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Channel Aware Decision Fusion in Wireless Sensor Networks

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***Abstract*—Information fusion by utilizing multiple distributed sensors is studied in this work. Extending the classical parallel fusion structure by incorporating the fading channel layer that is omnipresent in wireless sensor networks, we derive the likelihood ratio based fusion rule given fixed local decision devices. This optimum fusion rule, however, requires perfect knowledge of the local decision performance indices as well as the fading channel. To address this issue, two alternative fusion schemes, namely, the maximum ratio combining statistic and a two-stage approach using the Chair–Varshney fusion rule, are proposed that alleviate these requirements and are shown to be the low and high signal-to-noise ratio (SNR) equivalents of the likelihood-based fusion rule. To further robustify the fusion rule and motivated by the maximum ratio combining statistics, we also propose a statistic analogous to an equal gain combiner that requires minimum *a priori* information. Performance evaluation is performed both analytically and through simulation.**

***Index Terms*—Decision fusion, diversity combining, fading channel, wireless sensor networks.**

I. Introduction

Wireless sensor networks (WSNs) have generated intensive interest from the research community in the past few years. Typical applications include battlefield surveillance, environment, and structure monitoring, among others. In battlefield surveillance applications, microsensors are to be deployed in large numbers to form an intensive information network [1], [2]. Communication capabilities are integrated into each sensor node to allow transmission of the locally processed information to a central node, where information from various sensors is processed collectively to form a final situation assessment.

Much of current research effort on WSN is focused on the development of energy efficient routing protocols, distributed data compression and transmission schemes, and collaborative signal processing algorithms, as documented in [2] and references therein. The fact that locally processed information is transmitted through a fading channel has not attracted much attention. While channel fades may be treated purely as a communication issue and thus be dealt with exclusively through transceiver design, its effect on the signal processing task at the fusion center has not been carefully considered. Our attempt in this correspondence is to incorporate the communication aspects into the data processing stage and to design signal processing algorithms, in particular, a decision fusion algorithm, that can intelligently cope with channel fades at the decision-making stage.

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The problem of distributed detection, and in particular, decision fusion, has been studied extensively in the past decades. In the absence of fading channel consideration, optimum fusion rules have been obtained for both binary and multibit (soft) local sensor output under the conditional independence assumption [3], [4]. Fusion rules with statistically correlated observations have also been investigated though the results are considerably more involved [5], [6] and are mostly limited to binary decisions. Decision fusion with uncertainty has also been investigated and a Bayesian sampling approach has been proposed to address this issue [7]. Decision fusion has also been considered under some communication constraint [8]–[12], where the communication constraint is often in the form of total number of bits allowed to be transmitted from local sensors to the reciever without regard to the possible channel induced transmission errors. Decision fusion with nonideal channels has been investigated by Thomopoulos and Zhang [13]. where binary symmetric channels are used to model the transmission of local decisions to the fusion center. Person by person optimization is used in deterimining the likelihood ratio thresholds for both the local sensors and the fusion center. A similar problem is investigated in Duman and Salehi [14] where a multiple access channel (MAC) is used to model the collective transmission from multiple sensors to a fusion center and a more general multilevel quantization at local sensors is treated.

In this correspondence, we explore decision fusion algorithms that take into account channel fading effects. While it can be argued that at low-rate transmission, the physical layer can achieve arbitrary reliability, it is always desirable to reduce the communication power in energy constrained systems. This motivates designs that can achieve good fusion performance with minimum amount of power consumption. In other words, there is always an incentive in pushing the energy consumption to its minimum possible value for expanded sensor network lifetime. It will become clear later in this correspondence that channel-aware fusion strategies are much more energy efficient in this sense than the conventional two-stage approach, where communication and fusion are treated as independent processes. In addition, for sensor networks operating in a hostile environment, the transmitted signal should be kept at minimum power for low probability of intercept/detection (LPI/LPD).

The organization of this correspondence is as follows. In the next section we formulate the parallel fusion problem with a fading channel layer and derive the optimal likelihood ratio (LR)-based fusion rule with binary local decisions. The three alternative fusion rules are also presented: a two-stage approach using the Chair–Varshney fusion rule, a maximum ratio combining (MRC) fusion statistic, and an equal gain combiner (EGC) fusion statistic. We show that the first two schemes are respectively high and low signal-to-noise ratio (SNR) approximations of the LR-based fusion rule. Performance evaluation, including numerical examples, is contained in Section III. Assuming a Rayleigh flat fading channel model, the EGC statistic seems to provide the most robust fusion alternative among the three suboptimum fusion statistics while requiring minimum *a priori* information. We conclude in Section IV.

II. Decision Fusion Under Fading Channel Assumption

A. Problem Formulation

Fig. 1 depicts a typical parallel fusion structure where a number of sensors observe data generated according to either $\mathbf{H}_0$ (target-absent) or $\mathbf{H}_1$ (target-present), which are the two hypotheses under test. Each

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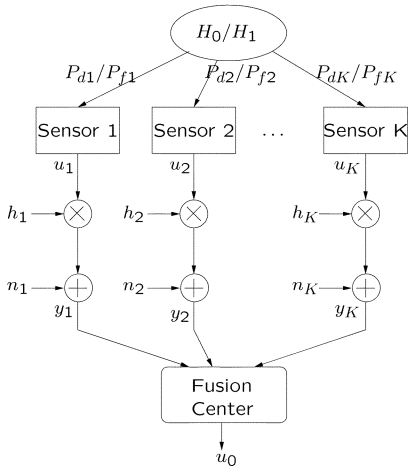

Fig. 1. Parallel fusion model in the presence of fading and noisy channel between local sensors and the fusion center.

sensor processes its observations and makes a preliminary decision about the hypothesis before sending it to a fusion center. The incorporation of the fading channel layer suggests that the local decisions may be subject to transmission errors. Incorrectly received local decisions will lead to performance loss. This loss can be minimized by properly considering and including the effect of channel impairments in the derivation of the decision fusion rule.

Assume that the kth local sensor makes a binary decision $u_k \in \{+1, -1\}$, with false alarm and detection probabilities P_{fk} and P_{dk}, respectively. That is, $P[u_k = 1|\mathbf{H}_0] = P_{fk}$ and $P[u_k = 1|\mathbf{H}_1] = P_{dk}$. From Fig. 1, each local decision u_k is transmitted through a fading channel and the output of the channel (or input to the fusion center) for the kth sensor is

$$y_k = h_k u_k + n_k \tag{1}$$

where h_k is a real valued fading envelope with $h_k > 0$, and n_k is zero mean Gaussian noise with variance σ^2. The above model assumes phase coherent reception, which can be either accomplished through training-based channel estimation for stationary channels or at a small cost of SNR degradation, by employing differential encoding for a fast fading channel. Our goal now is to derive a fusion rule based on y_k, for $k = 1, \ldots, K$, that can determine which hypothesis is true with the best achievable performance.

B. Optimal LR-Based Fusion Rule

Assuming complete knowledge regarding the fading channel and the local sensor performance indices, i.e., the P_{fk} and P_{dk} values, the LR at the fusion center, given the conditional independence assumption of local observations, can be easily derived as

$$\begin{aligned}\Lambda(\mathbf{y}) &= \frac{f(\mathbf{y}\,|\,H_1)}{f(\mathbf{y}\,|\,H_0)} \\ &= \prod_{k=1}^{K} \frac{P_{dk} e^{-\frac{(y_k-h_k)^2}{2\sigma^2}} + (1-P_{dk}) e^{-\frac{(y_k+h_k)^2}{2\sigma^2}}}{P_{fk} e^{-\frac{(y_k-h_k)^2}{2\sigma^2}} + (1-P_{fk}) e^{-\frac{(y_k+h_k)^2}{2\sigma^2}}}\end{aligned} \tag{2}$$

where $\mathbf{y} = [y_1, \ldots, y_K]^T$ is a vector containing observations received from all K sensors. While the form of the LR-based fusion rule is straightforward to implement, it does need both the local sensor performance indices and complete channel knowledge. In the next section, we investigate a number of suboptimum fusion rules that relieve the above requirements to a certain extent.

C. Suboptimum Fusion Rules

The first two alternatives are proposed as high and low SNR approximations to the LR fusion rule that partially relieve some of the requirements associated with the LR-based fusion rule. This is established by showing that the log likelihood nonlinearity converges to the two respective forms under the high and low SNR assumptions. The fact that these alternatives have familiar forms in the context of distributed detection and diversity combining provides some important insights. Motivated by the form of the low SNR alternative, we propose another statistic that requires minimum *a priori* information and, as it turns out, enjoys the most robust performance among the three suboptimal approaches for a wide range of channel SNR values.

1) Chair–Varshney Fusion Rule-Based Two-Stage Approximation: The fusion rule specified in (2) jointly considers the effects of the fading channel and the local sensor outputs to achieve optimal performance. A direct alternative is to separate this into a two stage process—first, y_k is used to infer about u_k, and then, the optimum fusion rule based on u_k (assuming that the estimates are reliable), as derived in [3], can be applied. Given (1) and with $u_k \in \{1, -1\}$, the maximum likelihood (ML) estimate for u_k is simply

$$\hat{u}_k = \text{sign}(y_k).$$

Applying the fusion rule derived in [3], herein termed the Chair–Varshney fusion rule, we obtain the following statistic:

$$\Lambda_1 = \sum_{\text{sign}(y_k)=1} \log \frac{P_{dk}}{P_{fk}} + \sum_{\text{sign}(y_k)=-1} \log \frac{1-P_{dk}}{1-P_{fk}}. \tag{3}$$

For large-channel SNR, the ML estimate of u_k is most likely to be correct and this statistic should be a good approximation for Λ. Indeed, we show below that, as $\sigma^2 \to 0$, the logarithm of Λ converges to Λ_1, i.e.,

$$\lim_{\sigma^2 \to 0} \log \Lambda = \Lambda_1$$

To show this, we define $\mathcal{S}_0 = \{k\colon y_k < 0\}$ and $\mathcal{S}_1 = \{k\colon y_k > 0\}$, and we rewrite the LR-based fusion statistic as

$$\begin{aligned}\Lambda = \prod_{k \in \mathcal{S}_0} \frac{P_{dk} + (1-P_{dk}) e^{-\frac{2y_k h_k}{\sigma^2}}}{P_{fk} + (1-P_{fk}) e^{-\frac{2y_k h_k}{\sigma^2}}} \\ \times \prod_{k \in \mathcal{S}_1} \frac{P_{dk} e^{\frac{2y_k h_k}{\sigma^2}} + (1-P_{dk})}{P_{fk} e^{\frac{2y_k h_k}{\sigma^2}} + (1-P_{fk})}.\end{aligned} \tag{4}$$

Given that $\sigma^2 \to 0$ (high SNR assumption), we have, for $k \in \mathcal{S}_0$, $e^{-(2y_k h_k)/(\sigma^2)} \gg 1$, whereas for $k \in \mathcal{S}_1$, $e^{(2y_k h_k)/(\sigma^2)} \gg 1$. Hence, the assumption $\sigma^2 \to 0$ can be used to obtain

$$\lim_{\sigma^2 \to 0} \Lambda = \prod_{k \in \mathcal{S}_0} \frac{1-P_{dk}}{1-P_{fk}} \prod_{k \in \mathcal{S}_1} \frac{P_{dk}}{P_{fk}}.$$

Taking logarithm of both sides, we get

$$\lim_{\sigma^2 \to 0} \log \Lambda = \sum_{k \in \mathcal{S}_0} \log\left[\frac{1-P_{dk}}{1-P_{fk}}\right] + \sum_{k \in \mathcal{S}_1} \log\left[\frac{P_{dk}}{P_{fk}}\right] = \Lambda_1$$

which is precisely the decision statistic of the optimum fusion rule derived in [3].

Notice that Λ_1 does not require any knowledge regarding the channel statistics but does require P_{dk} and P_{fk} for all k. Notice also that at low SNR, because of the increased likelihood of making an error in inferring u_k from y_k, performance degradation is expected using this two-stage approach.

2) Maximum Ratio Combining Fusion Statistic: We start by simplifying Λ in a similar fashion:

$$\Lambda = \prod_{k=1}^{K} \frac{P_{dk} + (1 - P_{dk}) e^{-\frac{2y_k h_k}{\sigma^2}}}{P_{fk} + (1 - P_{fk}) e^{-\frac{2y_k h_k}{\sigma^2}}}.$$

For low SNR, i.e., $\sigma^2 \to \infty$, we have $e^{-(2y_k h_k)/(\sigma^2)} \to 1$, which can be approximated by the first-order Taylor series expansion, i.e., $e^{-(2y_k h_k)/(\sigma^2)} \approx 1 - (2y_k h_k)/(\sigma^2)$. Therefore, we have

$$\begin{aligned}\lim_{\sigma^2 \to \infty} \Lambda &= \lim_{\sigma^2 \to \infty} \prod_{k=1}^{K} \frac{P_{dk} + (1 - P_{dk}) \left(1 - \frac{2y_k h_k}{\sigma^2}\right)}{P_{fk} + (1 - P_{fk}) \left(1 - \frac{2y_k h_k}{\sigma^2}\right)} \\ &= \lim_{\sigma^2 \to \infty} \prod_{k=1}^{K} \frac{1 - (1 - P_{dk}) \frac{2y_k h_k}{\sigma^2}}{1 - (1 - P_{fk}) \frac{2y_k h_k}{\sigma^2}}.\end{aligned}$$

Taking logarithm of both sides, we get

$$\begin{aligned}\lim_{\sigma^2 \to \infty} \log \Lambda = \lim_{\sigma^2 \to \infty} \Bigg\{ &\sum_{k=1}^{K} \log \left[1 - (1 - P_{dk}) \frac{2y_k h_k}{\sigma^2}\right] \\ &- \sum_{k=1}^{K} \log \left[1 - (1 - P_{fk}) \frac{2y_k h_k}{\sigma^2}\right] \Bigg\}.\end{aligned}$$

Using the fact that, for $x \to 0$

$$\log(1 + x) = x + o(x)$$

where $o(x)$ denotes a term with $\lim_{x \to 0} (o(x))/(x) = 0$, we have the following equivalence in the limit:

$$\begin{aligned}\lim_{\sigma^2 \to \infty} \log \Lambda &= \lim_{\sigma^2 \to \infty} \left[- \sum_{k=1}^{K} (1 - P_{dk}) \frac{2y_k h_k}{\sigma^2} \right. \\ &\quad \left. + \sum_{k=1}^{K} (1 - P_{fk}) \frac{2y_k h_k}{\sigma^2} \right] \\ &= \lim_{\sigma^2 \to \infty} \sum_{k=1}^{K} (P_{dk} - P_{fk}) \frac{2y_k h_k}{\sigma^2}. \qquad (5)\end{aligned}$$

Given that σ^2 is a (possibly unknown) constant and, hence, can be neglected, the above limiting statistic reduces to

$$\hat{\Lambda}_2 = \sum_{k=1}^{K} (P_{dk} - P_{fk}) h_k y_k.$$

Further, if the local sensors are identical, i.e., P_{dk} and P_{fk} are the same for all k's, then Λ reduces to a form analogous to a maximum ratio combiner [15]:

$$\Lambda_2 = \frac{1}{K} \sum_{k=1}^{K} h_k y_k. \qquad (6)$$

The factor $1/K$ in Λ_2 does not affect the detection performance but is introduced for the convenience of performance analysis. In essence, Λ_2 is the first-order approximation of the log likelihood ratio based fusion rule and is asymptotically accurate as $\sigma^2 \to \infty$. Notice that Λ_2 does not require the knowledge of P_{dk} and P_{fk}, provided $P_{dk} - P_{fk} > 0$. Knowledge of the channel gain is, however, required.

3) Equal Gain Combining Fusion Statistic: Motivated by the fact that Λ_2 resembles a MRC statistic for diversity combining, we propose a third alternative in the simple form of an equal gain combiner (EGC) that requires minimum amount of information:

$$\Lambda_3 = \frac{1}{K} \sum_{k=1}^{K} y_k.$$

While this heuristic and the simple fusion rule in the form of an EGC statistic does relieve most of the requirements compared with the optimal LR-based fusion rule, its usefulness largely depends on its performance compared with the optimum fusion rule as well as the two alternatives proposed above. In the context of diversity combining for wireless communications, EGC is considered a suboptimal approach to MRC due to the fact that the latter maximizes the output SNR. Interestingly, we show that in the context of decision fusion for WSN, this simple alternative outperforms both Λ_1 and Λ_2 for a wide range of SNR in terms of its detection performance.

III. Performance Evaluation

In this section, we evaluate the detection performance of various fusion rules. Under the Neyman–Pearson criterion, it is clear that the LR-based fusion rule provides the best detection performance. The question is, therefore, how much performance degradation the other three simple alternatives suffer and, among these three, which one provides the most robust detection performance. We emphasize here that among the three suboptimal approaches, the EGC and MRC are perhaps more desirable because of their performance advantage compared with the two-stage approach for low to medium SNR values. Most wireless sensor networks are energy limited—once the sensors are deployed, the lifetime may depend solely on the on-board battery supply. Given that RF communication is the most energy consuming function of a sensor node, it is, therefore, imperative to use as little power as possible for data transmission, which usually results in modest SNR values at the fusion center receiver.

Throughout this section, we assume a Rayleigh fading model for both analysis and simulation. Other fading types, such as Ricean fading, can be used instead, although the analysis is more involved.

A. Performance Analysis of MRC and EGC Fusion Rules

While it is well known that MRC is optimal in that it maximizes the output SNR, it relies on an assumption that is taken for granted in wireless communications, that is, the sources for multiple independently faded channels are identical to each other. Under this condition, MRC achieves maximum output SNR as it involves full coherent combining. In the context of sensor networks, this is not necessarily the case; the local sensors are prone to decision errors due to the nature of the problem. Clearly, without identical input to the multiple fading channels, there is no guarantee that MRC is still preferable compared with other alternatives such as EGC.

The model specified in Section II-A, together with the simple forms of MRC and EGC, allows the development of numerical procedures for the evaluation of the fusion network performance in terms of the probabilities of detection and false alarm. We call them system level detection probability and false alarm rate, which is denoted by P_{d0} and P_{f0}, to distinguish them from sensor level P_{dk} and P_{fk}. These procedures usually involve multiple integration and do not lead to any insight regarding the performance discrepancy between different fusion rules. If we assume that the sensors are identical to each other (thus, $P_{fk} = P_f$ and $P_{dk} = P_d$ for all k), then both MRC and EGC fusion statistics are sums of independent and identically distributed random variables. This allows direct application of the CLT and the limiting distributions corresponding to the underlying hypotheses are Gaussian with respective mean and variance. Detection and false alarm probabilities hence can be evaluated fairly easily [16]. To do so, we need the first two moments of the test statistics under both hypotheses and they are summarized in Table I for Rayleigh fading channel. Derivation of these statistics is straightforward hence is skipped for brevity.

Fig. 2 gives the receiver operating characteristic (ROC) curves obtained both by Monte Carlo simulation and analytical approximation

TABLE I
MEAN AND VARIANCE OF MRC AND EGC UNDER $\mathbf{H}_0$ AND $\mathbf{H}_1$ WITH K SENSORS

	MRC	EGC
$\mathbf{H}_0$	$\mu_{MRC0} = 2P_f - 1$ $\sigma^2_{MRC0} = \frac{1}{K}[1+\sigma^2+4P_f(1-P_f)]$	$\mu_{EGC0} = \frac{\sqrt{\pi}}{2}(2P_f-1)$ $\sigma^2_{EGC0} = \frac{1}{K}\left[\frac{4-\pi}{4}+\sigma^2+\pi P_f(1-P_f)\right]$
$\mathbf{H}_1$	$\mu_{MRC1} = 2P_d - 1$ $\sigma^2_{MRC1} = \frac{1}{K}[1+\sigma^2+4P_d(1-P_d)]$	$\mu_{EGC1} = \frac{\sqrt{\pi}}{2}(2P_d-1)$ $\sigma^2_{EGC1} = \frac{1}{K}\left[\frac{4-\pi}{4}+\sigma^2+\pi P_d(1-P_d)\right]$

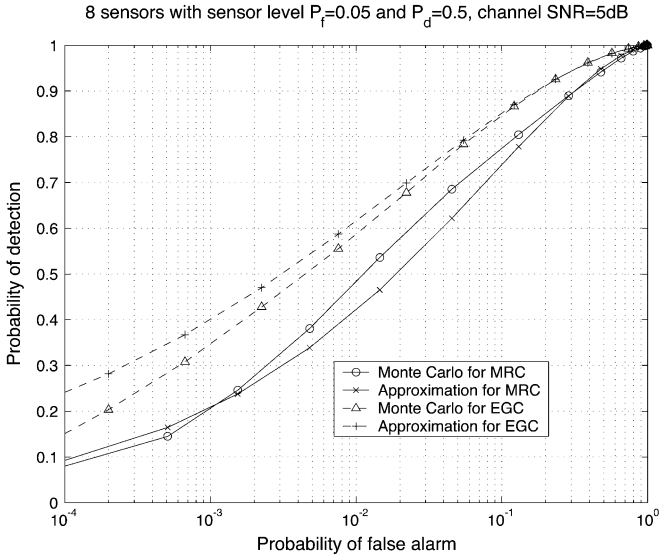

Fig. 2. ROC curves for MRC and EGC obtained by simulation and numerical approximation using the CLT.

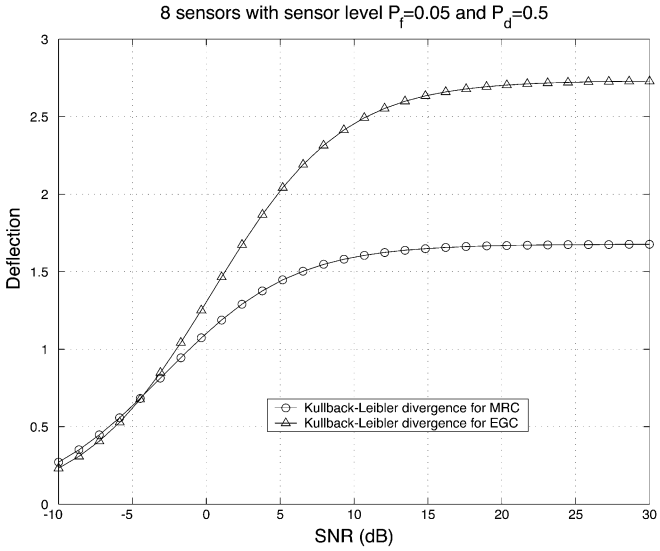

Fig. 3. Deflection measure of MRC and EGC statistics.

using the CLT. In this example, the total number of sensors is 8 with sensor level $P_f = 0.05$ and $P_d = 0.5$,[1] and the channel SNR is 5 dB. While some discrepancy exists, the approximations using the CLT match relatively well to the simulation results. We have also found through extensive simulations that the accuracy of the CLT approximation not only depends on the number of sensors involved, but also on other system parameters, such as the sensor performance indices (P_{fk} and P_{dk}) and the channel SNR.

As an alternative to using the ROC curve for performance comparison, one can also resort to the so-called deflection measure [17], which is defined as

$$D(\Lambda) = \frac{[E(\Lambda \mid H_1) - E(\Lambda \mid H_0)]^2}{\mathrm{Var}(\Lambda \mid H_0)}.$$

This is in essence the SNR of the detection statistic. This deflection measure can be easily calculated using the first- and second-order moments obtained in Table I. Plotted in Fig. 3 are the deflection values for both MRC and EGC given that the sensor level $P_f = 0.05$ and $P_d = 0.5$ with a total number of sensors equal to 8. Clearly, while MRC has slight advantage over EGC for very low channel SNR, it is dominated by EGC for most channel SNR values.

B. Simulation Results

In this section, we compare the performance of the four proposed fusion rules using simulations. The sensor level false alarm rate is assumed to be $P_f = 0.05$, whereas the detection probability is $P_d = 0.5$.

[1]If the local sensor observes a constant signal in additive white Gaussian noise, then the SNR corresponding to the above P_f and P_d values is roughly 4.3 dB.

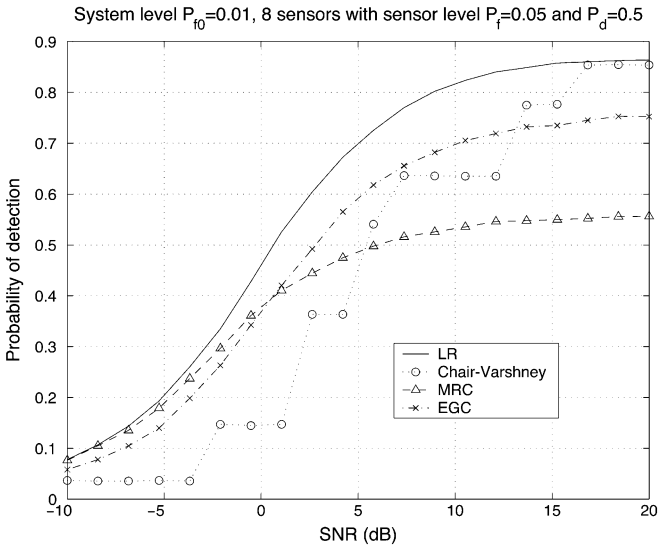

Fig. 4. Probability of detection as a function of channel SNR for Rayleigh fading channels with eight sensors. The system false alarm rate is fixed at $P_{f0} = 0.01$.

The total number of sensors is fixed at 8. Fig. 4 gives the probability of detection as a function of channel SNR for a fixed system false alarm at $P_{f0} = 0.01$. From this figure, it is easy to see that at very low and high SNR, MRC, and the Chair–Varshney statistic can approach the LR performance quite well, whereas the EGC fusion rule provides the most robust performance among the three suboptimal approaches.

TABLE II
PERFORMANCE COMPARISON AMONG THE FOUR FUSION RULES FOR DECISIONS TRANSMITTED THROUGH FADING CHANNELS

Fusion rule	*a priori* information required	Performance
Λ (LR)	Channel SNR and sensor performance indices	Optimum
Λ_1 (Chair-Varshney)	Sensor performance indices	Near-optimal for large SNR
Λ_2 (MRC)	Channel SNR	Near-optimal for low SNR
Λ_3 (EGC)	None	Robust for most SNR range

The tradeoff between detection performance and the requirement on *a priori* information for each of the fusion schemes is summarized in Table II. Among the three suboptimal alternatives, the EGC statistic provides the most robust detection performance while requiring a minimum amount of information.

IV. CONCLUSION

Fusion of binary decisions transmitted over fading and noisy channels in the context of WSNs was studied in this correspondence. Based on the canonical parallel fusion structure that incorporates the fading channel, a LR-based fusion rule has been derived. For robust performance in the absence of prior knowledge regarding the local sensors and/or fading channels, several alternatives were proposed. The two-stage implementation using the Chair–Varshney fusion rule provides high SNR approximation to the LR-based fusion rule, whereas the statistic in the form of a MRC statistic gives a low SNR approximation. Another heuristic scheme in the form of an EGC statistic was proposed and we demonstrated that it performs better than both the Chair–Varshney approximation and MRC for a wide range of SNR values. Performance evaluation is conducted using both the ROC curve as well as the deflection measure.

Fusion of binary decisions transmitted over fading channels has particularly important applications in low-cost low-power wireless sensor networks. The work reported here was based on the LR fusion with complete channel knowledge. We will investigate, in our future work, decision fusion schemes when only the fading statistics are available. Further, the dual problem to decision fusion, namely the optimal local sensor decision rule in the presence of nonideal transmission channels will also be investigated and reported elsewhere.

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