Serial Distributed Detection for Wireless Sensor Networks

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***Abstract*— Serial distributed detection for wireless sensor networks is studied in this paper. Unlike the traditional serial distributed detection schemes where it is assumed that the sensor decision at one stage is known exactly to the subsequent sensor node, we assume that the links between the consecutive sensor nodes are subject to fading and additive noise resulting in corruption of the transmitted decisions. Incorporating the effect of fading in the detection process, a decision fusion rule based on likelihood ratio tests is derived. Optimality of likelihood ratio test is also investigated. By numerical examples, we illustrate the performance of the proposed serial detection scheme and compare it with that of the parallel distributed detection.**

I. INTRODUCTION

Recently, wireless sensor networks (WSNs) have emerged as a new technology that experiences a pervasive trend in many application areas including environment monitoring, health, security and surveillance, and robotic exploration [1]. Networks of sensor systems allow for many distributed processing and cooperative communication techniques including distributed data compression [2], tracking and classification [3], and distributed detection [4,5]. In this paper, our focus is on distributed detection that are specially tailored for wireless sensor networks. In distributed detection, each sensor sends its observation to the fusion center where a global decision is made. Because of the bandwidth and energy limitations, instead of transmitting the raw data, each sensor performs a local detection process and sends its decision (possibly consisting of a few bits) to the fusion center. The fusion center collects all decisions from all sensors and performs a final decision on the hypothesis under investigation.

In the literature, distributed detection has been considered for three major topologies: parallel, serial, and tree configuration [4]. Several distributed detection algorithms have been investigated for such configurations [4–7]. Optimal distributed detection algorithms have been focused on optimality under the Neyman-Pearson and Bayesian detection criteria. Under the assumption of conditionally independent observations, the optimal fusion rules are given by likelihood ratio (LR) tests at the individual sensors and at the fusion center [8]. For conditionally dependent observations, the optimal fusion rules become intractable: they do not reduce to LR tests [9,10]. Recently, distributed detection algorithms have also been investigated under several communication-constraints [2,11,12]. Chamberland and Veeravalli [12] showed that under certain conditions, for an N-sensor network with a capacity constraint of N bits per time unit, having each sensor transmitting one bit is optimum. Thomopoulos and Zhang investigates the distributed detection in the case of non-ideal channels [13]. In [14], Duman and Salehi consider the distributed detection over multi access channels where the fusion center gathers the decisions from local sensors via a multi-access channel.

All the aforementioned algorithms assume that the sensor decision statistics, either quantized or at full precision, can be transmitted error-free to the fusion center. Even though this assumption is valid in traditional sensor networks such as radars and sonar [8], it is impractical in wireless sensor networks where wireless links are subject to fading and interference. Furthermore, due to bandwidth and energy constraints, the use of powerful error correction codes is not viable. Recently, Chen et al. introduced channel-based decision fusion for a parallel network of sensors linked with fading channels [6,15,16]. Assuming parallel configuration, the authors incorporate the effect of fading in the detection process, and derive optimal fusion rules and some alternative fusion rules based on diversity combining techniques. In [17], a similar decision fusion for a multihop transmission is considered. While the performance of the decision fusion based on some suboptimal methods are evaluated in these work, the optimality of the decision rules at local sensors and at the fusion center, and optimal designs are not considered. Recently, Chen and Willet have sown that optimal local decisions that minimize the error probability at the fusion center becomes a likelihood-ratio (LR) test under some particular constraints on the fusion rule [18].

In this paper, we consider the problem of binary serial distributed detection in wireless sensor networks. Our main goal is to analyze the performance of serial distributed detection scheme, and in particular, to develop tools to design the optimal detection rules under the assumption that the channels between consecutive sensor nodes are subject to flat fading. Using Neyman-Pearson criterion as a benchmark, we derive LR-based decision fusion rules and investigate their

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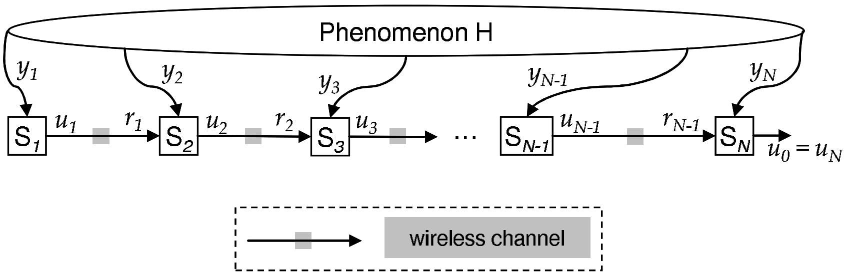


Fig. 1. Serial configuration for distributed detection for wireless sensor networks with fading channels

detection performance. For simple cases, we design optimal detection rules and compare the performance with the parallel fusion structure. Finally, using numerical examples, we illustrate the optimality of LR-test based serial detection and its performance for Rayleigh fading channels. The proposed distributed detection scheme is especially suitable for multihop transmission that is usually energy-efficient for large-scale sensor networks. One can also employ the serial detection in clustered sensor networks since local sensors may still use multihop strategy to reach the cluster head node.

The organization of the paper is as follows: In Section II, we describe the distributed detection structure being considered. We derive the decision fusion rules and the relevant equations for false alarm and detection probabilities in Section III. Section IV investigates the optimality of the LR based fusion at the local sensors and at the fusion center. The numerical examples are presented in Section V and finally, the conclusions are summarized in Section VI.

II. System Model

The block diagram of a serial network for distributed detection is depicted in Fig. 1. $u_j \in \{0, 1\}$ denotes the binary decision at the j^{th} sensor node, S_j. Binary modulation is used for transmitting the decisions from S_{j-1} to S_j. Assuming frequency flat fading and additive noise at each link, the received signal at S_j, denoted by r_{j-1}, is given by

$$r_{j-1} = \sqrt{\rho_{j-1}} g_{j-1} s_{j-1} + n_{j-1} \tag{1}$$

where g_{j-1} is the complex-valued channel gain between S_{j-1} and S_j, and n_{j-1} is the additive noise at S_j. Both g_{j-1} and $n_{j-1} \sim \mathcal{CN}(0, 1)^*$, and they are independent and identically distributed for $j = 2, \cdots, N$. We assume that channel state information (CSI), *i.e.,* g_{j-1}, can be estimated at S_j and can be forwarded to the fusion center with a control channel. The average energy of the transmitted signal is normalized to unity so that ρ_{j-1} is the signal-to-noise ratio (SNR) at stage j. It is possible to perform a suitable power allocation to improve the power-detection performance tradeoff. Since this will incur additional cost for the optimal detector design, we assume that each sensor transmits at the same power level, and hence, we set $\rho_{j-1} = \rho$, for $j = 2, \ldots, N$. Thus, we derive the optimal detection rules for a uniform power allocation scheme.

The decision at the j^{th} stage is based on the observation, y_j, and the received signal r_{j-1}. We assume that the observations and the received signals at the sensors are statistically independent conditioned on the hypothesis. That is, y_j and r_{j-1} are conditionally independent. We define the false alarm and detection probabilities at S_j as $P_{F,j} = \Pr(u_j = 1|H_0)$, $P_{D,j} = \Pr(u_j = 1|H_1)$. Our goal is to derive fusion rules based on the Neyman-Pearson lemma, that is, for a prescribed bound on the global false alarm rate, $P_{F,N}$, we wish to find the decision rules that maximize the global detection rate, $P_{D,N}$.

III. Serial Detection Rule for Fading Channels

A. Serial Detection

According to Neyman-Pearson lemma, the optimal decision rules at each stage reduces to LR tests, where the LR at the j^{th} stage can be computed using the received signal r_{j-1} and the observation y_j:

$$\begin{aligned}\Gamma(y_j, r_{j-1}) &= \frac{L(y_j, r_{j-1}|H_1, g_{j-1})}{L(y_j, r_{j-1}|H_0, g_{j-1})} \\ &= \frac{p(y_j|H_1)p(r_{j-1}|H_1, g_{j-1})}{p(y_j|H_0)p(r_{j-1}|H_0, g_{j-1})}\end{aligned} \tag{2}$$

where

$$\begin{aligned}p(r_{j-1}|H_1, g_{j-1}) = P_{D,j-1} p_n(r_{j-1} - \sqrt{\rho} g_{j-1} s^1) \\ +(1 - P_{D,j-1}) p_n(r_{j-1} - \sqrt{\rho} g_{j-1} s^0)\end{aligned} \tag{3}$$

$$\begin{aligned}p(r_{j-1}|H_0, g_{j-1}) = P_{F,j-1} p_n(r_{j-1} - \sqrt{\rho_j} g_{j-1} s^1) \\ +(1 - P_{F,j-1}) p_n(r_{j-1} - \sqrt{\rho} g_{j-1} s^0)\end{aligned} \tag{4}$$

Let $\Lambda(y_j) = p(y_j|H_1)/p(y_j|H_0)$, and $\Upsilon(r_{j-1}) = p(r_{j-1}|H_1, g_{j-1})/p(r_{j-1}|H_0, g_{j-1})$. Assuming binary phase shift keying (BPSK) modulation is employed for transmission, we can rewrite $\Upsilon(r_{j-1})$ as

$$\Upsilon(r_{j-1}) = \frac{P_{D,j-1}\xi_{j-1} + 1 - P_{D,j-1}}{P_{F,j-1}\xi_{j-1} + 1 - P_{F,j-1}} \tag{5}$$

where $\xi_{j-1} = \exp\left(4\sqrt{\rho}\Re\{r_{j-1} g_{j-1}^*\}\right)$. Using (2) and (5), the LR test at the j^{th} node is given by

$$\Lambda(y_j)\Upsilon(r_{j-1}) \underset{H_0}{\overset{H_1}{\gtrless}} t \tag{6}$$

$^*\mathcal{CN}(0, 1)$ denotes the circularly symmetric zero mean and unit variance Complex Gaussian random variable whose density is given by $p_n(z) = \frac{1}{\pi} e^{-|z|^2}$

where t is a threshold to be determined. For simplicity, it is convenient to use the log-likelihood ratios, $\Gamma^*(y_j, r_{j-1}) = \log(\Gamma(y_j, r_{j-1}))$, $\Lambda^*(y_j) = \log(\Lambda(y_j))$ and $\Upsilon^*(r_{j-1}) = \log(\Upsilon(r_{j-1}))$, and hence, we can rewrite the LR test (6) as

$$\Gamma^*(y_j, r_{j-1}) = \Lambda^*(y_j) + \Upsilon^*(r_{j-1}) \underset{H_0}{\overset{H_1}{\gtrless}} t^* \tag{7}$$

where $t^* = \log(t)$. For the first stage, we have $\Upsilon^*(r_{j-1}) = 0$. Although it is straightforward to implement the fusion rule described by (7), note that it requires the exact knowledge of the channel gain g_{j-1} and the false alarm & detection probabilities at the previous stage. We assume quasi-static fading so one can estimate the channel state information at the receiver.

B. False Alarm and Detection Probabilities

We next derive the false alarm and detection probabilities to evaluate the performance of the decision fusion rule in (7). At the j^{th} stage, the false alarm probability is given by

$$\begin{aligned} P_{F,j} = P_{F,j-1} \Pr\left(\Lambda^*(y_j) + \Upsilon_1^*(r_{j-1}) > t^* | H_0\right) \\ + (1 - P_{F,j-1}) \Pr\left(\Lambda^*(y_j) + \Upsilon_0^*(r_{j-1}) > t^* | H_0\right) \end{aligned} \tag{8}$$

where $\Upsilon_1^*(r_{j-1}) = \log \frac{P_{D,j-1} e^{4\rho|g_{j-1}|^2 + 4\sqrt{\rho} n'_{j-1}} + 1 - P_{D,j-1}}{P_{F,j-1} e^{4\rho|g_{j-1}|^2 + 4\sqrt{\rho} n'_{j-1}} + 1 - P_{F,j-1}}$, $\Upsilon_0^*(r_{j-1}) = \log \frac{P_{D,j-1} e^{-4\rho|g_{j-1}|^2 + 4\sqrt{\rho} n'_{j-1}} + 1 - P_{D,j-1}}{P_{F,j-1} e^{-4\rho|g_{j-1}|^2 + 4\sqrt{\rho} n'_{j-1}} + 1 - P_{F,j-1}}$, with $n'_{j-1} \sim \mathcal{C}(0, |g_{j-1}|^2/2)$. Let $\Gamma_i^* = \Lambda^* + \Upsilon_i^*$ (For brevity, we drop y_j and r_{j-1}). Denote the cumulative distributions of Γ_i^*, Λ^* under H_1 and H_0 as $F_{\Gamma_{i,1}^*}(\cdot)$, $F_{\Lambda_1^*}(\cdot)$ and $F_{\Gamma_{i,0}^*}(\cdot)$, $F_{\Lambda_0^*}(\cdot)$, respectively. Also denote the density functions of Υ_1^* and Υ_0^* as $f_{\Upsilon_1^*}(\cdot)$ and $f_{\Upsilon_0^*}(\cdot)$, respectively. Using probability theory [19], we can show that the support of $f_{\Upsilon_k^*}(\cdot)$, $k = 0, 1$ is the interval $\left(\log \frac{1-P_{D,j-1}}{1-P_{F,j-1}}, \log \frac{P_{D,j-1}}{P_{F,j-1}}\right)$ and the pdf can be evaluated as (9) displayed at the top of next page. The cumulative distribution function of Υ_k^* is given by (10) on the next page. Because of the conditional independence of y_j and r_{j-1}, $F_{\Gamma_{i,k}^*}$, $i, k \in \{0, 1\}$, can be expressed as

$$F_{\Gamma_{i,k}^*}(a) = \int_{\log \frac{1-P_{D,j-1}}{1-P_{F,j-1}}}^{\log \frac{P_{D,j-1}}{P_{F,j-1}}} f_{\Upsilon_i^*}(y) F_{\Lambda_k^*}(a - y) dy \tag{11}$$

Using (11) in (8), we finally obtain

$$\begin{aligned} P_{F,j} = 1 - \int_{\log \frac{1-P_{D,j-1}}{1-P_{F,j-1}}}^{\log \frac{P_{D,j-1}}{P_{F,j-1}}} \left(P_{F,j-1} f_{\Upsilon_1^*}(y) + (1 - P_{F,j-1}) f_{\Upsilon_0^*}(y)\right) \\ \times F_{\Lambda_0^*}(t^* - y) dy \end{aligned} \tag{12}$$

Similarly, the detection probability can be computed using

$$\begin{aligned} P_{D,j} = 1 - \int_{\log \frac{1-P_{D,j-1}}{1-P_{F,j-1}}}^{\log \frac{P_{D,j-1}}{P_{F,j-1}}} \left(P_{D,j-1} f_{\Upsilon_1^*}(y) + (1 - P_{D,j-1}) f_{\Upsilon_0^*}(y)\right) \\ \times F_{\Lambda_1^*}(t^* - y) dy \end{aligned} \tag{13}$$

Hence, if the distribution of the observations y_j is known, using Equations (9), (12) and (13), we can compute the $P_{D,j}$ recursively, provided that the $P_{F,j-1}$ are specified. A simplistic approach is to set the false alarm rates $P_{F,j}$ at all stages the same, however, in that case, one can not guarantee the maximization of $P_{D,N}$, the global detection probability. According to Neyman-Pearson lemma, for a given upper bound on $P_{F,N}$, we need to make an exhaustive search over all $P_{F,j}$, $j = 1, \cdots, N-1$ in order to find those that maximize the global detection probability $P_{D,N}$. As usual in distributed detection problems, an analytical solution is not feasible; therefore, we resort to numerical search procedures to determine the decision fusion rules.

IV. Optimality of LR-based Decision Fusion

So far, we used the LR based decision fusion rule without considering its optimality. If the channels between the consecutive sensors are error-free, that is, each sensor node can pass its decision to the next one without error, Viswanathan and Thomopoulos have shown that the optimality can be achieved using Neyman-Pearson test at each stage [20]. Here, we investigate the optimality under fading channels for the proposed fusion rule.

Consider the decision fusion at the last two stages. At the final node S_N, we have the log-likelihood ratio $\Gamma^*(y_N, r_{N-1}) = \Lambda^*(y_N) + \Upsilon^*(r_{N-1})$. Let $P_D = P_{D,N-1}$, $P_F = P_{F,N-1}$, and $\Lambda^* = \Lambda^*(y_N)$. We can rearrange (12) and (13) to obtain (14) and (15), respectively, shown at the next page. Integration of (14) and (15) by parts gives the equalities (16) and (17), respectively, which are also shown at the next page. Here, $F_{\Upsilon_k^*}$ is the cumulative distribution of Υ_k^*, $k = 0, 1$. It is required for some fixed $P_{F,N}$ and $P_{F,N-1}$ that the $P_{D,N}$ be a monotonic increasing function of $P_{D,N-1}$ so that the global detection probability takes larger values as $P_{D,N-1}$ is increased. The necessary conditions satisfying this requirement can be obtained by taking the derivative of (16) and (17) with respect to P_D: See Equations (18) and (19) on the following page. In (18) and (19), $U_{k,j} = \int_{\log \frac{1-P_D}{1-P_F}}^{\log \frac{P_D}{P_F}} F_{\Upsilon_k^*}(y) f_{\Lambda_j^*}(t^* - y) dy$. Note that if $P_{D,N-1}$ is changed, to keep $P_{F,N}$ at some fixed value, the threshold t^* at S_N needs to be changed as well. The required expression for t^* can be obtained by equating (18) to 0,

$$\left(\frac{dt^*}{dP_D} - \frac{1}{P_D}\right) f_{\Lambda_0^*}(t^* - \log \frac{P_D}{P_F}) = P_F \frac{dU_{1,0}}{P_D} + (1 - P_F) \frac{dU_{0,0}}{P_D} \tag{20}$$

Substituting (20) in (19), we finally arrive at (21) shown on the following page. It is usually required that $P_D > P_F$, which implies that $U_{1,1} - U_{0,1} < 0$. To have $\frac{dP_{D,N}}{P_D} > 0$, a sufficient condition is then given by

$$\frac{f_{\Lambda_1^*}(t^* - \log \frac{P_D}{P_F})}{f_{\Lambda_0^*}(t^* - \log \frac{P_D}{P_F})} \leq \frac{P_D \frac{dU_{1,1}}{P_D} + (1 - P_D) \frac{dU_{0,1}}{P_D}}{P_F \frac{dU_{1,0}}{P_D} + (1 - P_F) \frac{dU_{0,0}}{P_D}} \tag{22}$$

We observe that the left hand side of (22) is the likelihood ratio of the likelihood ratio. In [21], it is shown that the likelihood ratio of a likelihood ratio is the likelihood ratio itself. Hence, the condition in (22) can be reduced to

$$t^* - \log \frac{P_D}{P_F} \leq \log \frac{P_D \frac{dU_{1,1}}{P_D} + (1 - P_D) \frac{dU_{0,1}}{P_D}}{P_F \frac{dU_{1,0}}{P_D} + (1 - P_F) \frac{dU_{0,0}}{P_D}} \tag{23}$$

$$f_{\Upsilon_k^*}(y) = \frac{(P_{D,j-1} - P_{F,j-1})e^y}{(P_{D,j-1} - P_{F,j-1}e^y)((1-P_{F,j-1})e^y - (1-P_{D,j-1}))} \times \frac{1}{\sqrt{16\pi\rho|g_{j-1}|^2}} \exp\left(-\left(\log\frac{(1-P_{F,j-1})e^y - (1-P_{D,j-1})}{P_{D,j-1} - P_{F,j-1}e^y} - (2k-1)4\rho|g_{j-1}|^2\right)^2 / 16\rho|g_{j-1}|^2\right) \tag{9}$$

$$F_{\Upsilon_k^*}(a) = \begin{cases} 0 & a < \log\frac{1-P_{D,j-1}}{1-P_{F,j-1}} \\ Q\left(\left((2k-1)4\rho|g_{j-1}|^2 - \frac{(1-P_{F,j-1})e^a - (1-P_{D,j-1})}{P_{D,j-1} - P_{F,j-1}e^a}\right)/4|g_{j-1}|\sqrt{\rho}\right) & \log\frac{1-P_{D,j-1}}{1-P_{F,j-1}} < a < \log\frac{P_{D,j-1}}{P_{F,j-1}} \\ 1 & a > \log\frac{P_{D,j-1}}{P_{F,j-1}} \end{cases} \tag{10}$$

$$1 - P_{F,N} = \int_{\log\frac{1-P_D}{1-P_F}}^{\log\frac{P_D}{P_F}} (P_F f_{\Upsilon_1^*}(y) + (1-P_F) f_{\Upsilon_0^*}(y)) F_{\Lambda_0^*}(t^* - y) dy \tag{14}$$

$$1 - P_{D,N} = \int_{\log\frac{1-P_D}{1-P_F}}^{\log\frac{P_D}{P_F}} (P_D f_{\Upsilon_1^*}(y) + (1-P_D) f_{\Upsilon_0^*}(y)) F_{\Lambda_1^*}(t^* - y) dy \tag{15}$$

$$1 - P_{F,N} = F_{\Lambda_0^*}(t^* - \log\frac{P_D}{P_F}) - \int_{\log\frac{1-P_D}{1-P_F}}^{\log\frac{P_D}{P_F}} (P_F F_{\Upsilon_1^*}(y) + (1-P_F) F_{\Upsilon_0^*}(y)) f_{\Lambda_0^*}(t^* - y) dy \tag{16}$$

$$1 - P_{D,N} = F_{\Lambda_1^*}(t^* - \log\frac{P_D}{P_F}) - \int_{\log\frac{1-P_D}{1-P_F}}^{\log\frac{P_D}{P_F}} (P_D F_{\Upsilon_1^*}(y) + (1-P_D) F_{\Upsilon_0^*}(y)) f_{\Lambda_1^*}(t^* - y) dy \tag{17}$$

We can use the Leibniz's' formula [22] to evaluate $\frac{dU_{k,j}}{P_D}$, however, the resulting expression does not allow for a closed form expression for the sufficiency condition in (23). However, it is clear that at as long as the threshold t^* satisfies (23), we guarantee that $P_{D,N}$ is an increasing function of P_D and hence, global optimality is achieved by Neyman-Pearson test at each stage. In Section V, we present several numerical results that show that LR based decision fusion is optimal.

V. Simulation Results

In this section, we present several numerical examples for the analysis performed in the previous sections. We first illustrate the performance of the serial detection through numerical simulations. We consider the detection of a DC signal in additive white Gaussian noise (AWGN), i.e., $y = m + n$, where $m = k$ if H_k is correct for $k = 0, 1$, and $n \sim \mathcal{C}(0, 1)$. The sensor nodes use BPSK modulated signals ± 1 to transmit their decisions. By using the expressions (e.g., (12) and (13)) developed in Section III, we obtain the best detection probability $P_{D,N}$ for a given $P_{F,N}$ by an exhaustive search over $P_{F,j}$, $j = 1, \cdots, N-1$. We used the numerical integration routine QUADL in MATLAB©. In the optimization process, we observed that the best $P_{D,N}$ can always be achieved when the threshold is within the interval defined by the sufficiency condition in (23). In Figure 2, we illustrate two representative results for the design and performance of serial and parallel schemes. We consider the case of $N = 2$ and $N = 8$ sensors. For parallel scheme, identical thresholds are assumed at local sensors. The receiver operating characteristics (ROC) of both schemes for $\rho = 1$ and $\rho = 3$ are depicted. For the case of Rayleigh fading, we compute the average probabilities of the false alarm and detection. We observe that at when $N = 2$, the serial fusion structure achieves slightly better detection performance than the parallel fusion does for both values of $\rho = 1$ and $\rho = 3$. When the number of sensors is increased to $N = 8$, it is seen that the parallel distributed detection is superior to the serial one. For all cases in this figure, we also observe that the performance degradation due to the noise channel is significant with respect to the performance of the centralized detection.

VI. Conclusion

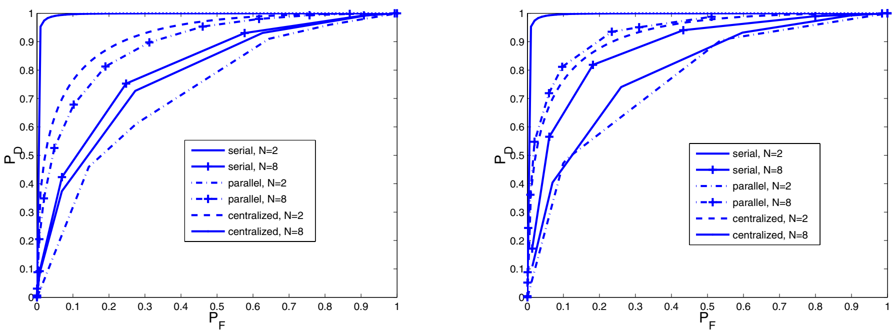
We investigated the serial distributed detection in WSN under the assumption of fading channels. We derived the LR based optimal fusion rules that incorporate fading in the distributed detection problem. Using the Neyman-Pearson criterion, we investigated the global optimality of the fusion rule and derived sufficiency conditions for the optimality. Through numerical analysis and simulations, we evaluated the performance of the proposed serial decision fusion.

In this paper, we assumed a uniform power allocation among the local sensor nodes. An interesting future work is to derive the optimal power allocation scheme for the serial distributed detection problem. Furthermore, in the current scheme, we assumed that only single-bit decisions are allowed at the local sensors. In case of flat fading between the senor nodes,

$$\frac{d(1-P_{F,N})}{P_D} = \left(\frac{dt^*}{dP_D} - \frac{1}{P_D}\right) f_{\Lambda_0^*}(t^* - \log\frac{P_D}{P_F}) - P_F\frac{dU_{1,0}}{P_D} - (1-P_F)\frac{dU_{0,0}}{P_D} \tag{18}$$

$$\frac{d(1-P_{D,N})}{P_D} = \left(\frac{dt^*}{dP_D} - \frac{1}{P_D}\right) f_{\Lambda_1^*}(t^* - \log\frac{P_D}{P_F}) + U_{1,1} - U_{0,1} - P_D\frac{dU_{1,1}}{P_D} - (1-P_D)\frac{dU_{0,1}}{P_D} \tag{19}$$

$$\frac{d(1-P_{D,N})}{P_D} = \left(P_F\frac{dU_{1,0}}{P_D} + (1-P_F)\frac{dU_{0,0}}{P_D}\right)\frac{f_{\Lambda_1^*}(t^* - \log\frac{P_D}{P_F})}{f_{\Lambda_0^*}(t^* - \log\frac{P_D}{P_F})} + U_{1,1} - U_{0,1} - P_D\frac{dU_{1,1}}{P_D} - (1-P_D)\frac{dU_{0,1}}{P_D} \tag{21}$$



(a) (b)

Fig. 2. ROC-curves for DC-level detection problem using serial and parallel networks. Simulation parameters: DC-level $m = 1$, $N = 2$ or 8 sensors, (a) $\rho = 1$ and (b) $\rho = 3$, Rayleigh fading channel.

letting the sensor nodes make multiple-bit decisions might improve the detection performance for a given energy budget. The proposed detection scheme also have implications to the determination of multihop paths that provide the best tradeoff between the energy and detection performance.

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