Optimal and Suboptimal Distributed Decision Fusion

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OPTIMAL AND SUBOPTIMAL DISTRIBUTED DECISION FUSION

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ABSTRACT

The problem of decision fusion in distributed sensor systems is considered. Distributed sensors pass their decisions about the same hypotheses to a fusion center that combines them into a final decision. Assuming that the sensor decisions are independent from each other conditioned on each hypothesis, we provide a general proof that the optimal decision scheme that maximizes the probability of detection for fixed probability of false alarm at the fusion, is the Neyman-Pearson test at the fusion and Likelihood-Ratio tests at the sensors. The optimal set of thresholds is given via a set of nonlinear, coupled equations that depend on the decision policy but not on the priors. The nonlinear threshold equations cannot be solved in general. We provide a suboptimal algorithm for solving for the sensor thresholds through a one dimensional minimization. The algorithm applies to arbitrary type of similar or disimilar sensors. Numerical results have shown that the algorithm yields solutions that are extremely close to the optimal solutions in all the tested cases, and it does not fail in singular cases.

INTRODUCTION

Systems of distributed sensors monitoring a common volume and passing their decisions into a centralized fusion center which further combines them into a final decision have been receiving a lot of attention in recent years [1]. Such systems are expected to increase the reliability of the detection and be fairly immune to noise interference and to failures. In a number of papers the problem of optimally fusing the decisions from a number of sensors has been considered. Tenney and Sandell [2] have considered the Bayesian detection problem with distributed sensors without considering the design of data fusion algorithms. Sadjadi [3] has considered the problem of hypothesis testing in a distributed environment and has provided a solution in terms of a number of coupled nonlinear equations. The decentralized sequential detection problem has been investigated in [4-5]. In [6] it was shown that the solution of distributed detection problems is non-polynomial complete. Chair and Varshney [7] have solved the problem of data fusion when the a-priori probabilities of the tested hypotheses are known and the Likelihood-Ratio (L-R) test can be implemented at the receiver. Thomopoulos, Viswanathan and Bougoulias [8,9] have derived the optimal fusion rule for unknown a-priori probabilities in terms of the Neyman-Pearson (N-P) test.

Recently, Srinivasan [10] has proved that the globally optimal solution to the fusion problem that maximizes the probability of detection for fixed probability of false alarm when sensors transmit independent, binary decisions to the fusion center, consists of L-R tests at all sensors and N-P test at the fusion center. This test will be referred to as N-P/L-R hereafter. The optimal thresholds in [10] were obtained in terms of a set of coupled, nonlinear equations that depend on the decision policy but not on the priors and cannot be solved in general. Several suboptimal fusion rules have also been considered in [10] and [11].

The proof of the optimality of the N-P/L-R test in [10] is based on the (first-order) Lagrange multipliers methods turns the constraint optimization problem of minimizing (maximizing) the function $f(x)$ subject to a constraint $g(x) = 0$, into an unconstrained optimization problem of minimizing (maximizing) a function L of the form $L(x) = f(x) + \lambda g(x)$ without constraints. This yields the Lagrange multipliers rule $\nabla L(x) = \nabla f(x) + \lambda \nabla g(x) = 0$ at the minimum (maximum) point, in addition to the original constraint $g(x) = 0$, provided that the Lagrangian L is convex and the minimum (maximum) lies in the interior of the domain of x. However, the (first-order) Lagrange multipliers methods often fails to converify the function L[13, Ch. 5].[†] If the optimal solution lies on the boundary of the domain of x (as in the decision fusion example described next), the Lagrangian formulation fails to guarantee the converity of L and consequently the optimality of the solution obtained using the Lagrange multipliers method. In that sense, the proof of the optimality in [10] which is based on a Lagrangian formulation, is not complete as the next example demonstrates.

An example of a distributed decision fusion where the Lagrange multipliers method fails to yield the correct operating points is given in [17]. The example refers to a three similar sensor fusion system, with all three sensors operating at the same signal-to-noise ratio in a slowly-fading Rayleigh environment. The sensor decisions are assumed to be binary. For an arbitrary numbering of the three sensors, if the decision rule at the fusion is the Boolean function $u_2(u_1+u_3)$ where $u_i=0$ or 1, i=1,2,3, it is shown in [17] that the optimal solution that maximizes the probability of detection at the fusion for a fixed probability of false alarm is to operate sensors one and three at the same threshold and push sensor two at the boundary so that its probability of false alarm P_F = probability of detection $P_D = 1$. With this choice of operating points, the decision rule is equivalent to an OR rule between the two sensors. However, because one of the operating points in the optimal solution lies on the boundaries of the domain of the variables involved (in this case the probabilities of false alarm and probabilities of detection at the sensors), the Lagrangian method fails. The solution that is obtained by the Lagrangian method [17] forces two out of the three sensors to operate at the extreme points $P_F = P_D = 1$ and relies only on one of the sensors for the final decision. Hence, the Lagrangian approach yields a solution which is by far inferior to the optimal solution, see Figs. 8.1 and 8.2. A detailed analysis of this singular case is given in [17].

In this paper we give a general proof of the optimality of the N-P/L-R test for the distributed decision fusion problem that is independent on the Lagrangian formulation. Moreover, we develop a computationally efficient algorithm to solve for the optimal fusion rule and the sensors operating points.

1. OPTIMALITY OF THE N-P/L-P TEST IN DISTRIBUTED DECISION FUSION

A number of sensors, N, receives data from a common volume. Sensor k receives data r_k and generates the first stage decision u_k, k=1,2,...,N. The decisions are subsequently transmitted to the fusion center where they are combined into a final decision u_0 about which of the hypotheses is true, Fig. 1. Assuming binary hypothesis testing for simplicity, we use u_i = 1 or 0 to designate that sensor i favors hypothesis H_1 or H_0 respectively.[1] In order to derive the globally optimal fusion rule we assume that the received data r_i at the N sensors are statistically independent conditioned on each hypothesis. This implies that the received decisions at the fusion center are independent conditioned on each hypothesis. Improvement in the performance of conventional diversity schemes is based on the validity of this assumption [16]. Given a desired level of probability of false alarm at the fusion center, $P_F = \epsilon_0$, the test that maximizes the probability of detection P_D (thus, minimizes the probability of miss $P_M = 1 - P_D$) is the Neyman-Pearson test [12]. Because of the comparison to a threshold this test will be referred to as a threshold optimal test hereafter.

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† A fix-up method, in case the (first-order) Lagrange multipliers method fails, is described in [13, Ch. 5].

Next, we prove that the optimal solution to the fusion problem involves an N-P test at the fusion center, and likelihood-ratio (L-R) tests at the sensors.

Let

$$d(u_1,u_2,\ldots,u_N) = p(u_0 = 1 | u_1,u_2,\ldots,u_N) \quad . \qquad (2)$$

be the decision function (rule) at the fusion.

Since $d(u_1,u_2,\ldots,u_N)$ is either 0 or 1, and all the possible combinations of decisions $\{u_1,u_2,\ldots,u_N\}$ that the fusion center can receive from the N sensors is 2^N, the set of all possible decision functions contain 2^{2^N} d functions. However, not all these functions d can be threshold optimal as the next lemma states.

Lemma 1 Let the decisions u_k be independent from each other conditioned on each hypothesis. A necessary condition for a function $d(u_1,u_2,\ldots,u_N)$ to be threshold optimal is

$$d(A_k, U-A_k) = 1 \Rightarrow d(A_n, U-A_n) = 1 \text{ if } A_n > A_k \ , \qquad (3)$$

where $U = \{u_1,u_2,\ldots,u_N\}$ denotes the set of the peripheral sensor decisions, A_k is a set of decisions with k sensors favoring hypothesis H_1 (whereas the complement set of decisions $U-A_k$ favors hypothesis H_0), and A_n is any set that contains the decisions from these k sensors. [The symbol ">" is used to indicate "greater than" in the standard multidimensional coordinate-wise sense, i.e. $A_n > A_k$ if and only if $u_{n_i} \geq u_{k_i}$ $\forall$ i, i = 1,2,...,N, with at least one holding as a strict inequality, where u_{n_i} (u_{k_i}) indicates the decision of the same i-th sensor in the A_n (A_k) decision set.]

Proof Let $P_{F_i} = P(U_i = 1 | H_0)$ = probability of false alarm and $P_{D_i} = P(u_i = 1 | H_1)$ = probability of detection at the i-th sensors. $d(A_k, U-A_k) = 1$ implies that the likelihood ratio

$$\frac{p(A_k, U-A_k | H_1)}{p(A_k, U-A_k | H_0)} = \frac{p(A_k | H_1) p(U-A_k | H_1)}{p(A_k | H_0) p(U-A_k | H_0)} > \lambda_0 \qquad (4)$$

which in turn implies that, for $A_n > A_k$,

$$\frac{p(A_n, U-A_n | H_1)}{p(A_n, U-A_n | H_0)} = \frac{p(A_k | H_1) p(A_n-A_k | H_1) p(U-A_n | H_1)}{p(A_k | H_0) p(A_n-A_k | H_0) p(U-A_n | H_0)} \geq \frac{p(A_k | H_1) p(U-A_k | H_1)}{p(A_k | H_0) p(U-A_k | H_0)} > \lambda_0 \qquad (5)$$

since, for every sensor i, we can assume without loss of generality that

$$\frac{p(u_i = 1 | H_1)}{p(u_i = 1 | H_0)} = \frac{P_{D_i}}{P_{F_i}} \geq \frac{p(u_i | H_1)}{p(u_i | H_0)} = \frac{1-P_{D_i}}{1-P_{F_i}} \qquad (6)$$

From (5), it follows that $d(A_n, U-A_n) = 1$.

Functions that do not satisfy (3) cannot lead to the set of optimal thresholds. A function d that satisfies Lemma 1, is called a monotone increasing function in the context of switching and automata theory [15].

Lemma 2 For any fixed threshold of λ_0 and any fixed monotonic function $t(u_1,u_2,\ldots u_N)$, P_{D_0} is an increasing function of the P_{D_i}'s, i=1, 2, ..., N.

Proof The decision function that corresponds to the likelihood test at the fusion is contained in the set of monotone functions of N variables. Consider one such monotone increasing decision function $d(u_1,u_2,\ldots u_N)$. The function d, when expressed in sum of product form iin the Boolean sense [15], contains only some of the literals $u_1,\ldots u_N$ in the uncomplemented form and none of the complemented variables $(\bar{u}_1, \bar{u}_2,\ldots,\bar{u}_N)$. Since the random variables $u_1,u_2,\ldots u_N$ are statistically independent, it is possible to compute P_{D_0} knowing the P_{D_i}'s Eq.'s (20), (21) and (22) in [9]. Taking partial derivatives of the P_{D_0} w.r.t. P_{D_i}'s, one obtains that $\frac{\partial P_{D_0}}{\partial P_{D_i}} > 0$ $\forall$ i, i.e. the desired result. (As an illustration, consider the function $d(u_1,u_2,u_3) = u_1 + u_2u_3$. For this function $P_{D_0} = P_{D_1} + P_{D_2}P_{D_3} - P_{D_1}(P_{D_2}P_{D_3})$, from which, $\frac{\partial P_{D_0}}{\partial P_{D_i}} > 0$ i = 1, 2, 3.) ∎

Theorem 1 The optimal decision rule for the distributed decision fusion proble involves a Neyman-Pearson test at the fusion center and Likelihood-Ratio tests at all sensors.

Proof Given the decisions $u_1, u_2,\ldots,u_N$ at the fusion center, the best fusion which achieves maximum P_{D_0} for fixed $P_{F_0} = \alpha_0$, is the Neyman-Pearson test. Call the best test at the fusion center $t(u_1,\ldots,u_N) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda_0$. From Lemma 1, it follows that the decision function that corresponds to the above test must be one of the monotone increasing functions $d(u_1,u_2,\ldots,u_N)$. Assume that the individual sensors use some test other than the L-R test and are operating with $\{(P_{F_i}, P_{D_i})\ \forall\ i\}$ such that the condition $P_F = \alpha_0$ is met. From [8] and [9] it is seen that P_{F_0} is a function of the P_{F_i}'s only, and that P_{D_0} is a function of the P_{D_i}'s only. Furthermore, from Lemma 2, $P_{D_0}^1$ is a monotonic increasing function of the $P_{D_i}^1$'s. Therefore, the L-R tests at the sensors which operate with $(P_{F_i}^* = P_{F_i}, P_{D_i}^*)$ will lead to the best performance at the fusion, since in this case, the achieved $P_{D_0}^*$ is greater than or equal to P_{D_0} that can be achieved with any other test at the sensors. ∎

Next we give a more precise characterization of the set of fusion functions that satisfy Theorem 1. According to Lemma 1, only monotone increasing functions may be candidate optimal solutions to the fusion problem. For an arbitrary number of sensors N, the number of monotone increasing functions d is not known in general [15]. However, for n=1, 2, ..., 6, the number of monotone functions can be computed and is given in Table I. From this table, one can see the dramatic reduction between all the 2^{2^N} decision functions that can be generated from all the possible combinations of N binary decisions, and the number of monotonic functions of N variables. Yet, the number of monotonic functions is still prohibitively large for N larger than five. Further reduction in the number of candidate optimal decision functions is possible as Lemma 3 suggests.

Lemma 3 The set of optimal decision (fusion) functions can be generated by considering only the monotone functions that depend on all the sensors and ingoring the monotone functions that depend on any subset of the sensors.

Proof Because of the monotonicity of the N-P test, inclusion of an additional sensor can only improve the performance of the fusion center. Furthermore, if the quality of the sensor is poor (e.g., very low signal-to-noise ratiio), the algorithm that determines the optimal set of thresholds will disregard the sensor by setting its threshold appropriately. Thus, the function d will still depend on all sensors with some of the sensors operating at probability of false alarm equal to one or zero. ∎

In order to reduce the number of monotone functions that correspond to N sensors further by applying Lemma 3, one needs to exclude all the monotone functions that correspond to any subset of N-k, k=1,...N-1, sensors.

If L_N indicates the number of the monotone decision functions for N sensors, excluding the trivial ones $d \equiv 0$ and $d \equiv 1$, and R_N indicates the reduced monotone functions due to the application of Lemma 3, the following relation is true:

$$R_N = L_N - \sum_{k=1}^{N-1} \binom{N}{k} R_k \qquad (7)$$

where

$$\binom{N}{k} = \frac{N!}{(N-k)!k!} \ ,$$

which leads to the following theorem.

Theorem 2 The number of candidate optimal fusion functions for the distributed decision fusion problem is given by (7).

Proof L_N indicates the number of monotone decision functions for N sensors excluding the trivial ones $d \equiv 1$ and $d \equiv 0$. From these functions, the ones that are monotone and correspond to any subset of the N sensors must be excluded. Since for any subset of k sensors there are R_k candidate threshold optimal functions, and there are $\binom{N}{k}$ possible combinations for choosing the subset, relationship (7) follows. ∎

Expression (7) can be solved recursively, and is being tabulated in Table II for N=1,..., 6. Theorem 2 can be used to estimate the numerical complexity of algorithms that seek the optimal fusion rule by searching over all possible candidate fusion rules such as the two algorithms that are described in the next section.

2. SUBOPTIMAL SOLUTIONS TO DISTRIBUTED DECISION FUSION

In [6] the optimal combining rule in a parallel sensor configuration was given in terms of a set of coupled, nonlinear equations whose solution depends on the decision rule and cannot be solved in general. Furthermore, they exhibit numerical problems related to the Lagrangian method which was used to derive them [7]. Two suboptimal algorithms that allow the determination of the decision rule have been developed. The two algorithms allow the determination of a fusion rule using a one dimensional minimization and a one dimensional search, and are computationally very efficient. The algorithms are based on the sequential optimization of the Lagrangian w.r.t. the different sensors assuming that the thresholds of previously optimized sensors are set so that the sensors operate at either zero or one probability of detection. The two algorithms will be referred as SOFA 1 and SOFA 2 respectively and are presented next. For the derivation of the two algorithm see [19].

SOFA 1 ALGORITHM: Let 1, 2, ..., N be an arbitrary ordering of N sensors. Starting from the N-th sensor, the threshold of the k-th sensor as determined by SOFA 1 is given by

$$\lambda_k = \lambda_0 \frac{C_0^{N,N-1,\ldots,k}}{C_1^{N,N-1,\ldots,k}} \tag{8}$$

where

$$C_i^{N,N-1,\ldots,k} = \sum_{U_{N,N-1,\ldots,k}} [d(0,0,\ldots,0,1,U_{N,N-1,\ldots,k}) - d(0,0,\ldots,0,0,U_{N,N-1,k})]P(U_{N,N-1,\ldots,k}|H_i) \tag{9}$$

i = 0, 1. In (8) λ_k designates the threshold of the k-th sensor, λ_0 is the threshold at the fusion, and

$$d(u_1, u_2, \ldots, u_N) = \Pr(u_0 = 1 \mid u_1, u_2, \ldots, u_N) \tag{10}$$

is the decision function at the fusion center with u_i designating the binary decision of the i-th sensor, u_0 the decision at the fusion, and $U_{N,N-1,\ldots,k}$ is the set of decisions of all the sensors excluding those (decisions) of the N, N-1, ..., k sensors whose thresholds have already been determined. Furthermore, for the first sensor

$$\lambda_1 = \lambda_0 \tag{11}$$

where λ_0 is the threshold at the fusion center.

SOFA 2 ALGORITHM: Let 1, 2, ..., N be an arbitrary ordering of N sensors. Starting from the N-th sensor, the threshold of the k-th sensor as determined by SOFA 2 is given by

$$\lambda_k = \lambda_0 \frac{D_0^{N,N-1,\ldots,k}}{D_1^{N,N-1,\ldots,k}} \tag{12}$$

where

$$D_i^{N,N-1,\ldots,k} = \sum_{U_{N,N-1,\ldots,k}} [d(1,1,\ldots,1,1,U_{N,N-1,\ldots,k}) - d(0,0,\ldots,0,0,U_{N,N-1,k})]P(U_{N,N-1,\ldots,k}|H_i) \tag{13}$$

i = 0, 1. In (12) where λ_k designates the threshold of the k-th sensor, λ_0 is the threshold at the fusion,

$$d(u_1, u_2, \ldots, u_N) = \Pr(u_0 = 1 \mid u_1, u_2, \ldots, u_N) \tag{14}$$

is the decision function at the fusion center with u_i designating the binary decision of the i-th sensor, u_0 the decision at the fusion, and $U_{N,N-1,\ldots,k}$ is the set of decisions of all the sensors excluding those (decisions) of the N, N-1, ..., k sensors whose thresholds have already been determined. Furthermore, for the first sensor

$$\lambda_1 = \lambda_0 \tag{15}$$

where λ_0 is the threshold at the fusion center.

Remarks (a) In the suboptimal minimization process, the thresholds of the different sensors are obtained in a sequential fashion. To obtain the threshold of the k-th sensor only the sensors with lower index are considered, whereas the sensors with higher indices are being ignored. This is equivalent to assuming that the thresholds of the higher indexed sensors are set to infinity (always say H_0).

(b) The derivation of SOFA 2 is similar to the derivation of SOFA 1. However, SOFA 2 is derived by first assuming that the operating points of previously considered sensors are set so that they always choose H_1, i.e. their $P_F = P_D = 1$, and then minimize the residual terms in the Lagrangian [19]. SOFA 1 and SOFA 2 were found to yield identical results under OR, Majority Logic (ML), and AND fusion rules in all tested cases. However, SOFA 2 was found to be more robust than SOFA 1 in singular cases, like the singular fusion rule discussed in introduction (see Section III; also see [18] and Appendix B in [19]).

(c) In determining the thresholds through (8) or (12), it may so happen that all the terms inside the parenthesis in the sum of equation (9) or (13) are equal to zero. However, by randomizing the decision function and using

$(1-\varepsilon)d(0,0,\ldots,0,U_{N,N-1,\ldots k}) + \varepsilon\bar{d}(0,0,\ldots,0,U_{N,N-1,\ldots k})$ instead of

$d(0,0,\ldots,0,U_{N,N-1,\ldots k})$ we can resolve the ambiguity of zero by zero division, if

it occurs in (8) and (12), by applying L'Hospital's rule and letting $\varepsilon \to 0$. The ratio in (8) or (12) then becomes equal to one and thus $\lambda_k = \lambda_0$.

(d) In the case of one sensor fusion system, N=1, the suboptimal scheme becomes optimal and $\lambda_0 = \lambda_1$ [19].

3. ALGORITHMIC IMPLEMENTATION AND NUMERICAL RESULTS

The suboptimal set of thresholds $\{\lambda_0, \lambda_1 = \lambda_0, \lambda_2, \ldots, \lambda_N\}$ can be obtained using SOFA 1 or SOFA 2 and a one dimensional minimization routine. The two algorithms have been optimized to obtain a suboptimal solution first and the optimal one, if wanted, subsequently in a minimum number of searches. The two algorithms have been implemented on an IBM PC/AT as follows.

First, a specific decision function $d(u_1, u_2, \ldots u_N)$ is selected. Then a value $\lambda_1 = \lambda_0$ is selected as threshold for one of the sensors. Using the statistical models for the sensors and equations (8) and (12), the thresholds λ_k and (P_{F_k}, P_{D_k}) k = 1,2,...,N, for all sensors are obtained sequentially. A set of thresholds for the other sensors is obtained by considering a specific function $d(u_1, u_2, \ldots, u_N)$. Using the ZEROIN routine, the P_{F_0} at the fusion is determined so that P_{F_0} is equal to the prespecified level. The algorithm then searches for the set of thresholds that maximizes P_{D_0} for the desired P_{F_0}, by varying P_{F_1} (or, equivalently, λ_1) in the range (0, 0.5). All the candidate switching functions d are searched, and the one that yields maximum probability of detection is maintained. If the user wishes to obtain the globally optimal solution, the two algorithms allow for this option. The optimal set of thresholds is achieved by direct minimization of the Lagrangian over the operating points (P_F, P_D) of all the sensors and search over all threshold optimal candidate decision rules. The numerical complexity of SOFA 1 and SOFA 2 is given by Theorem 2.

Performance curves from the use of the two algorithms in slowly fading Rayleigh channels [14] are given in Figures 2 through 5. Performance curves from the use of the two algorithms in additive Gaussian noise channels [12] are given in Figures 6 through 9. The suboptimal solutions obtained by the two algorithms have been compared with the optimal solution and found to be extremely close in most of the tested cases. (For additional numerical results see also [20].)

CONCLUSIONS

It is shown that the optimal fusion rule for the distributed detection problem of Figure 1 involves a Neyman-Pearson test at the fusion and Likelihood-Ratio tests at all sensors. Two computationally efficient suboptimal algorithms for solving the fusion problem for similar and dissimilar sensor configurations were introduced. The two algorithms were tested in slowly fading Rayleigh channels and in additive Gaussian noise channels and were found to yield solutions which were very close to the optimal ones in most tested cases.

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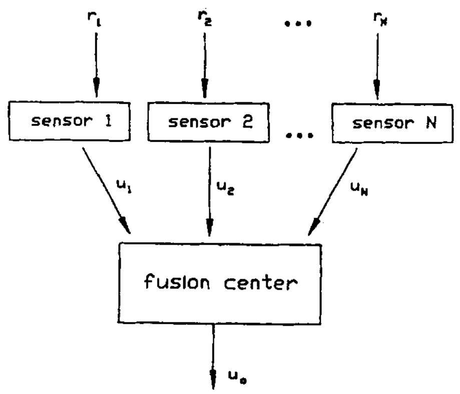

FIGURE 1 Distributed Sensor Fusion System

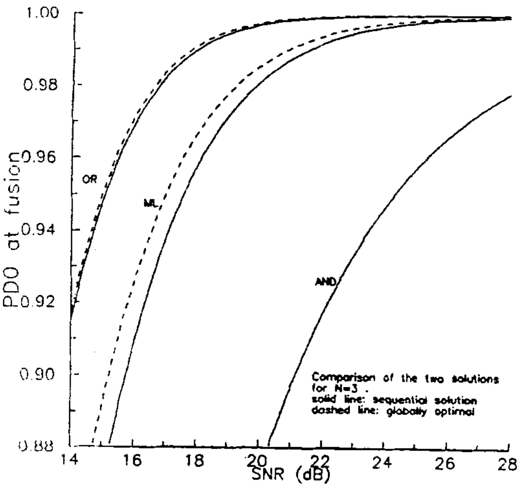

Figure 2 Optimal and SOFA 2 solutions for three equal SNR sensor fusion in slow fading Rayleigh channel. Probability of false alarm 10^{-6}.

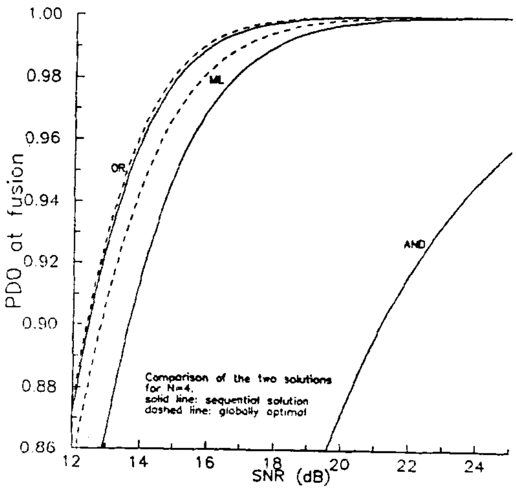

Figure 3 Optimal and SOFA 1 solutions for four equal SNR sensor fusion in [illegible] Probability of false alarm 10^{-6}.

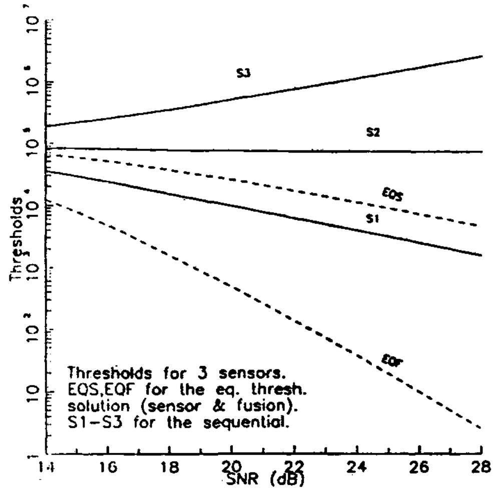

Figure 4 Thresholds for the optimal and SOFA 1 solutions for four equal SNR sensor fusion in slow fading Rayleigh channel. Probability of false alarm 10^{-6}.

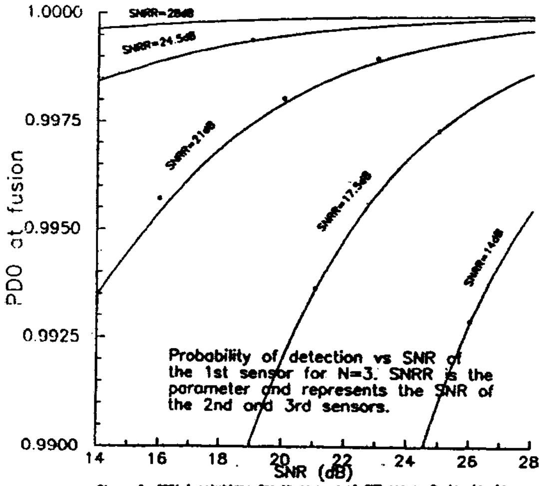

Figure 5 SOFA 1 solutions for three unequal SNR sensor fusion in slow fading Rayleigh channel and OR decision rule. The *'s represent optimal solutions. Probability of false alarm 10^{-6}.

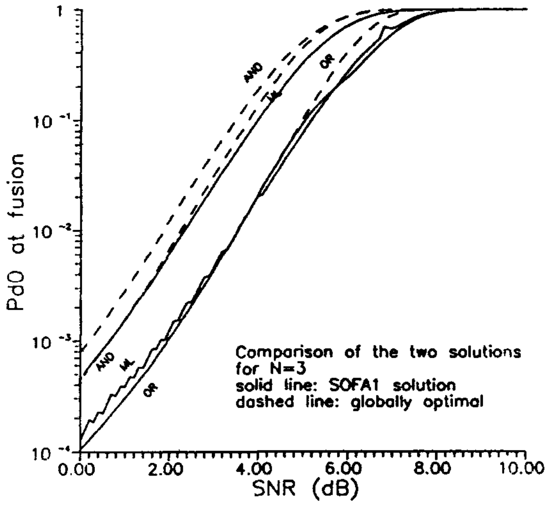

Figure 6 Optimal and SOFA 1 solutions for three equal SNR sensor fusion in additive Gaussian noise channel. Probability of false alarm 10^{-6}.

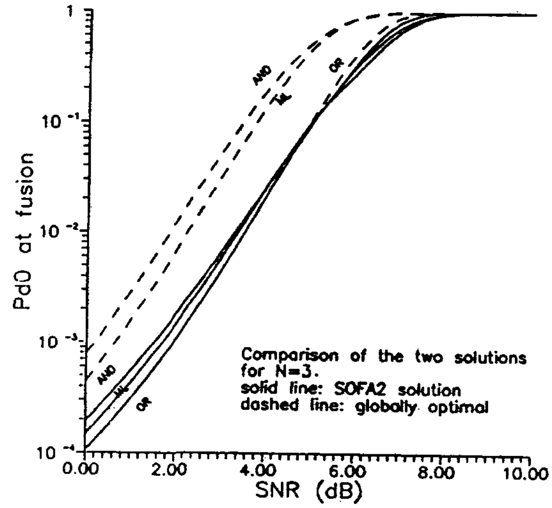

Figure 7 Optimal and SOFA 2 solutions for three equal SNR sensor fusion in additive Gaussian noise channel. Probability of false alarm 10^{-6}.

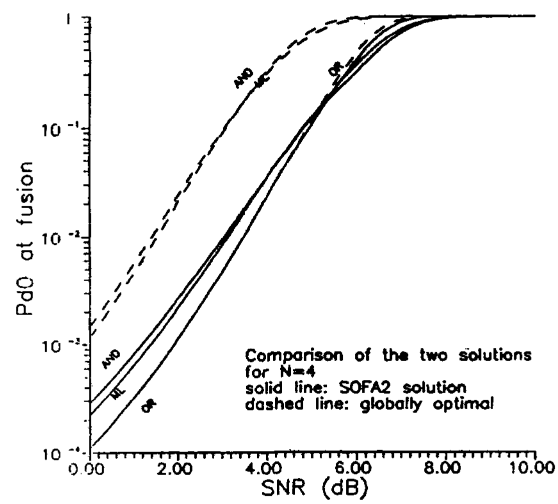

Figure 8 Optimal and SOFA 2 solutions for four equal SNR sensor fusion in additive Gaussian noise channel. Probability of false alarm 10^{-6}

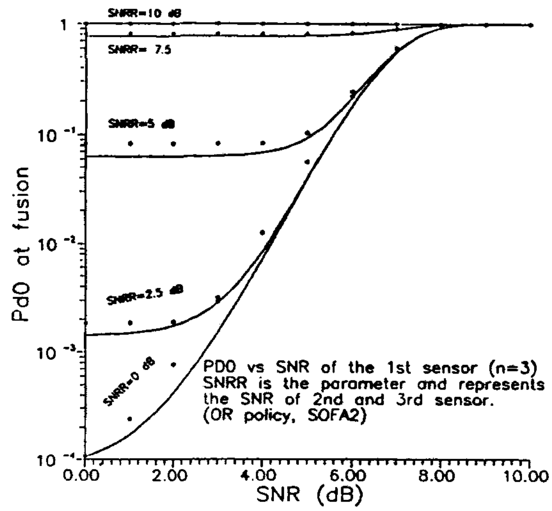

Figure 9 SOFA 2 solutions for three unequal SNR sensor fusion in additive Gaussian noise channel and OR decision rule. The *'s represent optimal solutions. Probability of false alarm 10^{-6}.