A Comparison of Fusion Rules for Cooperative Spectrum Sensing in Fading Channels

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Abstract—This paper presents a simulation comparison of six fusion rules for cooperative spectrum sensing: Likelihood Ratio combining, soft Optimal Linear combining, soft Equal Weight combining, and hard decision combining using the OR, AND, and the Majority counting rules. Simulation results are presented via Receiver Operating Characteristic (ROC) curves for cooperative sensing using the abovementioned fusion rules for a cognitive radio system operating in AWGN, correlated/uncorrelated shadowing, and in channels featuring composite large-scale and small scale fading. Simulations results using a Lab generated DTV signal in frequency selective fading channels are also presented. This work is very relevant in light of the inclusion of cooperative sensing in the FCC rules for unlicensed operation in the TV bands.

Index Terms—spectrum sensing, data fusion, cooperative sensing.

1. INTRODUCTION

In recent years, spectrum sensing has been gaining popularity as a prospective enabling technology for opportunistic spectrum access. One of the fundamental challenges in spectrum sensing is to reliably detect very weak, shadowed and faded signals received at levels well below the noise floor. This is difficult to accomplish with a single radio. With cooperative spectrum sensing, sensing information collected at various locations is used for jointly determining spectrum availability. Cooperative sensing provides diversity gains against channel fading effects because the odds of multiple radios experiencing adverse fading conditions simultaneously is much less likely than if only a single detector is employed [1,2]. The relevance of cooperative sensing for improving the ability to detect signals from licensed services has been acknowledged in the FCC’s recent rules for unlicensed operation in the licensed TV bands by requiring “that unlicensed TV band devices communicating in a local area network, either directly with one another or linked through a common base station, share information on channel occupancy determined by sensing” [3].

Detection performance of a cooperative sensing system is influenced by the signal levels received at the radios, the available observation time, the detection performance of the individual detectors, and the performance of the fusion rule used to make the group decisions. Due to its simplicity, its popularity and its well understood performance, this study uses energy detection (a.k.a radiometric detection) [4,5,6] as the underlying detection method. Employing energy detection for local detection, we examine, via simulations, the performance of three soft decision as well as three hard decision fusion rules for cooperative sensing in wireless fading channels. The paper considers the performance of soft decision fusion rules based on the log-likelihood ratio, soft optimal linear combining and equal weight combining, and hard decision fusion rules based on the AND, OR and Majority rules. The performance of these fusion rules is evaluated for AWGN channels, uncorrelated and correlated log-normal shadowing channels, and composite channels with large and small scale fading.

This paper is organized as follows: Section 2 describes the system model. Section 3 provides a brief overview of the fusion rules under investigation and their theoretical performance in AWGN channels. Simulation results are presented in Section 4. Finally, conclusions are presented in Section 5.

2. SYSTEM MODEL

This study focuses on the detection of a primary signal embedded in Additive White Gaussian noise by a group of secondary receivers that perform energy estimation and cooperative signal detection. In the cooperative detection system, N samples of the received signal are gathered by M secondary users in the system, and the signal energy/power is estimated by each user. The users either perform detection individually based on the measured energy, and send their individual hard decisions to a fusion center for decision combining, or they forward the soft information to be fused at the fusion center to make the final decision as to whether a primary is present or not.

This is a binary hypothesis testing problem where the noise only hypothesis (H₀) corresponds to the noise only case, and the signal plus noise hypothesis (H₁) corresponds to the signal present case:

\[ H₀ : x(n) = w_i(n) \]
\[ H₁ : x(n) = h_i s(n) + w_i(n), \quad n = 1, 2, \ldots N, \quad i = 1, 2, \ldots , M \]

where \( s(n) \) represents the samples of a primary signal with received power \( P \), \( w_i(n) \) represents the Additive White Gaussian noise.
Gaussian noise, and \( h_i \) is a scaling factor representing the channel fading experienced by the primary signal for user \( i \).

The energy detector takes the input samples \( x_i(n) \) and accumulates them for energy, or for power estimation respectively as:

\[
u_i = \frac{1}{N} \sum_{n=1}^{N} |x_i(n)|^2
\]

\[
u_i = \sum_{n=1}^{N} |x_i(n)|^2
\]

Assuming that the channel does not change within the observation interval and that a sufficiently large number of samples \( N \) is observed, then the sum of the squared magnitude of the samples \( x_i(n) \) can be approximated by Gaussian distribution [4]. The mean and variances of these distributions are shown in table 1 for both narrowband (i.e. \( s(n) \) is a constant) and wideband (i.e. \( s(n) \) is modeled as band-limited Gaussian signal) signals. In these expressions, \( \sigma_i \) is the standard deviation of noise samples \( w_i(k) \), and \( \gamma_i \) is the observed signal-to-noise ratio at the \( i^{th} \) node. Note that at low signal-to-noise ratios, the statistics of the narrowband and wideband signal are essentially the same for both hypotheses since for \( \gamma \ll 1 \) the approximation \((1+\gamma)^2 \sim 1+2\gamma\) holds. For results presented from here on a narrowband signal will be assumed.

### Table 1: Mean and Variance of the test statistics for power and energy detection of wideband and narrowband signals

<table>
<thead>
<tr>
<th></th>
<th>Narrowband Signal</th>
<th>Wideband Signal</th>
</tr>
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<tbody>
<tr>
<td><strong>Power</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( E{u_i/H_0} )</td>
<td>( \sigma_i^2 )</td>
<td>( \sigma_i^2 )</td>
</tr>
<tr>
<td>( E{u_i/H_1} )</td>
<td>( \sigma_i^2(1+\gamma_i) )</td>
<td>( \sigma_i^2(1+\gamma_i) )</td>
</tr>
<tr>
<td>( \text{Var}{u_i/H_0} )</td>
<td>( 2\sigma_i^4/N )</td>
<td>( 2\sigma_i^4/N )</td>
</tr>
<tr>
<td>( \text{Var}{u_i/H_1} )</td>
<td>( 2\sigma_i^4(1+2\gamma_i)/N )</td>
<td>( 2\sigma_i^4(1+2\gamma_i)/N )</td>
</tr>
<tr>
<td><strong>Energy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( E{u_i/H_0} )</td>
<td>( N\sigma_i^2 )</td>
<td>( N\sigma_i^2 )</td>
</tr>
<tr>
<td>( E{u_i/H_1} )</td>
<td>( N\sigma_i^2(1+\gamma_i) )</td>
<td>( N\sigma_i^2(1+\gamma_i) )</td>
</tr>
<tr>
<td>( \text{Var}{u_i/H_0} )</td>
<td>( 2N\sigma_i^4 )</td>
<td>( 2N\sigma_i^4 )</td>
</tr>
<tr>
<td>( \text{Var}{u_i/H_1} )</td>
<td>( 2N\sigma_i^4(1+2\gamma_i) )</td>
<td>( 2N\sigma_i^4(1+2\gamma_i) )</td>
</tr>
</tbody>
</table>

At each individual secondary node, we can use the Neyman-Pearson (NP) criteria to decide between the two hypotheses by comparing the test statistic to the detection threshold \( \lambda \), according to:

\[
u_i > \lambda, i = 1,2,...M
\]

The detection performance of an individual node can be calculated according to:

\[
P_{fa} = Pr(u_i > \lambda_i / H_0) = Q\left(\frac{\lambda_i - E\{u_i/H_0\}}{\sqrt{\text{Var}\{u_i/H_0\}}}\right)
\]

\[
P_d = Pr(u_i > \lambda_i / H_1) = Q\left(\frac{\lambda_i - E\{u_i/H_1\}}{\sqrt{\text{Var}\{u_i/H_1\}}}\right)
\]

For hard decision combining, the individual decisions are forwarded to a fusion center where hard decision combining is performed. For soft decision combining each secondary node forwards its test statistic \( u_i \) to the fusion center where it is combined with the test statistics from all \( M \) nodes to reach a global decision as to whether a signal is present or absent.

### 3. FUSION RULES

This section presents a summary of the fusion rules that are being compared in the study.

#### 3.1 Likelihood Ratio Test (LRT)

The likelihood ratio in the Neyman-Pearson test is defined as:

\[
L(u) = \frac{p(u/H_1)}{p(u/H_0)} > \frac{\lambda}{\lambda_0}
\]

Assuming that each measurement \( u_i \) is uncorrelated and has a normal distribution, as described above, then the likelihood ratio becomes:

\[
L(u) = \prod_{i=1}^{M} \frac{p(u_i/H_1)}{p(u_i/H_0)} = \prod_{i=1}^{M} \left( \frac{\text{Var}\{u_i/H_1\}}{\text{Var}\{u_i/H_0\}} \right)^{-\frac{1}{2}} \cdot \exp \left( -\frac{1}{2} \sum_{i=1}^{M} \left( \frac{u_i - E\{u_i/H_1\}}{\sqrt{\text{Var}\{u_i/H_1\}}} - \frac{u_i - E\{u_i/H_0\}}{\sqrt{\text{Var}\{u_i/H_0\}}} \right)^2 \right) < \frac{\lambda}{\lambda_0}
\]

where the statistical quantities \( E\{\cdot\} \) and \( \text{Var}\{\cdot\} \) are listed in Table 1. Re-arranging and taking the logarithm on both sides, one obtains the test statistic \( T(u) \):

\[
T(u) = \sum_{i=1}^{M} \left( \frac{u_i - E\{u_i/H_1\}}{\sqrt{\text{Var}\{u_i/H_1\}}} - \frac{u_i - E\{u_i/H_0\}}{\sqrt{\text{Var}\{u_i/H_0\}}} \right)^2 \geq \frac{\lambda_i}{\lambda_0}
\]

For power estimation and narrowband signal then \( (6a) \) becomes:

\[
T(u) = \sum_{i=1}^{M} \frac{\gamma_i (u_i^2 - \sigma_i^2 u_i)}{\sigma_i^2 (1+2\gamma_i)} \geq \lambda_2
\]

Normally, one finds \( \lambda_2 \) by defining a required \( P_{fa} \) and solving for this threshold in:

\[
P_{fa} = Pr(T(u) > \lambda_2 / H_0) = \int_{\lambda_2}^{\infty} p(T(u) / H_0) du
\]

As we can see from (6), it is not an easy task to find a closed form distribution of the test statistic \( T \) since we have first order and second order Gaussian distributions added together. To get around this difficulty, in our simulations the thresholds were computed empirically from histograms of the \( H_0 \) test statistics.
3.2 Soft Linear Combining

With soft linear combining the test statistic at the fusion center corresponds to:

\[
y_f = \sum_{i=1}^{M} w_i u_i = w^T u
\]  

(7)

where \( w = [w_1, w_2, \ldots w_M]^T \), \( u = [u_1, u_2, \ldots u_M]^T \).

Since \( y_f \) is a sum of Gaussian distributions, then it also follows a Gaussian distribution with mean and variance given by (for a narrowband signal and power measurement):

\[
E[y_f/H_0] = \sum_{i=1}^{M} w_i E[u_i/H_0] = \sum_{i=1}^{M} w_i \sigma_i^2 = s_{H_0}^T w
\]

(8)

\[
E[y_f/H_1] = \sum_{i=1}^{M} w_i E[u_i/H_1] = \sum_{i=1}^{M} w_i \sigma_i^2 (l + \gamma_i) = s_{H_1}^T w
\]

Thus the test to determine whether a primary is present or not is:

\[
y_f \geq \lambda_f \quad \text{H}_1
\]

(10)

The detection performance at the fusion center is given by:

\[
P_{fa} = Pr(y_f > \lambda_f / H_0) = Q \left( \frac{\lambda_f - E[y_f / H_0]}{\sqrt{Var[y_f / H_0]}} \right)
\]

\[
P_d = Pr(y_f > \lambda_f / H_1) = Q \left( \frac{\lambda_f - E[y_f / H_1]}{\sqrt{Var[y_f / H_1]}} \right)
\]

(11)

For a CFAR detection given \( P_{fa} \), we can solve for the required threshold and then substitute in (4) to obtain \( P_d \).

\[
P_d = Q \left( \frac{Q^{-1}(P_{fa}) \sqrt{Var[y_f / H_0] + E[y_f / H_0] - E[y_f / H_1]}}{\sqrt{Var[y_f / H_1]}} \right)
\]

\[
P_f = Q \left( \frac{Q^{-1}(P_{fa}) \sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 / N} - \sum_{i=1}^{M} w_i \sigma_i^2 \gamma_i}}{\sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 (l + 2 \gamma_i) / N}} \right)
\]

(12)

3.2.1 Soft Optimal Linear Combining

For soft optimal linear combining the optimization problem corresponds to finding the optimum weight vector \( w \) that maximizes \( P_d \) in (12) constrained to \( w \geq 0 \). This is equivalent to minimizing:

\[
f(w) = \frac{Q^{-1}(P_{fa}) \sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 / N} - \sum_{i=1}^{M} w_i \sigma_i^2 \gamma_i}}{\sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 (l + 2 \gamma_i) / N}}
\]

(13)

This minimization problem is challenging to solve in the general case, however for the specific ranges of \( P_{fa} \) and \( P_d \) of interest in cognitive radio (i.e., \( P_{fa} < 0.05, P_d < 0.5 \)) the problem is tractable since \( Q^{-1}(P_{fa}) > 0 \), and \( f(w) < 0 \). For these range, the optimization problem can then be constructed as:

\[
\min_w \left\{ Q^{-1}(P_{fa}) \sqrt{2 \sum_{i=1}^{M} z_i^2 \sigma_i^4 / N} - \sum_{i=1}^{M} z_i \sigma_i^2 \gamma_i \right\}
\]

s.t. \( \sum_{i=1}^{M} z_i^2 \sigma_i^4 (l + 2 \gamma_i) / N \leq 1 \)

(14)

where \( z = w/\bar{w} \), \( \bar{w} > 0 \). Solution to this optimization problem was obtained using sequential quadratic programming (SQP)[7]. An approximation to the optimal solution was proposed in [8] based on a modified deflection coefficient approach. The modified deflection coefficient can thus be used as an alternative function to be maximized and is given by:

\[
d_m^2(w_i) = \frac{\left[ E[y_f / H_1] - E[y_f / H_0] \right]^2}{Var[y_f / H_1]} = \frac{(g^T w)^2}{w^T L_{H_1} w}
\]

(15)

Thus the test to determine whether a primary is present or not is:

\[
y_f \geq \lambda_f
\]

(10)

The detection performance at the fusion center is given by:

\[
P_{fa} = Pr(y_f > \lambda_f / H_0) = Q \left( \frac{\lambda_f - E[y_f / H_0]}{\sqrt{Var[y_f / H_0]}} \right)
\]

\[
P_d = Pr(y_f > \lambda_f / H_1) = Q \left( \frac{\lambda_f - E[y_f / H_1]}{\sqrt{Var[y_f / H_1]}} \right)
\]

For a CFAR detection given \( P_{fa} \), we can solve for the required threshold and then substitute in (4) to obtain \( P_d \).

\[
P_d = Q \left( \frac{Q^{-1}(P_{fa}) \sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 / N} - \sum_{i=1}^{M} w_i \sigma_i^2 \gamma_i}}{\sqrt{2 \sum_{i=1}^{M} w_i^2 \sigma_i^4 (l + 2 \gamma_i) / N}} \right)
\]

3.2.2 Equal Weight Linear Combining

Equal weight linear combining employs straightforward averaging of the received soft decision statistics. The test statistic at the fusion center for equal weight combining corresponds to:

\[
y_f = \sum_{i=1}^{M} w_i u_i = w^T u
\]

(18)

where \( w = [1, 1, \ldots 1]^T \), \( u = [u_1, u_2, \ldots u_M]^T \). This approach is also known as equal gain combining.

3.3 Hard Decision Counting Rules

With a hard decision counting rule, the fusion center implements an \( n \)-out-of-\( M \) rule that decides on the signal present hypothesis whenever at least \( n \) out of the \( M \) local decisions indicate \( H_i \). [8]

Assuming uncorrelated decisions, the probability of detection at the fusion center is given by:

\[ P_d \]

\[ P_f \]
\[ P_d = \sum_{n=1}^{M} \binom{M}{k} P_{d,i}^k (1 - P_{d,i})^{M-k} \]  
\[ (19) \]

where \( P_{d,i} \) is the probability of detection for each individual node.

### 3.3.1 OR Combining

Cooperative detection performance with this fusion rule can be evaluated by setting \( n=1 \) in equation (19).

\[ P_{d,OR} = 1 - (1 - P_{d,i})^M \]  
\[ (20) \]

### 3.3.2 Majority Combining

Fusion is based on a majority rule.

Cooperative detection performance with this fusion rule can be evaluated by setting \( n=[M/2] \) in equation (19).

\[ P_{d,Maj} = \sum_{k=[M/2]}^{M} \binom{M}{k} P_{d,i}^k (1 - P_{d,i})^{M-k} \]  
\[ (21) \]

where \([ \cdot ]\) represents the floor operator.

### 3.3.3 AND Combining

The fusion center’s decision is calculated by a logic AND of the received hard decision statistics.

Cooperative detection performance with this fusion rule can be evaluated by setting \( n=M \) in equation (19).

\[ P_{d,AND} = P_{d,i}^M \]  
\[ (22) \]

Where \([ \cdot ]\) represents the floor operator.

### 4. SIMULATION RESULTS

#### 4.4 Simulations using Quasi-Analytical method

A first set of simulations was performed using a quasi-analytic approach where the test statistics were generated from the theoretical distributions of the \( H_0 \) and \( H_1 \) hypotheses. The first set of simulations were run to generate the ROC curves of the collaborative sensing schemes with the soft and hard combining fusion rules under study for the case of an AWGN channel model. This simulations assume a cognitive system with \( M=9 \) cooperative users operating at a mean SNR \( \gamma=-20 \text{ dB} \) and local decisions made with energy detection after observing the signal for \( N=1000 \) samples. For these simulations, the SNR and noise variance estimates needed employed for the optimal weight estimation in the soft combining case are assumed to be known, and it is assumed that all the collaborative nodes have the same noise floor.

Figure 1 shows the resulting ROC curves for the fusion rules under examination when the collaborative nodes experience no channel fading effects and the only noise in the system is additive receiver noise. As the figure indicates in this situation, soft likelihood ratio test combining, soft optimum linear combining and equal weight combining have the same performance. For the AWGN channel, the weights of the soft optimal linear combiner are all equal.

The ROC of the Majority rule comes close to the ROCs of the soft fusion rules. The performance of the AND and the OR rules follows, with the AND fusion rule providing slightly better performance at low \( P_{fa} \) than the OR. All fusion methods outperform single node sensing. This curves show that even without fading cooperative sensing provides a some level of detection performance gains over the single user case.

Figure 2 shows the ROC curves based on the same simulation setup, for the case where the received signals experience uncorrelated shadowing. For these simulations, a Gaussian distribution of zero mean and standard deviation \( \sigma=10 \text{ dB} \) [10] was used to model the variations in signal attenuation around the mean distance dependent path loss. The curves in Figure 2, indicate that in log-normal shadowing the LRT combiner and the soft optimum linear fusion rule provides improved performance over the remaining rules. The performance of both the OR and equal gain combining rules falls somewhat below that of the optimal combiners. They, however, significantly outperform the Majority rule. Finally, the performance of the AND rule is quite close to the single user case. With exception of the AND rule, the remaining fusion rules achieve significant diversity gains compared to the single user case. The enhanced performance observed in the curves of Figure 2 compared to those of Figure 1 are the result of the diversity provided by devices at locations where the path loss resulted in a mean received SNR>-20 dB.

**Figure 1.** ROC for the fusion rules under study for the case of AWGN receiver noise only, \( \gamma=-20 \text{ dB} \), \( M=9 \) users and energy detection over \( N=1000 \) samples.

**Figure 2.** ROC for the fusion rules under study for the case of Log-normal shadowing with \( \sigma=10 \text{ dB} \), mean SNR \( \gamma=-20 \text{ dB} \), \( M=9 \) users and energy detection over \( N=1000 \) samples.
The performance of the fusion rules was then investigated for the case of correlated log-normal shadowing. In these simulations, shadowing correlation was modeled according to the Gudmundson model with a correlation factor $\beta=0.1204$ as in [11]. For these simulations, the nine secondary users were uniformly distributed in a square of area 225 m$^2$. The ROCs show a behavior similar to their counterparts in Figure 3, where received signal correlation, has diminished the diversity gains.

$$\beta=0.1204, \sigma_{th}=10\text{dB}$$

$$\gamma=-20\text{ dB}, M=9$$

Performance of the fusion rules also was examined for the case of composite uncorrelated log-normal shadowing and Rayleigh fading. The Suzuki [12, 13] model is appropriate for modeling composite fading of narrowband signals. In this curves again, the LRT and soft optimal combining fusion rules perform best. The performance of the OR rule and the equal weight combining rule is considerably worse but much better than that of the LRT and the soft optimal linear combiners. The performance of the majority fusion rule is considerably worse than that of the LRT and the soft optimal combining fusion rules. As an example, for the frequency selective fading had a maximum excess delay correlation of $-116\text{dBm}$, and a mean SNR of about $\gamma=-20\text{ dB}$ over 6MHz. The shadowing variance was chosen to be $10\text{dB}$ with shadowing correlation of $\beta=0.1204$. The average power delay profiles used for the frequency selective fading had a maximum excess delay of 15$\mu$s. In these simulations each collaborative radio collects 512 and 52224 complex signal samples per detection decision.

More specifically, in this simulation we assume receivers with noise figure (NF) of 11dB and a broadcast transmitter 40 Km away at a height of 30m with transmit power of 20KW or 73dBm. The collaborative receivers are uniformly distributed in a 900m$^2$ area. The path loss model used is consistent for urban environments at UHF frequencies, where the path loss at 1m is 28dB and the path loss coefficient is 3.5. This will result at an average received power at the collaborative receivers of -116dBm, and a mean SNR of about $\gamma=-20\text{ dB}$ over 6MHz. The shadowing variance was chosen to be $10\text{dB}$ with shadowing correlation of $\beta=0.1204$. The average power delay profiles used for the frequency selective fading had a maximum excess delay of 15$\mu$s. In these simulations each collaborative radio collects 512 and 52224 complex signal samples per detection decision.

The effects of large scale and frequency selective fading are apparent.

4.5 Simulations using a Lab Generated DTV Signal

For the next part of the comparative study a simulation framework was developed that supports modeling of the propagation environment including the effects of the propagation channel and its effect on representative transmitted primary signals received at cognitive radios distributed over a geographic area. The channel simulator models path loss, correlated/uncorrelated shadowing, fast fading based on delay profiles (frequency selective fading), and Doppler shift according to a variety of cognitive system specifications. In order to duplicate real world conditions, this part of our simulation study uses as input an actual complex Lab generated ATSC signal of 6MHz band-width that is critically sampled. The channel simulator is used to reproduce the radio channel propagation characteristics between the broadcast transmitter and each of the individual radios deployed over a geographic area. An alternative to this method albeit painstaking, is to perform an actual measuring campaign that captures DTV signals in different environments as described in [14], for different number of collaborative radios at each area of interest. Figure 5 shows a block diagram of the simulation framework used for these simulations.
This simulation framework was used to evaluate the detection performance of three practical fusion rules as a function of the number of cooperating users for the case of a cooperative detection system, with a system target Pfa of 10%.

In these simulations, the optimal weights of the soft optimal linear are estimated from the received signal. The system probability of detection as a function of the number of collaborating users for three different combining rules is shown in Figure 7 and 8 for different number of collected complex samples per cooperating radio. Note that comparing the results from Figure 7 (512 complex samples is 1024 total samples) for 9 users, we get about the same probability of detection as the quasi analytic simulation result in Figure 4 for system Pfa=0.1 and 1000 samples, which agrees with the theoretical results. The curves in Figure 7, 8, suggest that in practical scenarios where each individual radio is expected to operate at a high Pd, the OR rule performs closely to the soft optimum linear combining and the equal weight combining fusion rules. For these three fusion rules, as the number of cooperating users increases, the performance of cooperative spectrum sensing improves, while the difference in their performance decreases as illustrated in Figure 8.

5. CONCLUSIONS

In this paper a simulation comparison of soft and hard fusion rules for cooperative sensing was presented. In our simulations the LRT and soft optimal linear combining fusion rules outperform the OR, equal weight combining, Majority and AND hard decision counting rules. The performance of the OR and equal weight combining was somewhat worse than the optimal combining rules with perfect parameter estimation. The performance gap narrows however when the detector parameters are estimated and each collaborative radio operates at high Pd, either due to large number of nodes collaborating or large number of signal samples per radio used for detection. That being said, when choosing an algorithm for implementation, one should also weigh in the advantages and disadvantages on the communication burden and computational capabilities of the sensors and the fusion center.

REFERENCES