals transmitted from all the nodes $\sum_{k=1}^{n} g_k \mathbf{s}_k Z_k$ corrupted by additive noise. A sufficient statistic for the fusion center processing is obtained by passing this received signal through a bank of matched filters (each matched to a signaling waveform s_k of a particular node). The output of this bank of matched filters at the fusion center can be written in vector notation as

$$\mathbf{Y} = \mathbf{RU} + \boldsymbol{W}, \tag{6.4}$$

$$= \mathbf{RAZ} + \boldsymbol{W}, \tag{6.5}$$

where we have defined $\mathbf{A} = diag(g_1, g_2, \cdots, g_n)$, $\mathbf{U} = [U_1, \cdots, U_n]^T$, $\mathbf{Z} = [Z_1, \cdots, Z_n]^T$, and $\mathbf{R}$ is the $n \times n$ symmetric and normalized received signal correlation matrix in which the (k, k')-th element is given by $\mathbf{s}_k^T\mathbf{s}_{k'}$. If we define the $N \times n$ matrix $\mathbf{S}$ such that its k-th column is the waveform $\mathbf{s}_k$, then it is easily shown that

$$\mathbf{R} = \mathbf{S}^T\mathbf{S}. \tag{6.6}$$

Note that, in the special case of orthogonal sensor-to-fusion center communication, the received signal model (6.4) simplifies such that $\mathbf{R} = \mathbf{I}$. In (6.4), $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \sigma_w^2\mathbf{R})$ is the n-dimensional filtered noise vector.

A sensible way to model a system in which the most important objective is to extend the whole network lifetime, is to impose a total average power constraint P on the whole sensor system. According to this model, as the number of nodes in the system increases, the power available for each node correspondingly decreases. This allows trading off individual node power against the number of nodes in the network and vice versa. For example, in certain applications the cost of a node may be dominated by the cost of batteries. In such situations it may be necessary to determine whether to deploy a few nodes with high power or a large number of nodes with low power. Also, when the sensor system is powered by a distributed power source with a certain power density per unit area the total available power may be constant, justifying application of a global power model. With this model, g_k, for $k = 1, \cdots n$, depends on the total average power constraint P. For simplicity, throughout this discussion we assume $g_k = g$ for all k. With these assumptions the average radiated power of node k is given by $\mathbb{E}\{|U_k|^2\} = g^2\mathbb{E}\{|Z_k|^2\} = g^2(\frac{m^2+\sigma_x^2}{2} + \sigma_v^2)$, where σ_x^2 and σ_v^2 are the variances of the signal of interest and the observation noise, respectively, and we have assumed that $\pi_0 = \frac{1}{2}$. Hence, the local amplifier gain g is given by

$$g^2 = \frac{P}{n\left(\sigma_v^2 + \frac{m^2+\sigma_x^2}{2}\right)}. \tag{6.7}$$

Observe that, as more nodes are introduced the gain at each node correspondingly decreases. With equal amplifier gains at the nodes (6.5) simplifies to

$$\mathbf{Y} = g\mathbf{RZ} + \mathbf{W}. \tag{6.8}$$

The detection problem at the fusion center is then given by the following binary hypothesis testing problem:

$$\begin{aligned} H_0: &\quad \mathbf{Y} \sim \mathcal{N}(\mathbf{0}, \Sigma_0) \\ H_1: &\quad \mathbf{Y} \sim \mathcal{N}(\mathbf{m}, \Sigma_1), \end{aligned} \tag{6.9}$$

where $\Sigma_0 = g^2\mathbf{R}\Sigma_v\mathbf{R} + \sigma_w^2\mathbf{I}$, $\Sigma_1 = g^2\mathbf{R}(\Sigma_x + \Sigma_v)\mathbf{R} + \sigma_w^2\mathbf{I} = g^2\mathbf{R}\Sigma_x\mathbf{R} + \Sigma_0$, $\mathbf{m} = g\mathbf{R}\mathbb{E}\{\mathbf{X}\} = gm\mathbf{R1}$ and $\mathbf{1}$ is the vector of all ones. Because the quantity $\frac{P}{\sigma_w^2}$ is a measure of how good the channel is, let us define the channel quality SNR as $\gamma_c \triangleq \frac{P}{\sigma_w^2}$.

6.4.1 Distributed Detection of a Deterministic Signal in a Total Power and Bandwidth Constrained System

Au: Sense? In this section, we consider the detection of a deterministic signal so that $\mathbf{X} = m\mathbf{1}$, for $m > 0$, is known in uncorrelated observation noise. Hence, $\Sigma_v = \sigma_v^2\mathbf{I}$. Then $\Sigma_0 = \Sigma_1 = \Sigma$, where

$$\Sigma = g^2\sigma_v^2\mathbf{R}^2 + \sigma_w^2\mathbf{R}. \tag{6.10}$$

Accordingly, the amplifier gain g in (6.7) is simplified as

$$g = \sqrt{\frac{P}{n\left(\frac{m^2}{2} + \sigma_v^2\right)}}. \tag{6.11}$$

The quality of local observations are then characterized by the ratio $\frac{m^2}{\sigma_v^2}$. Hence, let us define the local observation quality SNR as $\gamma_0 \triangleq \frac{m^2}{\sigma_v^2}$.

The fusion center design problem is then a standard Gaussian hypothesis testing problem with the only additional caveat being that the gain g depends on the total power constraint P as in (6.11). It is well-known that the the optimal fusion rule is a LR threshold test of the form of

$$\delta_0(\mathbf{y}) = \begin{cases} 1 & \geq \\ & \text{if } T(\mathbf{y}) \quad \tau', \\ 0 & < \end{cases} \tag{6.12}$$

where we have defined the decision variable T as $T(\mathbf{y}) = \mathbf{m}^T\Sigma^{-1}\mathbf{y} = gm\mathbf{1}^T\mathbf{R}\left(g^2\sigma_v^2\mathbf{R}^2 + \sigma_w^2\mathbf{R}\right)^{-1}\mathbf{y}$ and τ' is the threshold that depends on the specific optimality criteria. It can be shown that the false-alarm P_f and miss P_m probabilities of the detector (6.12) are given by

$$P_f = Q\left(\frac{\tau'}{gm\sqrt{\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1}}}\right), \tag{6.13}$$

and

$$P_m = Q\left(\frac{g^2m^2\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1} - \tau'}{gm\sqrt{\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1}}}\right). \tag{6.14}$$

In the case of Neyman–Pearson optimality at the fusion center, τ' is chosen to minimize P_m subject to an upper bound on P_f. On the other hand, under Bayesian minimum probability of error optimality one would choose τ' to minimize $P_e = \pi_0 P_f + \pi_1 P_m$. In the following we explicitly consider Bayesian optimality with equal prior probabilities (i.e., $\pi_0 = \pi_1 = \frac{1}{2}$), in which case the threshold simplifies to

$$\tau' = \frac{1}{2}g^2m^2\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1}. \tag{6.15}$$

The resulting minimum fusion probability of error is given by

$$P_e = Q\left(\frac{gm}{2}\sqrt{\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1}}\right). \tag{6.16}$$

The above analysis characterizes the fusion performance for a deterministic signal in a resource-constrained, noisy, bandlimited wireless sensor network. Of course, to say anything beyond this point we need to specify the particular signaling scheme used to share the total available bandwidth because the performance depends on the particular waveforms (or codes) assigned to each sensor node as seen from (6.16). This hinders drawing general conclusions regarding the fusion system. However, such conclusions can be reached for large systems through asymptotic (in large n) analysis, as we show next.

Let us assume that the signaling codes are chosen randomly, so that each element of $\mathbf{s}_k$ takes either $\frac{1}{\sqrt{N}}$ or $-\frac{1}{\sqrt{N}}$ with equal probability, and that, as assumed above, sensor observations are independent so that $\Sigma_v = \sigma_v^2\mathbf{I}$. Consider a large sensor system in which both n and N are large, such that $\lim_{N\longrightarrow\infty}\frac{n}{N} = \alpha$. Using the definitions of Σ, $\mathbf{R}$, $\mathbf{S}$, and $\mathbf{1}$, we can show that

$$\begin{aligned} g^2\mathbf{1}^T\mathbf{R}\Sigma^{-1}\mathbf{R}\mathbf{1} &= g^2\mathbf{1}^T\mathbf{S}^T\mathbf{C}^{-1}\mathbf{S}\mathbf{1} \\ &= g^2\left(\sum_{k=1}^{n}\mathbf{s}_k^T\mathbf{C}^{-1}\mathbf{s}_k + \sum_{k=1}^{n}\sum_{\substack{k'=1\\k'\neq k}}^{n}\mathbf{s}_k^T\mathbf{C}^{-1}\mathbf{s}_{k'}\right), \end{aligned} \tag{6.17}$$

where we have defined $\mathbf{C} = g^2\sigma_v^2\mathbf{S}\mathbf{S}^T + \sigma_w^2\mathbf{I}$. Let $\mathcal{I}$ denote a set of sensor indices (i.e., $\mathcal{I} \subset \{1, 2, \cdots, n\}$), $\mathbf{S}_{\mathcal{A}}$ denote the matrix $\mathbf{S}$ with column indices specified by set $\mathcal{A}$ deleted, $\Lambda_k = g^2\sigma_v^2\mathbf{I}_k$ and $\mathbf{Q}_{\mathcal{A}} = \left(\mathbf{S}_{\mathcal{A}}\Lambda_{n-|\mathcal{A}|}\mathbf{S}_{\mathcal{A}} + \sigma_w^2\mathbf{I}_n\right)$, where $\mathbf{I}_k$ and $|\mathcal{A}|$ denote the $k\times k$ identity matrix and the cardinality of set $\mathcal{A}$, respectively. Then, using the matrix inversion lemma[2] we can show that, for $k = 1, \cdots, n$,

$$\mathbf{s}_k^T\mathbf{C}^{-1}\mathbf{s}_k = \mathbf{s}_k^T\mathbf{Q}_{\{k\}}^{-1}\mathbf{s}_k / \left(1 + g^2\sigma_v^2\mathbf{s}_k^T\mathbf{Q}_{\{k\}}^{-1}\mathbf{s}_k\right). \tag{6.18}$$

The key to large system asymptotic analysis in this situation is the theory of large random matrices [57]. In particular, under the assumed conditions for signaling codes, the empirical distribution of eigenvalues of the large random matrix $\mathbf{R}$ converges almost surely to a deterministic distribution characterized by the parameter α [58–60]. Applying Theorem 7 of [60], which essentially relies on the above result, and using (6.11), we can show that [24],

$$\mathbf{s}_k^T\mathbf{Q}_{\{k\}}^{-1}\mathbf{s}_k \overset{\text{a.s.}}{\longrightarrow} \frac{\beta_0}{\sigma_w^2}, \tag{6.19}$$

where $\beta_0 = \frac{\sqrt{(\gamma+\sigma_w^2)^2\alpha^2+2\gamma(\sigma_w^2-\gamma)\alpha+\gamma^2}-(\gamma+\sigma_w^2)\alpha+\gamma}{2\gamma}$ and $\gamma = \frac{P}{N(1+\frac{\gamma_0}{2})}$. Substituting (6.19) in (6.18) we have, for $k = 1, \cdots, n$,

$$\mathbf{s}_k^T\mathbf{C}^{-1}\mathbf{s}_k \overset{\text{a.s.}}{\longrightarrow} \left(\frac{\sigma_w^2}{\beta_0} + g^2\sigma_v^2\right)^{-1}. \tag{6.20}$$

Similarly, repeated application of the matrix inversion lemma twice yields, for $k \neq k'$

$$\mathbf{s}_k^T\mathbf{C}^{-1}\mathbf{s}_{k'} = \frac{\mathbf{s}_k^T\mathbf{Q}_{\{k,k'\}}^{-1}\mathbf{s}_{k'}}{\left(1 + g^2\sigma_v^2\mathbf{s}_k^T\mathbf{Q}_{\{k\}}^{-1}\mathbf{s}_k\right)\left(1 + g^2\sigma_v^2\mathbf{s}_{k'}^T\mathbf{Q}_{\{k,k'\}}^{-1}\mathbf{s}_{k'}\right)} \overset{\text{a.s.}}{\longrightarrow} 0. \tag{6.21}$$

where we have again used Theorem 7 of [60] in the last step to obtain (6.21). Substituting (6.20) and (6.21) in (6.17) gives

$$g^2\mathbf{1}^T\mathbf{R}\boldsymbol{\Sigma}^{-1}\mathbf{R}\mathbf{1} \overset{\text{a.s.}}{\longrightarrow} \left(\frac{\sigma_v^2}{n} + \frac{\sigma_v^2\left(1+\frac{\gamma_0}{2}\right)}{\gamma_c\beta_0}\right)^{-1}. \tag{6.22}$$

This asymptotic convergence result can be used to characterize the large sensor system Bayesian fusion error probability when $\lim_{N\longrightarrow\infty}\frac{n}{N} = \alpha$. Substituting (6.22) in (6.16) gives,

$$P_e(\alpha) \overset{\text{a.s.}}{\longrightarrow} Q\left(\frac{m}{2\sqrt{\frac{\sigma_v^2}{n} + \frac{\sigma_v^2(1+\frac{\gamma_0}{2})}{\gamma_c\beta_0}}}\right). \tag{6.23}$$

[2] If $\mathbf{A}$, $\mathbf{C}$ and $\left(\mathbf{C}^{-1} + \mathbf{D}\mathbf{A}^{-1}\mathbf{B}\right)$ are all nonsingular square matrices, then $(\mathbf{A} + \mathbf{B}\mathbf{C}\mathbf{D})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{B}\left(\mathbf{C}^{-1} + \mathbf{D}\mathbf{A}^{-1}\mathbf{B}\right)^{-1}\mathbf{D}\mathbf{A}^{-1}$.

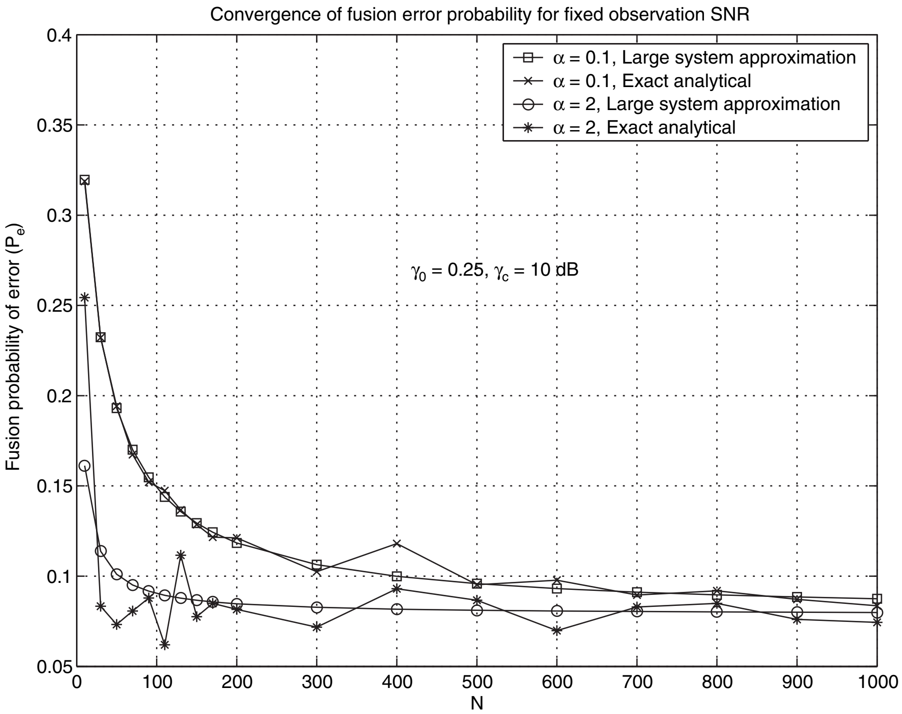

Figure 6.3 Large Sensor System Fusion Performance in a Noisy, Bandlimited Channel Subjected to a Total Power Constraint

Figure 6.3 shows the convergence of the random waveform based decentralized detection performance as predicted by (6.23). Note that the exact analysis result in Figure 6.3 was obtained from (6.16) by using a random choice of the code matrix **S** where the large system approximation results are from (6.23). As can be seen from Figure 6.3, (6.23) provides a very good approximation to the fusion performance for large code lengths N, and thus for large-sensor systems (because $n = N\alpha$). More importantly, we can observe from Figure 6.3 that for each fixed N, increasing α improves the decentralized detection performance. Because this is equivalent to increasing the number of sensors n allowed in the system for a fixed bandwidth, we conclude that it is better to allow as many sensors to send their local decisions to the fusion center.

In fact, for large α, one can show that $\beta_0 \xrightarrow{\text{a.s.}} 1$, and as a result in this case, the error probability in (6.23) goes to (see Figure 6.4).

$$P_e(\alpha) \longrightarrow Q\left(\frac{1}{2}\sqrt{\frac{\gamma_c}{\frac{1}{2}+\frac{1}{\gamma_0}}}\right). \tag{6.24}$$

On the other hand, if one were to allocate all available power P and the total bandwidth to just one sensor node, the fusion center performance will be given by

$$P_{e,1} = Q\left(\sqrt{\frac{\gamma_c}{\frac{\gamma_c}{\gamma_0}+\frac{1}{\gamma_0}+\frac{1}{2}}}\right). \tag{6.25}$$

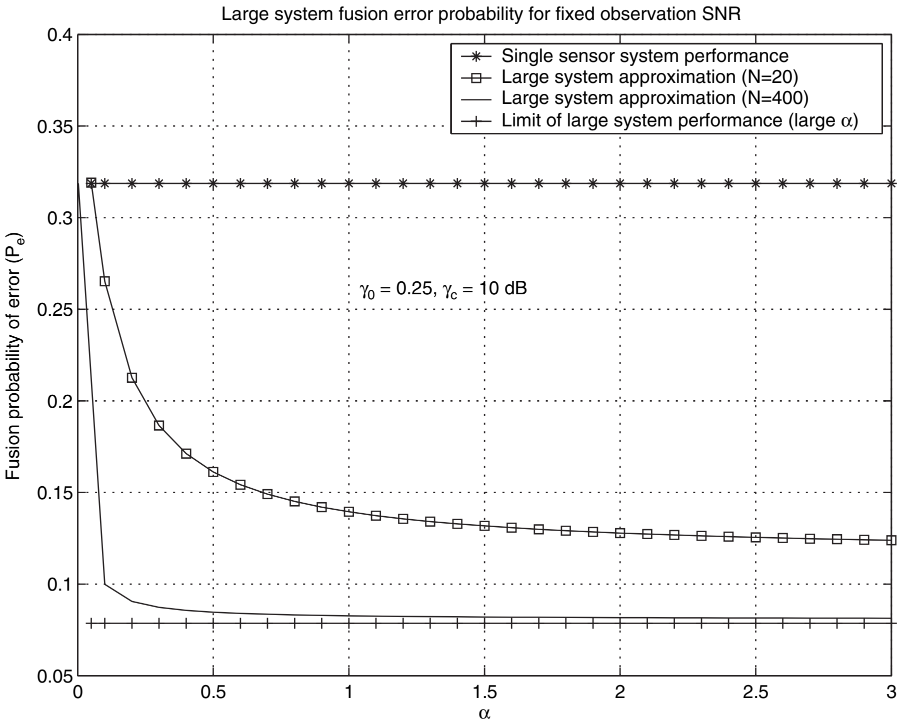

Figure 6.4 Limit of Large Sensor System Approximation to the Fusion Performance in a Noisy, Bandlimited Channel Subjected to a Total Power Constraint when $\alpha \longrightarrow \infty$

Comparison of (6.24) and (6.25) shows that allowing more sensor nodes in the network is even better if the channel is both noisy and bandlimited. This comparison is shown in Figure 6.4, in which the limit of large system performance and the single sensor system performance refer to, respectively, (6.24) and (6.25). The large system approximations for finite N values shown in Figure 6.4 were obtained from (6.23). First, observe from Figure 6.4 that as N increases the fusion center performance improves. Secondly, note that as $N \longrightarrow \infty$, the performance for large α indeed goes to (6.24). Third, Figure 6.4 confirms that combining more local decisions is better than allocating all available power and bandwidth to one sensor. Moreover, the performance improves monotonically with increasing α (for a fixed N) showing that it is better to combine as many local decisions as possible at the fusion center. We should divide the available power among all nodes and allow them to share the available bandwidth, even if they interfere with each other due to nonorthogonality.

6.4.2 Distributed Detection of a Random Gaussian Signal in a Total Power and Bandwidth Constrained System

In the previous section, we could derive the exact fusion error probability in closed form for any finite n due to the assumed simplicity of the model. In particular, if instead of a deterministic signal, the POI to be detected happened to be a random signal (e.g., a

Gaussian signal), the analysis quickly becomes much more difficult. The present convenience is quickly lost when we consider more involved signaling and channel models. In those situations, asymptotic performance analysis (for large n) becomes a necessity in order to establish any meaningful characterization of performance. Recently, several works have employed large deviations theories and error exponent analysis to achieve this goal. In this section, we illustrate some of these ideas in fusion performance analysis, assuming the POI to be detected in (6.2) to be a zero-mean Gaussian signal such that $X_k \sim \mathcal{N}(0, \sigma_x^2)$, for $k = 1, \cdots, n$. Again assuming both signal of interest and the additive noise V_k are independent at each node, the set of observation noise samples and the set of desired signal samples are then distributed as $\mathbf{A} \sim \mathcal{N}(\mathbf{0}, \sigma_v^2\mathbf{I})$ and $\mathbf{X} \sim \mathcal{N}(\mathbf{0}, \sigma_x^2\mathbf{I})$, respectively. Accordingly, we redefine the local observation quality SNR at each node as $\gamma_0 \stackrel{\Delta}{=} \frac{\sigma_x^2}{\sigma_v^2}$.

As before, assume that the local decisions sent to the fusion center are generated via analog-relay amplifier processing, so that $U_k = g_k Z_k$, for $k = 1, \cdots n$, where $g_k > 0$ is the gain at the k-th node that depends on either the global system power constraint P on the whole sensor system. For simplicity, suppose also that $g_k = g$ for all k, and that the k-th node transmits its local decision U_k to the fusion center after modulating it with a normalized signaling waveform $\mathbf{s}_k$. A sufficient statistic for the fusion center processing is again given by $\mathbf{Y}$ in (6.8). The matrix $\mathbf{R} = \mathbf{S}^T\mathbf{S}$ in which the (k, k')-th element is given by $\mathbf{s}_k^T\mathbf{s}_{k'}$ reflects the possible nonorthogonality of signaling due to a finite total bandwidth constraint. Under the global average power constraint P on the system, the local amplifier gain is now given by

$$g^2 = \frac{P}{n\left(\sigma_v^2 + \frac{\sigma_x^2}{2}\right)}. \tag{6.26}$$

With these definitions, the new fusion problem is reduced to the following binary hypothesis testing problem

$$\begin{aligned} H_0: &\quad \mathbf{y} \sim p_0(\mathbf{y}) \;=\; \mathcal{N}(\mathbf{0}, \Sigma) \\ H_1: &\quad \mathbf{y} \sim p_1(\mathbf{y}) \;=\; \mathcal{N}\left(\mathbf{0}, g^2\sigma_x^2\mathbf{R}^2 + \Sigma\right), \end{aligned}$$

where $p_j(\mathbf{y})$ is the density of $\mathbf{Y}$ under the hypothesis H_j, for $j = 0, 1$, and Σ is as defined in (6.10). The optimal (e.g. Bayesian, minimax or Neyman–Pearson) fusion rules should then be based on the LR $\mathcal{L}(\mathbf{y}) = \frac{p_1(\mathbf{y})}{p_0(\mathbf{y})}$ that can be written as

$$\mathcal{L}(\mathbf{y}) = \left(\frac{|\Sigma|}{|g^2\sigma_x^2\mathbf{R}^2 + \Sigma|}\right)^{\frac{1}{2}} \exp\left(\frac{1}{2}\mathbf{y}^T\left(\Sigma^{-1} - \left(g^2\sigma_x^2\mathbf{R}^2 + \Sigma\right)^{-1}\right)\mathbf{y}\right). \tag{6.27}$$

Let us define the spectral decomposition of $\mathbf{R}$ to be $\mathbf{R} = \sum_{k=1}^n \lambda_k \boldsymbol{\xi}_k \boldsymbol{\xi}_k^T$. Under the assumption that the signaling waveforms (equivalently, codes) of the sensors are all linearly independent of each other, the set of orthonormal eigenvectors $\boldsymbol{\xi}_k$s forms a complete basis for $\mathbb{R}^n$ and λ_k's are the corresponding eigenvalues. In that case, we have that $\mathbf{R}^2 = \sum_{k=1}^n \lambda_k^2 \boldsymbol{\xi}_k \boldsymbol{\xi}_k^T$ and $\Sigma = \sum_{k=1}^n \left(g^2\sigma_v^2\lambda_k + \sigma_w^2\right) \lambda_k \boldsymbol{\xi}_k \boldsymbol{\xi}_k^T$. Using these in (6.27) leads to

$$\mathcal{L}(\mathbf{y}) = \exp\left(\frac{1}{2}\sum_{k=1}^{n}\frac{g^2\sigma_x^2}{(g^2\sigma_v^2\lambda_k+\sigma_w^2)\left(g^2\left(\sigma_x^2+\sigma_v^2\right)\lambda_k+\sigma_w^2\right)}|\boldsymbol{\xi}_k^T\mathbf{y}|^2\right)$$

$$\times\prod_{k=1}^{n}\left(\frac{g^2\sigma_v^2\lambda_k+\sigma_w^2}{g^2(\sigma_x^2+\sigma_v^2)\lambda_k+\sigma_w^2}\right)^{\frac{1}{2}}. \tag{6.28}$$

For $k = 1, \cdots, n$, let us define a new set of random variables $\bar{Y}_1, \cdots, \bar{Y}_n$ by projecting the observation vector $\mathbf{Y}$ onto each of the eigenvectors $\boldsymbol{\xi}_k$ followed by scaling:

$$\bar{Y}_k = \sqrt{\frac{g^2\sigma_x^2}{(g^2\sigma_v^2\lambda_k+\sigma_w^2)\left(g^2\left(\sigma_x^2+\sigma_v^2\right)\lambda_k+\sigma_w^2\right)}}\boldsymbol{\xi}_k^T\mathbf{r}. \tag{6.29}$$

Due to the orthonormality of $\boldsymbol{\xi}_k$s, it is easy to show that $\bar{Y}_k$s are a set of zero-mean independent Gaussian random variables under both hypotheses, that is equivalent to the original statistic $\mathbf{y}$. However, Y_ks are not identically distributed under either hypothesis. In fact, if the variance of the k-th sample $\bar{Y}_k$ under H_j is $\sigma_{j,k}^2$, for $j = 0, 1$, and $k = 1, \cdots, n$, then it can be shown that

$$\sigma_{j,k}^2 = \begin{cases} \frac{g^2\sigma_x^2\lambda_k}{g^2(\sigma_x^2+\sigma_v^2)\lambda_k+\sigma_w^2} & \text{if } j=0 \\ \frac{g^2\sigma_x^2\lambda_k}{g^2\sigma_v^2\lambda_k+\sigma_w^2} & \text{if } j=1 \end{cases}. \tag{6.30}$$

Substitution of (6.29) in (6.28) allows us to write the fusion center LR as

$$\mathcal{L}(\mathbf{y}) = \exp\left(\frac{1}{2}\sum_{k=1}^{n}|\bar{y}_k|^2\right)\prod_{k=1}^{n}\left(\frac{g^2\sigma_v^2\lambda_k+\sigma_w^2}{g^2(\sigma_x^2+\sigma_v^2)\lambda_k+\sigma_w^2}\right)^{\frac{1}{2}}. \tag{6.31}$$

The optimal fusion decision rule is then given by

$$\delta_{opt}(\mathbf{y}) = \begin{cases} 1 & \\ & \text{if } T\left(\mathbf{y}\right) \begin{matrix}\geq \\ \\ <\end{matrix} \tau', \\ 0 & \end{cases} \tag{6.32}$$

where

$$\tau' = 2\log\tau + \sum_{k=1}^{n}\log\left(\frac{g^2(\sigma_x^2+\sigma_v^2)\lambda_k+\sigma_w^2}{g^2\sigma_v^2\lambda_k+\sigma_w^2}\right), \tag{6.33}$$

and the decision variable T is the quadratic form $T\left(\mathbf{y}\right) = \sum_{k=1}^{n}|\bar{y}_k|^2$. We again restrict our discussion to the minimum probability of error in Bayes detection with equal priors so that $\tau = 1$.

In certain special circumstances one can evaluate the exact probability of error P_e of the optimal quadratic detector (6.32) in closed form. A common method in such situations is to obtain good error bounds or error exponents. While they may not be exact, in most situations error exponents (and the bounds based on them) can be helpful in characterizing the performance of a detection procedure. The most commonly used bound for Bayesian detection is the Chernoff upper bound to the probability of error which (assuming equal priors) can be written as $P_e \leq \frac{1}{2}e^{\mu_C}$, where the Chernoff error exponent is defined as [11]

$$\mu_C = \min_{s\in[0,1]} \log \mathbb{E}\left\{\mathcal{L}^s(\mathbf{r})|H_0\right\}. \tag{6.34}$$

Although somewhat looser than the Chernoff bound, an easier-to-evaluate related bound is the Bhattacharyya upper bound. Specifically, analogous to the Chernoff error exponent, we define the Bhattacharyya error exponent as

$$\mu_B = \log \mathbb{E}\left\{\mathcal{L}^{\frac{1}{2}}(\mathbf{r})|H_0\right\}, \tag{6.35}$$

so that the Bhattacharyya upper bound to the probability of error is given by $P_e \leq \frac{1}{2}e^{\mu_B}$.

The special case in which performance can be characterized in closed form is the orthogonal signaling: i.e., $\mathbf{R} = \mathbf{I}$. In this case, it is easy to show that the $\bar{Y}_k$s are a collection of independent Gaussian random variables such that:

$$H_0: \quad \bar{Y}_k \sim \mathcal{N}\left(0, \sigma_0^2\right)$$

$$H_1: \quad \bar{Y}_k \sim \mathcal{N}\left(0, \sigma_1^2\right),$$

where,

$$\sigma_j^2 = \begin{cases} \frac{g^2\sigma_x^2}{\sigma_w^2+g^2(\sigma_x^2+\sigma_v^2)} & \text{if } j=0 \\ \frac{g^2\sigma_x^2}{\sigma_w^2+g^2\sigma_v^2} & \text{if } j=1 \end{cases}$$

$$= \begin{cases} \frac{\gamma_0}{1+\gamma_0+\frac{n}{\gamma_c}(1+\frac{\gamma_0}{2})} & \text{if } j=0 \\ \frac{\gamma_0}{1+\frac{n}{\gamma_c}(1+\frac{\gamma_0}{2})} & \text{if } j=1 \end{cases}. \tag{6.36}$$

Hence, the decision variable T is a Gamma random variable of the form $T \sim G\left(\frac{n}{2}, \frac{1}{2\sigma_j^2}\right)$ under the hypotheses H_j. The false alarm and the miss probabilities of the detector (6.32) can then be computed as

$$P_f = 1 - \frac{\Gamma\left(\frac{n}{2}; \frac{\tau'}{2\sigma_0^2}\right)}{\Gamma\left(\frac{n}{2}\right)}, \tag{6.37}$$

and

$$P_m = \frac{\Gamma\left(\frac{n}{2}; \frac{\tau'}{2\sigma_1^2}\right)}{\Gamma\left(\frac{n}{2}\right)}, \tag{6.38}$$

where $\Gamma(a) = \int_0^\infty e^{-y} y^{a-1} dy$ is the Gamma function and $\Gamma(a, t) = \int_0^t e^{-y} y^{a-1} dy$ is the incomplete Gamma function. In addition, the threshold τ' in (6.33) simplifies to

$$\tau' = 2 \log \tau + n \log \left(\frac{g^2 \sigma_v^2 (1 + \gamma_0) + \sigma_w^2}{g^2 \sigma_v^2 + \sigma_w^2} \right)$$

$$= n \log \left(1 + \frac{\gamma_c \gamma_0}{n \left(1 + \frac{\gamma_0}{2}\right) + \gamma_c} \right), \tag{6.39}$$

where in the last step we used the fact $\tau = 1$. Substitution of definitions for γ_c and γ_0 gives the minimum error probability achieved by the optimal Bayesian fusion rule for a random Gaussian signal to be

$$P_e = \frac{1}{2} \left[1 + \frac{\Gamma\left(\frac{n}{2}; \frac{\tau'}{2\sigma_1^2}\right) - \Gamma\left(\frac{n}{2}; \frac{\tau'}{2\sigma_0^2}\right)}{\Gamma\left(\frac{n}{2}\right)} \right], \tag{6.40}$$

where σ_0^2 and σ_1^2 are given by (6.36).

Note from (6.39) that for minimum probability of error criterion with equal priors is

$$\lim_{n \longrightarrow \infty} \tau' = \frac{\gamma_c}{\frac{1}{2} + \frac{1}{\gamma_0}}. \tag{6.41}$$

Taking the limit in (6.40) with the aid of (6.41), it can be shown that

$$\lim_{n \longrightarrow \infty} P_e = 0.5. \tag{6.42}$$

Moreover, the minimum fusion error probability exhibits the following asymptotic in the observation SNR:

Au: Missing word?

$$\lim_{\gamma_0 \longrightarrow \infty} P_e = \frac{1}{2} \left(1 - \frac{\Gamma\left(\frac{n}{2}; t_0\right) - \Gamma\left(\frac{n}{2}; t_1\right)}{\Gamma\left(\frac{n}{2}\right)} \right), \tag{6.43}$$

where $t_0 = t_1 + \frac{n}{2} \log \left(1 + \frac{\gamma_c}{n/2}\right)$ and $t_1 = \frac{n^2}{4\gamma_c} \log \left(1 + \frac{\gamma_c}{n/2}\right)$.

Investigating the fusion error behavior given by (6.40) shows that the final fusion performance is not monotonic in the number of nodes n. Additionally, (6.42) shows that in contrast to the deterministic signal fusion considered earlier, dividing the available total power infinitesimally among many sensors is bound to degrade the performance. In fact, as can be seen from Figure 6.5, there is an optimal number of sensor nodes for each γ_0 and γ_c combination beyond which the performance monotonically degrades. Figure 6.6 shows the convergence of fusion probability of error to the asymptotic bound (6.43) for large γ_0 values.

The exact fusion error probability in (6.40), however, is too complicated for investigating this optimal number of nodes, $n = n_0$, that leads to the lowest possible error probability. To that purpose, we resort to the error exponents. It can be shown that the Chernoff and Bhattacharyya error exponents for this situation are given by [43],

$$\mu_C = \frac{n}{2} \left[\log \frac{1 + \sigma_1^2}{1 + (1 - s_0)\sigma_1^2} - s_0 \log \left(1 + \sigma_1^2\right) \right] \tag{6.44}$$

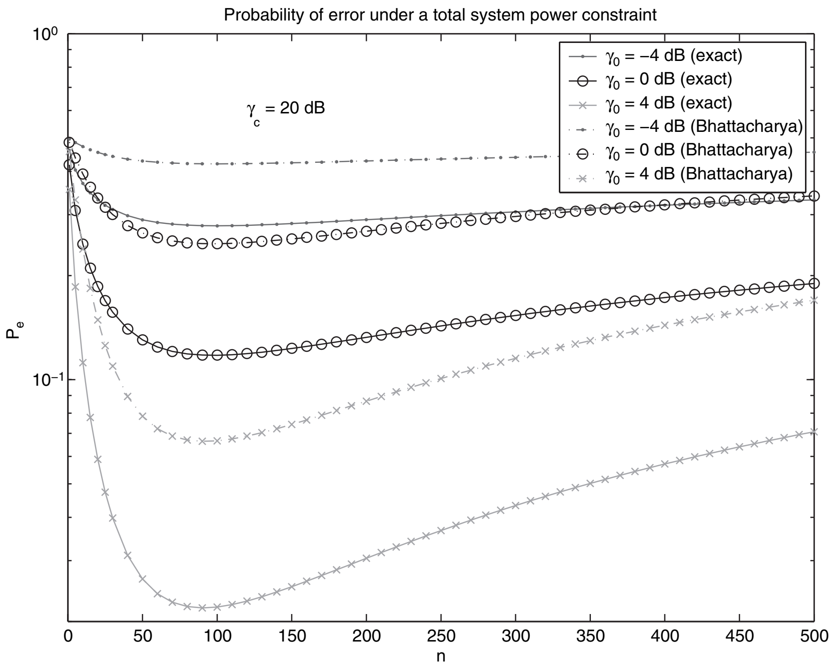

Figure 6.5 Exact and the Bhattacharyya Upper-bound to the Minimum Achievable Fusion Probability of Error in Distributed Detection of a Random Signal with Orthogonal Sensor-to-Fusion Center Communication under a Global Power Constraint. $\gamma_c = 20$ dB

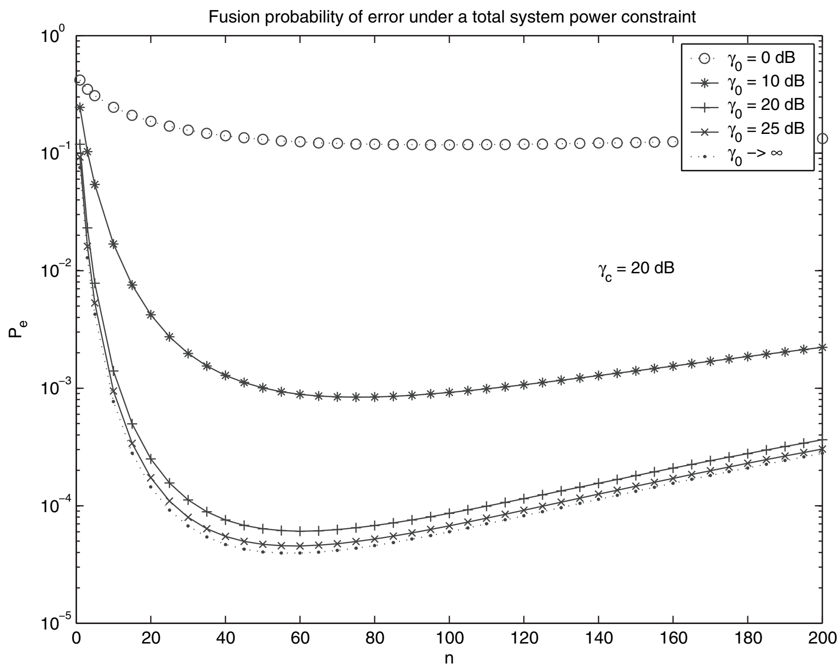

Figure 6.6 Large γ_0 Limiting Behavior of the Minimum Achievable Fusion Probability of Error in Distributed Detection of a Random Signal with Orthogonal Sensor-to-Fusion Center Communication under a Global Power Constraint. $\gamma_c = 20$ dB

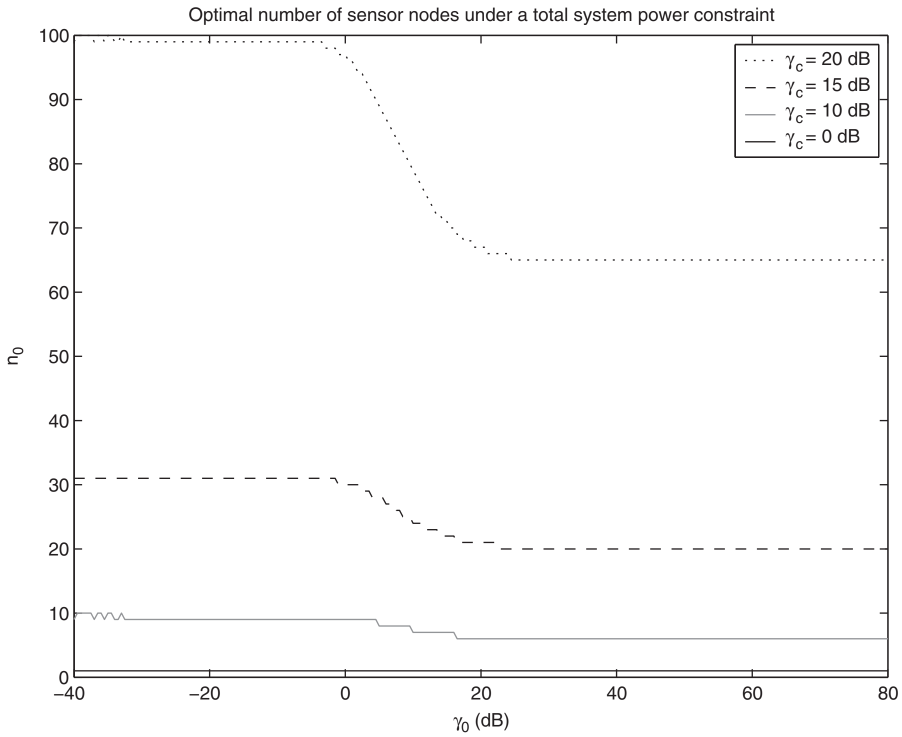

Figure 6.7 Optimal Number of Sensor Nodes as a Function of the Observation SNR for a Given Channel SNR. The System is Under a Global System Power Constraint with Orthogonal Sensor-to-Fusion Center Communication

and

$$\mu_B = \frac{n}{2}\left[\frac{1}{2}\log\left(1+\sigma_1^2\right) - \log\left(1+\frac{\sigma_1^2}{2}\right)\right], \tag{6.45}$$

where $s_0 = 1 + \frac{1}{\sigma_1^2} - \frac{1}{\log(1+\sigma_1^2)}$ in (6.44). Interestingly, using the fact that $\sigma_1^2 \ll 1$ for $n \gg 1$, one can show that $\lim_{n\longrightarrow\infty} \mu_B = 0$. This indicates that the Bhattacharyya upper bound to the error probability goes to unity, suggesting that fusion error may also degrade in large systems. Figure 6.5 includes the behavior of μ_B as a function of n for a fixed γ_c. Clearly there is an optimal value of n for which the μ_B-based bound is also minimized. Although the bound could be somewhat loose, the optimal $n = n_0$ for the Bhattacharyya bound seems to be almost the same as that for the exact error probability. This motivates the use of the Bhattacharyya exponent as the basis for optimizing the sensor system size due to its relative simplicity.

Using standard optimization techniques, it was shown in [43] that in orthogonal signaling ($\rho = 0$) under a global power constraint P, the optimal number of nodes n_0 that results in the minimum Bhattacharyya upper bound to the fusion error probability is given by,

$$n_0 = \gamma_c\left(\frac{1}{2x_0} - \frac{1}{\gamma_0}\right)\left(\frac{1}{2} + \frac{1}{\gamma_0}\right)^{-1}, \tag{6.46}$$

where $x = x_0$ is the unique positive solution to the equation $f_{\gamma_0}(x) = 0$ with $f_{\gamma_0}(x) = \log \frac{\sqrt{1+2x}}{1+x} + \left(1 - 2x/\gamma_0\right) \frac{x^2}{(1+x)(1+2x)}$. This optimal number of sensors can also be approximated as follows (where $\tilde{x}_0 \approx 1.535$):

$$n_0 \approx \begin{cases} \gamma_c/\tilde{x}_0 & \text{if } \gamma_0 \gg 1 \\ \gamma_c & \text{if } \gamma_0 \ll 1 \end{cases}. \tag{6.47}$$

Figure 6.7 shows the optimal number of nodes $n = n_0$ for distributed detection of a stochastic signal under a global power constraint obtained via the exact solution to the zero of f_{γ_0}. Figure 6.7 also shows that the asymptotic solutions given in (6.47) provide a very good approximation except for a small range of values for the observation SNR γ_0. In the case of nonorthogonal communication with an equicorrelated signaling model, [43] generalized the above approach to obtain the final fusion performance as well as the optimal number of sensors to use.

6.5 FUTURE DIRECTIONS

In channel-aware decision fusion, the decentralized detection system needs to be adapted to the conditions of the sensor-to-fusion center communication channel. Recently, [61] pointed out how the design of quantizers at distributed nodes could be optimized depending on the channel state information. However, such an optimization procedure is in general complex, and is restricted to relatively small-size networks. Thus alternative channel-aware decision fusion techniques are to be developed in the future. In particular, instantaneous CSI-based low-complexity, adaptive local decision rules at the distributed nodes as well as adaptive fusion rules are to be investigated.

In large networks, communications between sensors and fusion centers need to be coordinated with a multiple access channel (MAC) algorithm. With bandwidth constraints, a typical MAC protocol might provide nonorthogonal links thereby causing multiple-access interference. While this issue was addressed for a DS-CDMA-based sensor system in [24], as we discussed in Section 6.4, this remains a topic for further research.

The interplay between sensing, signal processing, and communications in wireless sensor networks is discussed in a recent special issue [62]. Some of the topics presented there have a direct bearing on the research issues presented here. Other future research directions include decentralized estimation/detection with correlated sensor data, when correlation models are derived from realistic physical measurements and a study of reliability achievable through codes, such as low density parity check (LDPC) codes, which may be employed in sensor communication links.

6.6 CHAPTER SUMMARY

In this chapter we reviewed the recent advances in distributed signal processing in resource-constrained wireless sensor networks. The particular attention was on distributed detection and decision fusion in large sensor systems. However, we also briefly outlined recent results on distributed estimation.

We first described the basic problem of distributed detection and fusion in the specific context of wireless sensor networks. The recent work on this topic differs from that of early work in the sense that, in wireless sensor networks, the communication errors between the distributed nodes and the decision fusion center are nonnegligible. This is due to the unreliable nature of wireless channels (due to fading, shadowing, and interference) as well as limited resources (limited battery power and finite channel bandwidth) in wireless sensor networks. We discussed some important recent work that has specifically taken into account such channel errors in distributed detection and fusion system design and performance analysis. We were particularly interested in outlining large system analysis based results that provide useful insight into the fusion system performance.

In the final section of this chapter, we distnctly considered a specific wireless sensor system in which local processing is assumed to be analog-relay amplifier processing. The fusion center performance was investigated for a distributed binary hypothesis testing problem assuming that the sensor network is both power as well as bandwidth limited. We showed one of the interesting conclusions regarding deterministic versus random signal detection in this context, i.e., while in the case of a deterministic signal it is better to divide the available power and bandwidth among as many nodes as possible, in the case of a random signal there is an optimal number of nodes that provides the best fusion performance. A large system analysis was employed to characterize this fusion performance and obtain the optimal number of nodes to be used.

Finally, we have outlined several open issues and future research directions in Section 6.5.

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