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Channel-Aware Decision Fusion for Distributed Classification in MIMO Wireless Sensor Networks

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Channel-Aware Decision Fusion for Distributed Classification in MIMO Wireless Sensor Networks

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Dedication

To the memory of my father (may Allah grant him His Mercy), to my mother who has been supporting and encouraging me all the way, to my beloved wife, for her outstanding and highly appreciated patience day and night throughout the time of my study, to my son and daughter, to my brother and sister.

friends and all of my family

Declaration

I certify that this thesis submitted for the degree of Master is the result of my own research, except where otherwise acknowledged, and that this thesis (or any part of the same) has not been submitted for higher degree to any other university or institution.

Signed:.......................

Rushdi Nadi Mahmoud AbuAwad

Date:19/5/2019

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As always, I am thankful to my parents for supporting me to pursue my academic goal. Their encouragement and support through all these years meant more than what I can express in words.

Last but by no means least, I am thankful to all my teachers and friends. Their support is indispensable to my completing the master degree.

Abstract

Wireless sensor networks (WSNs) have become a rich research area through the last few years. That is because of its high flexibility, mobility and cost efficiency. WSNs have many application such as security, surroundings and battlefield monitoring. The very important part must be investigate in the design of WSN is how to transact with the observed information at the decision fusion center (DFC) so as to obtain the final decision about a certain phenomena.

We study several fusion rules such as optimum rule, maximum ratio combiner (MRC), equal gain combiner (EGC), max-log rule, chair varshney-maximum likelihood (CV-ML) and chair varshney-minimum mean square error (CV-MMSE) applied at the DFC for one hypothesis which requires both the channel state information (CSI) and the sensors indices. The need of these information is assumed as an overhead in power and bandwidth obliged systems such as WSNs. The above rules used to fixed the matter about implementations and give a wide spectrum of choices for reducing complication and minimal system knowledge. All these rules still significantly interest from adding several antennas at the DFC.

We study in this thesis the fusion of decisions in distributed multiple input multiple output (MIMO) WSN with M-ary hypothesis and binary local decisions, where M is the number of hypothesis to be classified. The detection of distributed schemes for testing of M-ary hypothesis often assume that for every observed phenomena the local detector transmits at least $log_2 M$ bits to DFC. We formulate three fusion rules for the DFC such as Optimum maximum a posteriori (MAP) rule, Augmented Quadratic Discriminant Analysis (A-QDA) rule and MAP Observation bound.

A comparison performance has been obtained through simulation between three different fusion rules, optimum (MAP), MAP observation bound, augmented quadratic discriminant analysis (A-QDA) applied at MIMO WSN system model. We assumed Rayleigh fading and additive white Gaussian noise (AWGN) channels between the local detectors (sensors) and the DFC. We investigate the system parameters effect on the system performance at the DFC. We study the effect of the local detector (sensors) performance indices in the case in which all indices are identical. also investigate the effect of the total number of antenna at the DFC, the number of local detectors, the number of hypothesis and the effect of the value of channel signal to noise ratio (SNR) between the sensing elements and the DFC. Results obtained by simulation show that the MIMO WSN system model provide a relatively good performance in terms of detection performance when increasing the number of antenna at the DFC with lower number of hypothesis for the applied fusion rules. In addition, simulation results show that the optimum (MAP) rule has the best performance than A-QDA rule, also the A-QDA needs higher signal to noise ratio to obtain suitable performances comparable with the optimum (MAP) rule.

Keywords: Wireless Sensor Networks (WSNs), Distributed hypothesis testing, Decisions fusion, fading channels, distributed detection, MIMO, Optimum (MAP) classifier, Augmented Quadratic Discriminant Analysis (A-QDA).

List of Figures

Acronyms and Abbreviations

A-QDA	Augmented Quadratic Discriminant Analysis
BPSK	Binary Phase Shift Keying
AWGN	Additive White Gaussian Noise
CSI	Channel State Information
CV-ML	Chair Varshney-Maximum Likelihood
CV-MMSE	Chair Varshney-Minimum Mean Square Error
DaF	Decode-and-Fuse
DFC	Decision Fusion Center
DtF	Decode-then-Fuse
EGC	Equal Gain Combiner
LDs	Local Detectors
LLR	Log Likelihood Ratio
LRT	Likelihood Ratio Test
MAC	Multiple Access Channel
MAP	Maximum A Posteriori
MIMO	Multiple Input Multiple Output

MMSE	Minimum Mean Square Error
MRC	Maximum Ratio Combiner
PAC	Parallel Access Channel
PMF	Probability Mass Function
ROC	Receiver Operating Characteristics
SNR	Signal to Noise Ratio
WSN	Wireless Sensor Network

Contents

Chapter 1

Introduction

1.1 Wireless Sensor Networks Overview

Dispersal sensing technology has the potential to enhance information gathering and processing in many applications. The ideal Wireless sensor networks (WSNs) employs multiple local detectors, each local detector equipped with appliances able to realizing, processing, and communication [1–4]. The interest points of WSN contain pliability in deployment and the ability of a process, soft charges and quick introductory setup. Recently many applications has been enabled such as security, surroundings and battlefield monitoring. [5, 6].

Every local detector collects and potentially processes information about the phenomenon and transmits its observations to decision fusion center (DFC) for a final decision. The DFC makes a final decision about the certain phenomenon based on the received local decisions from the local detectors, and potentially triggers an appropriate action. DFC combines information from several sources in order to improve the fusion of decisions in WSNs and get better classification precision while diminishing the power utilization and bandwidth demand for information transmission [7, 8].

Every local detector node in the system has the ability to observe a specific phenomenon and to send information over a parallel access channel (PAC) or multiple access channel (MAC) to the DFC, in order to makes a final decision about the specific phenomenon. Considerable difficulties exist and should be classified in respect of the visualized application to become actuality. However, the individual local detector are extraordinarily resource obliged. They have restricted limitation of capacity and bandwidth of communication. In addition, in many WSN applications, local detectors operate on indispensable power supply, making it necessary for energy conservation for long existence [9].

The usual architecture for WSN assumes that each local detector communicates through PAC, where each local detector can exploit a channel to communicate with the DFC as shown in Figure 1.1. As of late, it has been recommended to utilize the wireless medium as a MAC for DFC, where several sensors communicate with a single DFC through a common channel as shown in Figure 1.2 [10, 11].

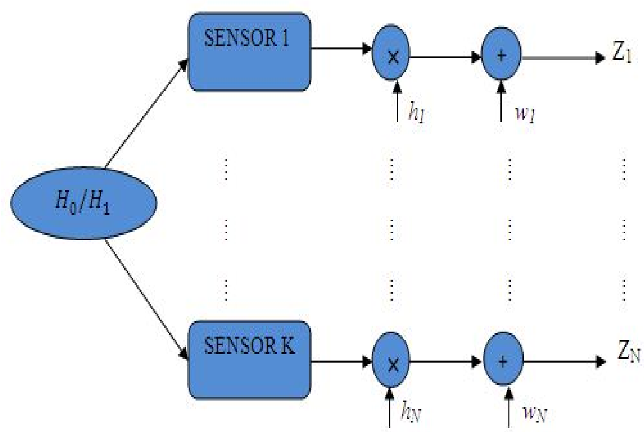


Figure 1.1: General system of decentralized detection for PAC

The structure of any WSN could be either decentralized or centralized as appeared in Figure 1.3(a) and Figure 1.3(b) [12]. In the decentralized scheme, every sensor gets noisy measurements and makes a local decision regarding a specific phenomena and sends its local decision to the DFC where the final decision about the phenomena is taken. In the centralized scheme, each sensor gets noisy measurements and transmit their raw information to the DFC to make a final decision. In this scheme, there are no decisions regarding the phenomena obtained by the sen-

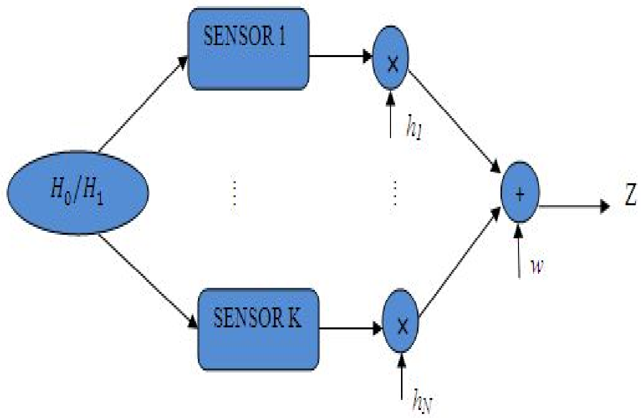
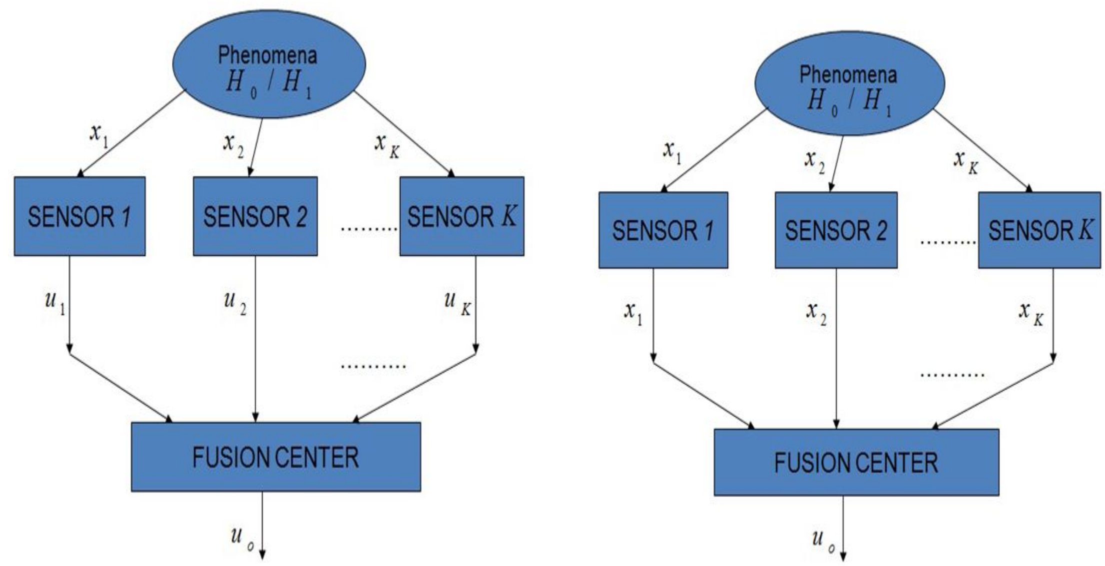


Figure 1.2: General system decentralized detection for MAC

sors and the sensors just re-transmit the received measurement to the DFC. While the centralized scheme performs better than the decentralized scheme, the power consumption and the channel bandwidth requirements for the centralized scheme is much more than that for the decentralized scheme because each sensor transmits a raw data to the DFC, so the decentralized scheme is of particular interest [12].

There are three primary topologies for WSN, parallel, serial and tree [13]. Figure 1.3a shows the parallel topology for WSN which is the most widely recognized topology considered in literature [12]. In this topology, every sensor, k, gets an observation denoted by x_k regarding a specific phenomena. All sensors make their own decisions regarding the phenomena and transmit their own decisions, u_k, to the DFC. The final decision, u_o, in the case of parallel topology settled on dependent on the own decisions for all sensors and not on their individual got observations.

The serial topology is appeared in Figure 1.4. Considering K sensors in the network, only the first sensor makes the local decision dependent on its own per-



(a) Decentralized (b) Centralized

Figure 1.3: WSN structures

ception, while the $K - 1$ sensors did their local decisions based on their own got observations and the got local decisions from the previous sensors. The final decision in serial topology based WSN is created at the Kth sensor in the network.

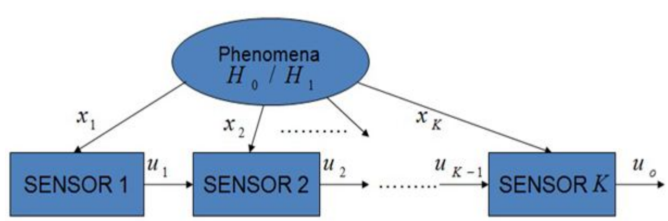


Figure 1.4: Serial topology for WSN

The tree topology for WSN is appeared in Figure 1.5. Considering K sensors in the network, the network is divided into levels up to $\frac{K}{2}$ levels. In Level 1, the first two sensors get their own observations and transmit their local decisions to the next sensor in Level 2. The remaining $\frac{K}{2}$ sensors in the network get their own observations regarding the phenomena and also get the local decisions from two sensors in the higher level. Decision fusion is applied and the sensors transmit their local decisions and observations to the sensor in the next level. The final decision takes place at the $\frac{K}{2}th$ level. However, in our research we consider the MAC architecture with decentralized structure for WSN.

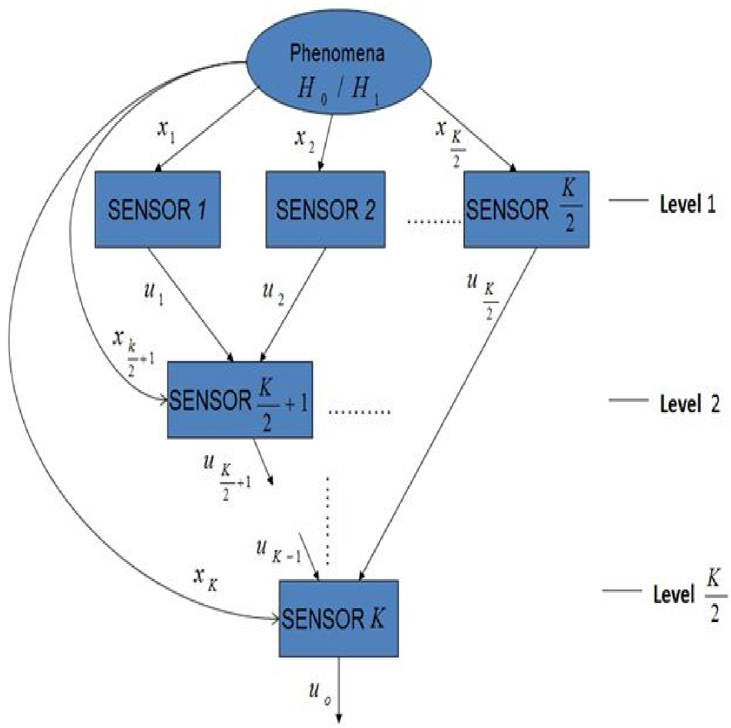


Figure 1.5: Tree topology for WSN

The central interest in this thesis is making use of signal processing algorithms for a WSN engaged in a detection task. As with any detection problem, including classical distributed detection theory, decision making is confronted with the uncertainty in the state of the phenomenon. This uncertainty may be due to observation noise and propagation distortion from the target of interest to the sensors.

1.2 Literature Review

The issue of distributed detection has been contemplated broadly in the previous decades. In [14], distributed detection algorithm proposed in the case of two sensors. A careful and relatively recent overview on distributed detection can be discovered in [15] and [16].

Decisions combination represents a formal system that arrangements with an information gathered from different resources to obtain a more quality of final decision about a specific hypothesis [17]. Choices combination with vulnerability has been inspected and a bayesian testing approach has been proposed to address this issue [18].

Combination of decisions under communication constraints has been explored by various authors earlier. In [19] and [20], optimum fusion rule has been obtained under the restrictive autonomy presumption. Distributed detection in a constrained network has been also considered in [21–23]. Decisions combination which are associated to one another has been examined in [24]. Decisions combination in WSN worked in multiple input multiple output (MIMO) channel has been studied in [25, 26].

In [11, 25, 27] the authors studied channel-aware decision fusion through a Rayleigh flat fading channel with various antennas at the DFC, they offered diverse imperfect rules for fusion with minimized system awareness and instantaneous channel state information (CSI). As of late, a few sub-optimal fusion rules have been inspected in the ongoing writing, such as log likelihood ratio (LLR), maximum ratio combiner (MRC), equal gain combiner (EGC), chair varshney-maximum likelihood (CV-ML). In [28] the authors have presented theoretical performance analysis of the MRC rule for channel-aware decision fusion over MIMO channels for independent and dependent local decisions.

The distributed detection of channel-aware has been advised in [29–31] which combine the wireless channel conditions in calculation structure. Fading channels get more consideration in recent research reports [32]. A majority logic fusion rule which combines the fading channels among the local detectors and the DFC has been suggested in [33]. Most designs commonly expect that the information about channel is known at the DFC. A new fusion rule was studied in [32], which needs just the channel statistics rather than the instantaneous CSI has been constructed. This is more practical since the accurate information of CSI may be costly to acquire.

In [25], for complexity limitation, the authors assume that the sensors make independent local decisions on the hypotheses based on their respective observations and forward these decisions over a MIMO channel to a DFC which makes a final decision about the state of the phenomenon based on the hypothesis. The use of multiple antennas at the DFC in order to avoids deep fading scenarios. The authors in [34] demonstrate that when the quantity of reception antennas at DFC is very large, low intricacy calculations can asymptotically achieve an upper bound on performance of detection nevertheless using a receiver with incomplete CSI.

Most researches of parallel distributed detection for M-ary hypothesis expect that for every observation the sensor sends at minimum log_2M binary data to the DFC, where M is the number of hypothesis to be classified. However, the authors in [35] assuming that it is possible to transmit bits using less than log_2M.

1.3 Thesis Contributions and Organization

The fusion of decisions model describing WSNs in the existence of MIMO channel is illustrated in figure (1.6). This system model assumes that each sensor communicates through MAC for DFC while coping with existence of substantial interference.

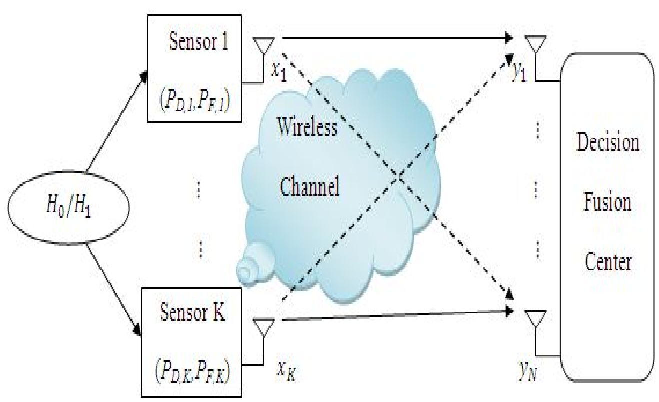


Figure 1.6: The decision fusion model in existence of MIMO channel [36]

In our research work, the propose model in [36] is extended to include dis-

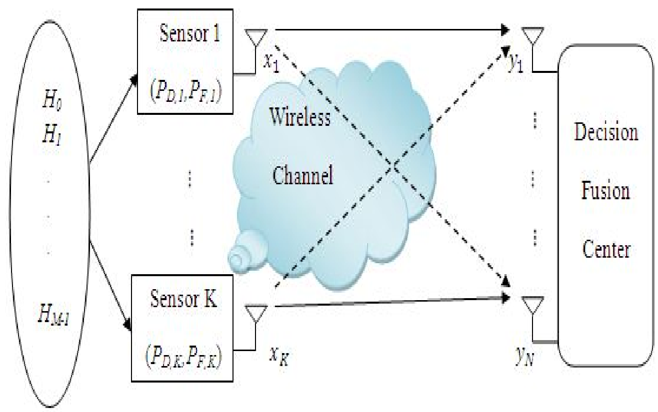


Figure 1.7: Proposed decision fusion model with distributed M-ary hypothesis and MIMO channel

tributed M-ary hypothesis testing [35]. Particularly, we will consider channel-aware decision fusion in distributed MIMO WSN with M-ary hypothesis testing and binary local decisions as shown in Figure 1.7. In addition, we will design fusion rules with simpler implementation and possibly reduced system knowledge.

Chapter 2

Fusion of Decision Model in Existence of MIMO Channel

In this chapter, the fusion of decisions model describing WSN in the existence of MIMO channel that incorporates fading and noisy channels between the sensors and the DFC. The system model is divided into three categories and each category is illustrated in details in the next sections. Moreover, the state of the art of the decision fusion rules are presented which have been described and derived in [36].

2.1 WSN System Model Categories

The fusion of decisions model describing WSN in the existence of MIMO channel is illustrated in Figure 2.1. This system model assumes that each sensor communicates through MAC for DFC while coping with existence of Substantial interference.

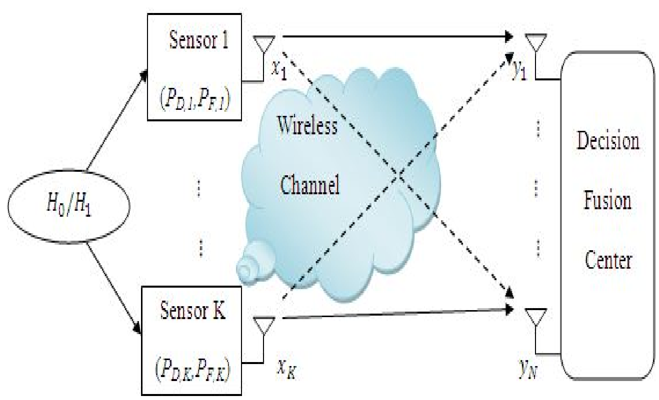


Figure 2.1: The fusion decision model in existence of MIMO channel [36]

There are two hypotheses under test, H_1 (present of target), and H_0 (absent of target). Each sensing elements gets noisy measurements and processes these measurements for the sake of making local decision regarding the hypothesis under test. At that point, every sensor transmits the got information to the DFC through multiple access channels (MACs) which hew Rayleigh flat fading and additive white Gaussian noise (AWGN) due to the bandwidth of channel is larger than the bandwidth of the transmitted signal.

2.1.1 Category 1: Sensors (Local Detectors)

In this category, all the local detector get noisy measurements according to a certain hypothesis. In this work, the observations are assuming independent of each other. After getting its observation, x_k, each local detector , k, makes binary local decision: $u_k = 1$ is sent if H_1 is decided, and $u_k = -1$ is sent otherwise, where $k = 1, \ldots, K$ and K is the total number of local detectors in the network. The local binary decision is made by each local detector upon the below equation:

$$u_k = \left\{ \begin{array}{ll} 1 & : x_k > 0 \\ -1 & : x_k < 0 \end{array} \right\} \tag{2.1}$$

In addition, we assume that every sensor node makes a binary local decision based on its own observation. The detection performance of every local detector node can be characterized by its corresponding detection probability which denoted by $P_{D,k}$ and false alarm probability which also denoted by $P_{F,k}$.

In general, the detection and false alarm probabilities may not be equal and they are functions of signal to noise ratios as long as the detection sill at every local detector. Figure 2.2 describes these two probabilities.

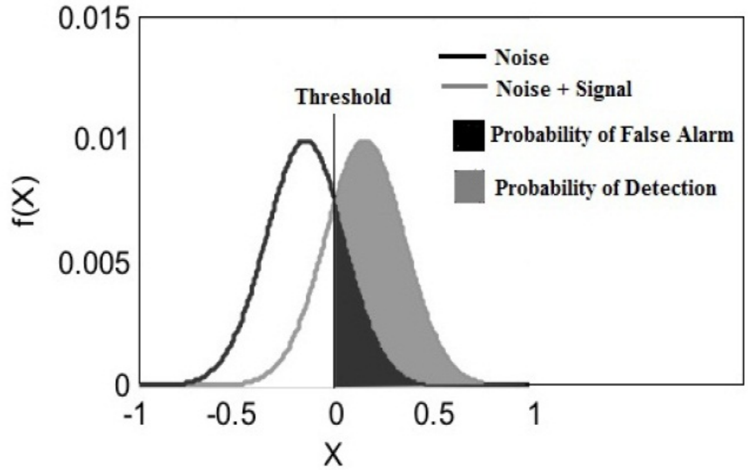


Figure 2.2: Conditional detection and false alarm probabilities [12].

2.1.2 Category 2: Fading and Noisy Channels

The sensing element communicate with the DFC through a wireless MAC. The N receive antennas are utilized at the DFC in order to take the advantage of diversity and combat the attenuation in the signal because of small-scale fading of the wireless medium, this configuration determines basically a distributed MIMO channel, as shown in Figure 2.1 [8].

The obtained signal for nth receiving antenna of the DFC after filtering and sampling is denoted by y_n, the fading coefficient between sensors and DFC is denoted by $h_{n,k} \sim N_c(0,1)$, also the AWGN with zero mean and variance σ_w^2 is denoted by w_n.

This model at the DFC is obtained upon the following:

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{d} + \boldsymbol{w} \tag{2.2}$$

where $\boldsymbol{y} \in \mathbb{C}^N$, $\boldsymbol{H} \in \mathbb{C}^{N \times K}$, $\boldsymbol{d} \in \mathcal{X}^K$, $\boldsymbol{w} \sim \mathcal{N}_{\mathbb{C}}(\boldsymbol{0}_N, sigma_w^2 \boldsymbol{I}_N)$, are the received signal vector at the DFC, the channel matrix of y, the transmitted signal vector and the noise vector of y respectively.

2.1.3 Category 3: Decision Fusion Center:

The most important Category in WSN system is DFC. It will be prepared with N received antennas so as to makes a final decision u_o regarding a certain hypothesis based on the received y_k information for all local detector. This is might a chance to be carried out by applying a certain fusion rule at the DFC. In order to make final decision, the CSI and the local sensing elements performance parameters are required according to the used fusion rule at the DFC. The following mathematical statement portrays those capacity of the DFC after forming a certain statisticΛ:

$$u_o = \left\{ \begin{array}{ll} 1 & : \Lambda > T \\ -1 & : \Lambda < T \end{array} \right\} \tag{2.3}$$

where u_o is the final decision, Λ is the fusion statistic and T is the decision threshold at the DFC.

2.2 State of the Art on Decision Fusion Rules

The decision fusion rule through MIMO channels are arranged under Decode-and-Fuse (DaF) and Decode-then-Fuse (DtF) methodologies. A short survey of the developed fusion rules was given in [36].

2.2.1 Decode-and-Fuse:

1. Optimum Rule: The optimal test [37] for the considered problem can be formulated as:

$$\Lambda_{opt} = \ln \left[\frac{p(y|H_1)}{p(y|H_0)} \right] \underset{\hat{H}=H_0}{\overset{\hat{H}=H_1}{\lessgtr}} \tag{2.4}$$

where $p(y|H_1)$ is the probability of y when H_1 is present, $p(y|H_0)$ is the probability of y when H_0 is present and $\hat{H}$ is the decided hypothesis.

2. (MRC) : The LLR of (2.4) can be rearranged under those suspicion of typical local detectors [38, 39] i.e.$(P_{D,k}, P_{F,k}) = (1, 0)\,, k \in K$. In this case the sending vector $x \in (1_K, -1_K)$ and the (2.4) reduces to:

$$\Lambda_{MRC} = \ln \left[\frac{e^{-\frac{\|y-H1_K\|^2}{2\sigma^2}}}{e^{-\frac{\|y+H1_K\|^2}{2\sigma^2}}} \right] \propto \mathrm{Re}\left(1_K^t H^\dagger y\right) \tag{2.5}$$

where $(\cdot)^t$ the matrix transpose and $(\cdot)^\dagger$ the matrix conjugate transpose

3. (EGC): Prompted by the fact that resembles a MRC fact for differing diversity combining, an third elective in the form of an EGC has been suggested previously [40], which obliges little amount of data:

$$\Lambda_{EGC} = \mathrm{Re}\left(z^\dagger y\right) z = e^{j\angle(H1_K)} \tag{2.6}$$

4. Max-Log Rule: The approximation of max-log is expressed as in [41] as below:

$$\Lambda_{max-log} = \min_{x \in X^K} \left[\frac{\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2}{2\sigma^2} - \sum_{k=1}^{K} \ln P(x_k|H_0) \right] - \min_{x \in X^K} \left[\frac{\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2}{2\sigma^2} - \sum_{k=1}^{K} \ln P(x_k|H_1) \right] \tag{2.7}$$

2.2.2 Decode-then-Fuse:

1. CV-ML: The following statistic, termed as the CV fusion statistic has been indicate in (2.8) [41] as:

$$\Lambda_{CV-ML} = \arg\min_{x \in X^K} \|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2 \tag{2.8}$$

where Λ_{CV-ML} is fusion statistic of CV-ML, y is the received signal vector at the DFC, H the channel matrix of y and x is the transmitted signal vector.

2. CV-MMSE: In order to reduce the system complexity, a sub-optimal rule obtained via the MMSE solution [41] and it is concern with correlation between symbols which obtain the same hypothesis. This problem was discussed in [42], the following MMSE decoder should be considered [37]:

$$\Lambda_{MMSE} = sign\left[\boldsymbol{\bar{x}} + \boldsymbol{C}^{\dagger}\boldsymbol{H}\left(\boldsymbol{H}\boldsymbol{C}^{\dagger}\boldsymbol{H} + \boldsymbol{2\sigma^2 I_N}\right)^{\boldsymbol{-1}}\left(\boldsymbol{y} - \boldsymbol{H}\boldsymbol{\bar{x}}\right)\right] \tag{2.9}$$

where $\bar{x} = E(x)$ and $C \triangleq E(x - \bar{x})(x - \bar{x})^{\dagger}$.

In the Figure 2.3 shown, a performance comparison between the above fusion rules in term of receiver operating characteristics curves (ROC). These curves obtained by MATLAB simulation. In this simulation, first, a noisy data is generated for both phenomena (H_0, H_1), then each sensing element make its decision based on the sign of the received measurement according to (2.1). The obtained decisions are then transmitted to the DFC by each sensor and it is assumed that the channel between each sensor and the DFC undergoes independent Rayleigh fading and AWGN and the channel signal to noise ratio (SNR) is 15 dB, also with 8 sensors and 2 antennas at the DFC. The local sensing elements performance indices values, i.e. the $P_{D,k}$ and $P_{F,k}$ are 0.5 and 0.05 respectively. The global decisions are obtained by the DFC according to (2.1). Through this simulation, the range of threshold (i.e. -30:30) is made in order to get a wide range of $P_{D,k}$ and $P_{F,k}$.

It is apparent in the figure shown above that the ROC for max-log rule is much similar with optimum rule ROC, where this result is independent on channel SNR. However, there are an intersection point between the ROCs of MRC and EGC, CV-ML and CV-MMSE, respectively. However, while in the first case the result is independent of the specific channel SNR, in the latter case it depends on the poor performances of CV-ML statistics, due to the low channel SNR.

The performance comparison between the above fusion rules is shown in Figure 2.4 as a function of probability of detection and the channels SNR, in a network with number of sensor $K = 8$; we plot the cases $N \in (1, 2)$ to investigate the effect

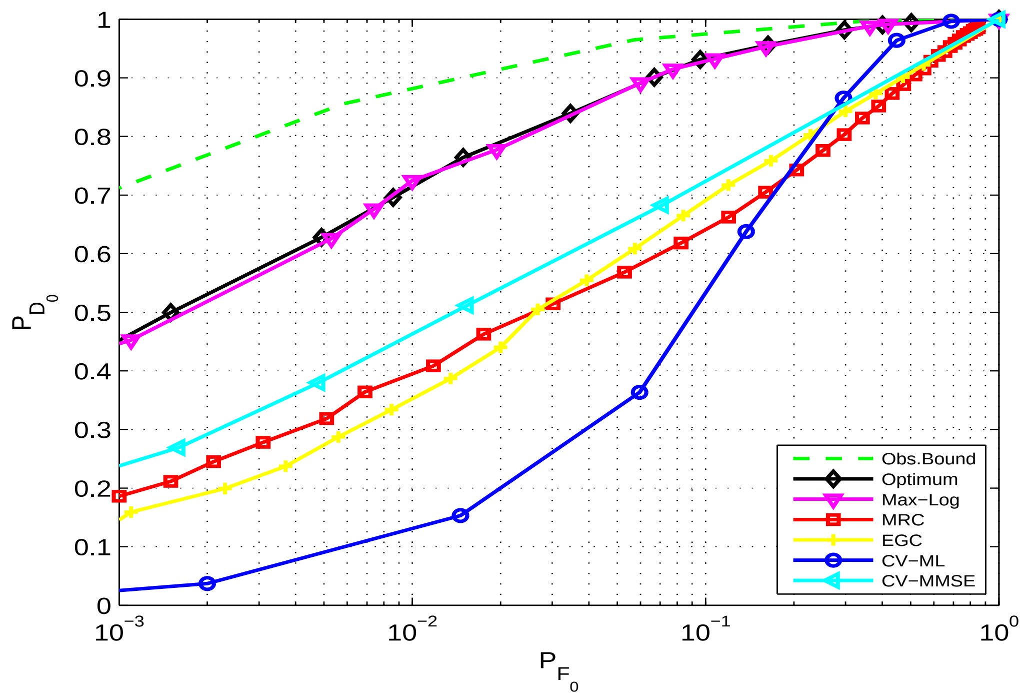


Figure 2.3: ROCs for the presented fusion rules, channel $SNR = 15$ dB, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of sensors K=8 and number of antenna $N = 2$.

on performances when two antennas are employed at the DFC. At high and low channel SNR the CV-ML and MRC curves approach the optimum curve, respectively, also max-log achieve same performance as optimum rule at all channel SNR range.

Figure 2.5 shows the performance comparison for the above fusion rules as a function of probability of detection and the number of antennas for the cases $(SNR) \in (5, 15)dB$ under $P_{F_0} \leq 0.01$, the plotted cases are examined the performance when increasing the number of antennas under channel SNR values. We notice when we increasing the number of antennas at the DFC is beneficial for all the fusion rules.

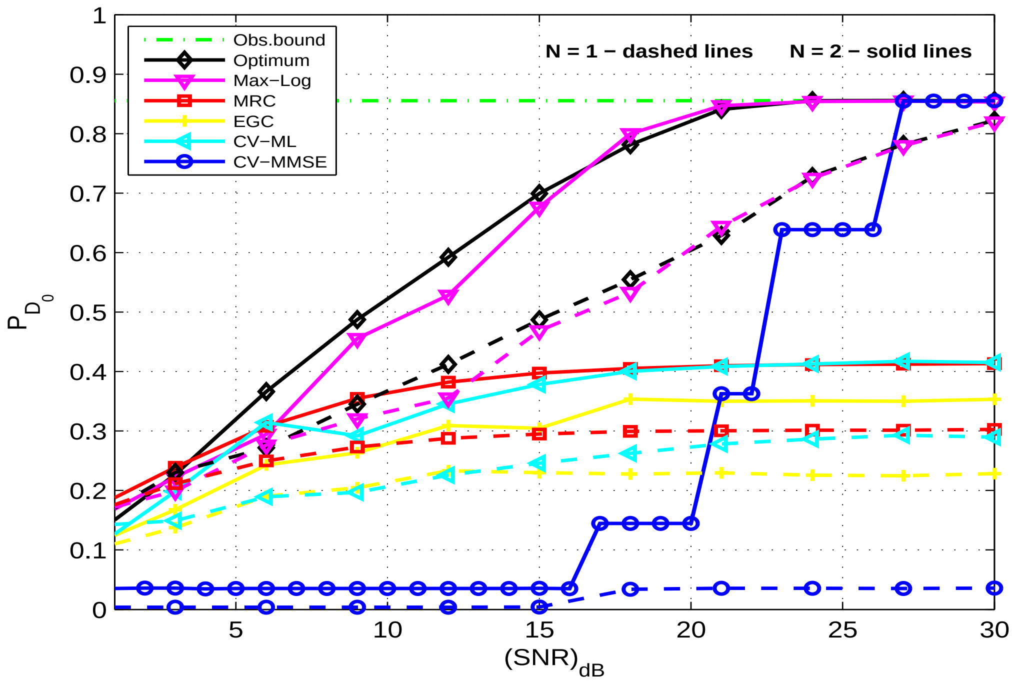


Figure 2.4: P_{D_0} vs average channel (SNR) for the presented fusion rules, channel $SNR = 15$ dB, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of sensors K=8 and number of antennas $N = (1, 2)$.

Comparison between the presented rules in term of the probability of error P_{E_0} in the network as a function of the number of sensors K, we plot the case $P_{D,k} = (0.7)$, $P_{F,k} = (0.05)$ to investigate the results observed. We assume a network with different number of antennas at DFC and the average channel $(SNR) = 15$ dB.

Another performance comparison between the above fusion rules is shown

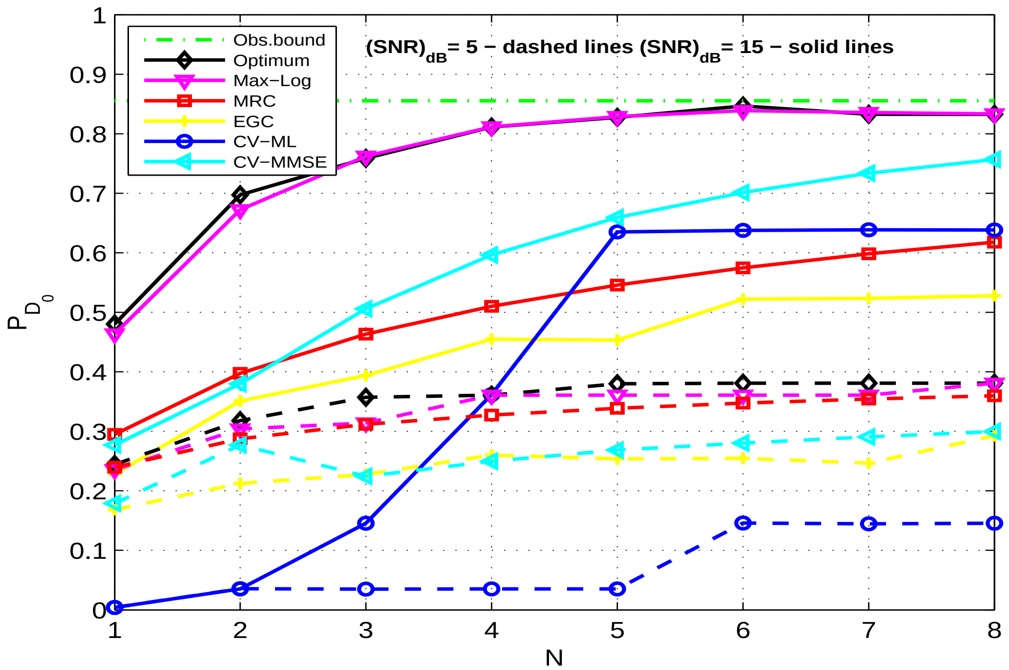


Figure 2.5: P_{D_0} vs number of antenna N for the presented fusion rules, number of sensors K=8, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$. $SNR = (5, 15)$ dB.

in Figure 2.6, Figure 2.7 as a function of probability of error and the number of sensor for the cases $N \in (1, 2)$ under fixed SNR channel. It can be notice that the probability of error for EGC is lower than the probability of error for MRC due to the intersection point in the ROCs curves. However, increasing the number of received antennas at the DFC will reducing probability of error attainable by each rule. In addition, the minimum error probability is obtained by using large number of sensor, also effects slop and limiting value of probability of error for MRC.

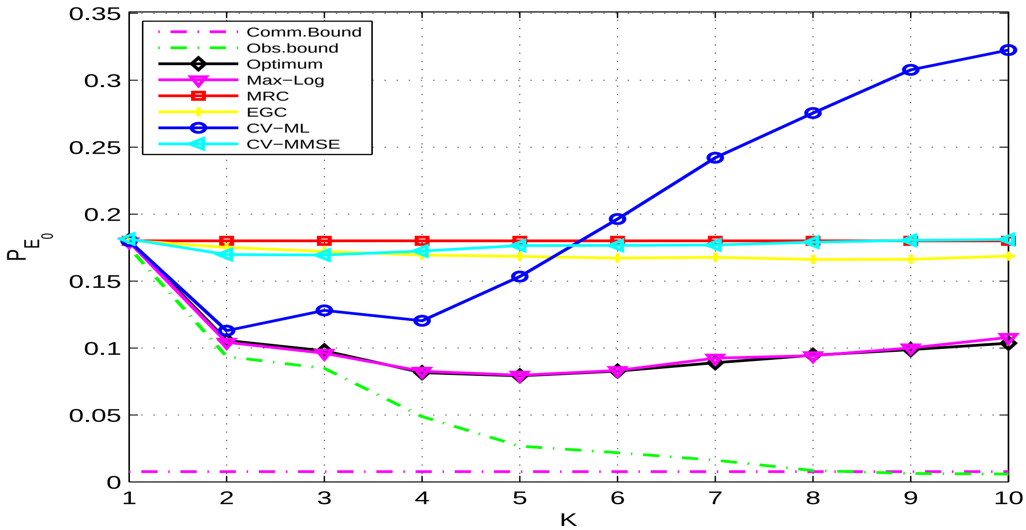


Figure 2.6: P_{E_0} vs number of sensors K for presented fusion rules, number of antenna $N = 1$ at DFC and channel $SNR = 15$ dB, $P_{D,k} = (0.7)$, $P_{F,k} = (0.05)$.

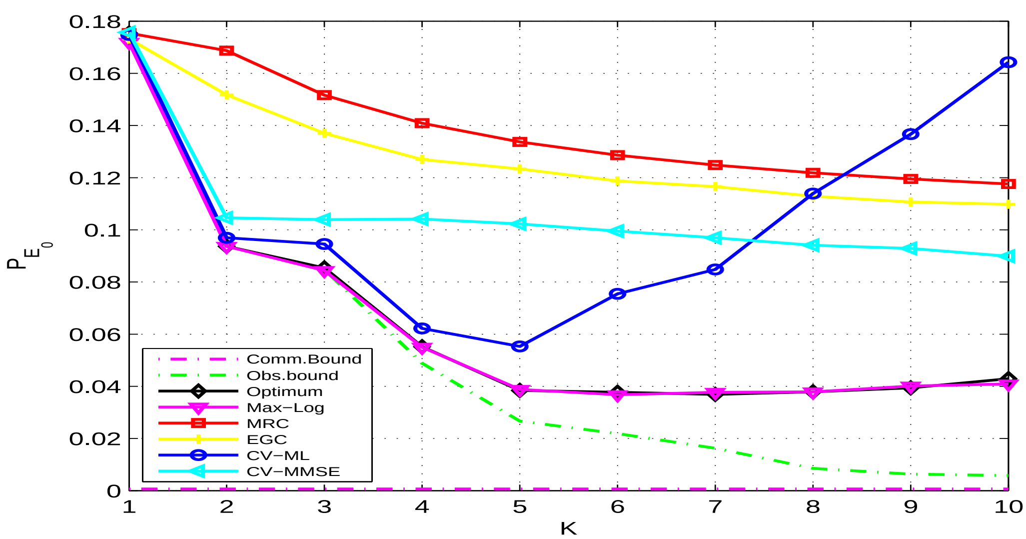


Figure 2.7: P_{E_0} vs number of sensors K for presented fusion rules, number of antenna $N = 2$ at DFC and channel $SNR = 15$ dB, $P_{D,k} = (0.7)$, $P_{F,k} = (0.05)$.

Chapter 3

Proposed WSN System Model

3.1 Motivation

In the previous chapter we study the fusion rules. The study was inspired by the need of multiple received antennas at the DFC to acquire an emotional improvement in exhibitions with a diminished WSN power budget. The introduced choices solve the problem in about implementations and spectrum to diminished complexity and lower information about the system. All these rules still significantly still altogether profit by the expansion of antennas at the DFC. However, in this chapter we will consider channel-aware decision fusion in distributed MIMO WSN with M-ary hypothesis testing and binary local decisions. In addition, extending the analysis for optimum and observation bound rule to include M-ary hypothesis testing and design other fusion rules with less complexity of implementation and conceivably diminished information about the system.

3.2 System Model

In our system we consider M-hypotheses test, where K local detectors are utilized to segregate among the hypotheses of the set $\mathcal{H} = \{H_1, \ldots, \mathcal{H}_M\}$. The *a priori* probability of hypothesis $\mathcal{H}_i \in \mathcal{H}$ is denoted $P(\mathcal{H}_i)$. The kth local detector observed a binary data $d_k \in \mathcal{X}$, where $\mathcal{X} \triangleq \{-1, 1\}$, about the obtained phenomenon on the premise of its own measurements.

Our distributed detection system utilize K local detectors to study a typical volume for evidence of one of the M-hypotheses within $\mathcal{H}$. These local detectors are registered to did a single binary decision per observation, representing a binary phase shift keying (BPSK) modulation. The DFC uses the vector of local binary decisions $\boldsymbol{d} \in \{-1, 1\}^K$ to form a final decision $\hat{H}$ for one of the M-hypotheses.

We appropriate to this model the marginal probability mass function (pmf) of kth sensor decisions over the probabilities of transition $\rho_{k,m}$, $m = 1, \dots M$, where $\rho_{k,m}$ is the probability that the kth sensor transmits $d_k = 1$ to the DFC when presented one of the M-hypotheses is namely,

$$\rho_{k,m} \triangleq \Pr \{d_k = 1 | \mathcal{H}_m\} \ . \tag{3.1}$$

The above probabilities are summarized for kth sensor in the vector as the following:

$$\boldsymbol{\rho}_k \triangleq \begin{bmatrix} \rho_{k,1} & \cdots & \rho_{k,m} \end{bmatrix}^T \tag{3.2}$$

The N receive antennas are utilized at the DFC in order to take the advantage of diversity and combat the attenuation in the signal because of small-scale fading of the wireless medium, this configuration determines mainly a distributed MIMO channel as shown in [8] MIMO channel.

The obtained signal for nth receiving antenna of the DFC after filtering and sampling is denoted by y_n, the fading coefficient between sensors and DFC is denoted by $h_{n,k} \sim N_c(0, 1)$, also the AWGN with zero mean and variance σ_w^2 is denoted by w_n.
where $N_c(0, 1)$ is the complex normal distribution with zero mean vector and unity covariance matrix. This model at the DFC is obtained upon the following:

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{d} + \boldsymbol{w} \tag{3.3}$$

where $\boldsymbol{y} \in \mathbb{C}^N$, $\boldsymbol{H} \in \mathbb{C}^{N\times K}$, $\boldsymbol{d} \in \mathcal{X}^K$, $\boldsymbol{w} \sim \mathcal{N}_{\mathbb{C}}(\boldsymbol{0}_N, sigma_w^2\boldsymbol{I}_N)$, $sigma_w^2$, $\boldsymbol{I}_N$ are the received signal vector, the channel matrix, the transmitted signal vector and the noise vector, variance of white gaussian noise, the null vector of length N respectively. It is not difficult to show that the received signal, under hypothesis $\mathcal{H}_m$, is distributed as:

$$\boldsymbol{y}|\mathcal{H}_m \sim \sum_{\boldsymbol{d}\in\mathcal{X}^K} \mathcal{N}_{\mathbb{C}}(\boldsymbol{H}\boldsymbol{d}, \sigma_w^2\boldsymbol{I}_N)\, P(\boldsymbol{d}|\mathcal{H}_m)\,, \tag{3.4}$$

The system model in (3.3) can be underloaded when the number of sensor less than number of antenna at DFC, fully-loaded when the number of sensor equal to the number of antenna at the DFC or overloaded when the number of sensor more than number of antenna at DFC. The reasonable case in WSN is overloaded case, typically when the number of antenna employed at the DFC is much less than the number of sensor.

The total average of SNR in the WSN is formulated as:

$$SNR \triangleq \mathcal{E}_s/\sigma_w^2 = {}^{KN}/_{\sigma_w^2} \tag{3.5}$$

where σ_w^2 is the variance of white Gaussian noise, $\mathcal{E}_s$ power spectral density of the signal, K total number of sensor, N total number of antenna at DFC.

The second order characterization of the received vector under hypothesis $\mathcal{H}_m$ (i.e.

$\boldsymbol{y}|\mathcal{H}_m)$ is given by:

$$\mathbb{E}\{\boldsymbol{y}|\mathcal{H}_m\} = \boldsymbol{H}\,\mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\} \tag{3.6}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{y}|\mathcal{H}_m} = \boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\boldsymbol{H}^{\dagger} + \sigma_w^2\,\boldsymbol{I}_N \tag{3.7}$$

$$\bar{\boldsymbol{\Sigma}}_{\boldsymbol{y}|\mathcal{H}_m} = \boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\boldsymbol{H}^{T} \tag{3.8}$$

where $E\{\boldsymbol{y}|\mathcal{H}_m\}$ is the mean vector of y, $\boldsymbol{\Sigma}_{\boldsymbol{y}|\mathcal{H}_m}$ is the covariance of y and $\bar{\boldsymbol{\Sigma}}_{\boldsymbol{y}|\mathcal{H}_m}$ is the pseudo-covariance of y, respectively.

The proof is given in Appendix 5.2.

The *augmented covariance* of $\boldsymbol{y}|\mathcal{H}_m$ is given in closed form as:

$$\boldsymbol{\Sigma}_{\underline{\boldsymbol{y}}|\mathcal{H}_m} = \underline{\boldsymbol{H}}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\underline{\boldsymbol{H}}^{\dagger} + \sigma_w^2\,\boldsymbol{I}_{2N}\,. \tag{3.9}$$

where σ_w^2, $\boldsymbol{I}_{2N}$ is the variance of white Gaussian noise, the null vector of length $2N$ respectively.

3.3 Fusion Rules

3.3.1 Optimum Maximum A Posteriori (MAP) Rule

The test of optimal [37] for the assumed issue is that minimizing the fusion error-probability, that is the MAP criterion, formulated as

$$\begin{aligned}
\widehat{\mathcal{H}}_{\text{map}} &\triangleq \arg\max_{\mathcal{H}_m} P(\mathcal{H}_m|\boldsymbol{y}) && (3.10)\\
&= \arg\max_{\mathcal{H}_m} \frac{p(\boldsymbol{y}|\mathcal{H}_m)\, P(\mathcal{H}_m)}{p(\boldsymbol{y})} && (3.11)\\
&= \arg\max_{\mathcal{H}_m} p(\boldsymbol{y}|\mathcal{H}_m)\, P(\mathcal{H}_m) && (3.12)\\
&= \arg\max_{\mathcal{H}_m} \ln p(\boldsymbol{y}|\mathcal{H}_m) + \ln \pi_m. && (3.13)
\end{aligned}$$

where $\widehat{\mathcal{H}}$ and $\pi_m \triangleq P(\mathcal{H}_m)$. An explicit expression of the log-likelihood $\ln p(\boldsymbol{y}|\mathcal{H}_m)$ from (3.10) is given by

$$\begin{aligned}
\ln p(\boldsymbol{y}|\mathcal{H}_m) &= \ln \left[\sum_{\boldsymbol{d}\in\mathcal{X}^K} p(\boldsymbol{y}|\boldsymbol{d})\, P(\boldsymbol{d}|\mathcal{H}_m) \right] && (3.14)\\
&= \ln \left[\sum_{\boldsymbol{d}\in\mathcal{X}^K} \frac{1}{\sigma_w^2} \exp\left(-\frac{\|\boldsymbol{y}-\boldsymbol{H}\boldsymbol{d}\|^2}{\sigma_w^2} \right) P(\boldsymbol{d}|\mathcal{H}_m) \right]
\end{aligned}$$

where we have abused the conditional independence of $\boldsymbol{y}$ from $\mathcal{H}_m$ (given $\boldsymbol{d}$).

3.3.2 MAP Observation bound Rule

For examination purposes we refer to “observation bound” [10],where the optimum performances through a noise free channel, given by the following classifier:

$$\widehat{\mathcal{H}}_{\mathrm{obs}} \triangleq \arg\max_{\mathcal{H}_m} P(\mathcal{H}_m|\boldsymbol{d}) \tag{3.15}$$

$$= \arg\max_{\mathcal{H}_m} \ln p(\boldsymbol{d}|\mathcal{H}_m) + \ln \pi_m \,. \tag{3.16}$$

It is clearly the MAP observation bound rule should be intended as an optimistic upper bound on the classification performance which can be achieved over a virtual MIMO channel.

3.3.3 Augmented Quadratic Discriminant Analysis (A-QDA) Rule

The following classifier based on a complex version of quadratic discriminant analysis can be obtained [43]:

$$\begin{aligned}\widehat{\mathcal{H}}_{\mathrm{qda}} \triangleq \arg\min_{\mathcal{H}_m} \Big\{ &(\underline{\boldsymbol{y}} - \mathbb{E}\{\underline{\boldsymbol{y}}|\mathcal{H}_m\})^{\dagger}\, \boldsymbol{\Sigma}_{\underline{\boldsymbol{y}}|\mathcal{H}_m}^{-1}\, (\underline{\boldsymbol{y}} - \mathbb{E}\{\underline{\boldsymbol{y}}|\mathcal{H}_m\}) \\ &+ \ln\det\left(\boldsymbol{\Sigma}_{\underline{\boldsymbol{y}}|\mathcal{H}_m}^{-1}\right) + \ln \pi_m \Big\}\end{aligned} \tag{3.17}$$

where $\mathbb{E}\{\underline{\boldsymbol{y}}|\mathcal{H}_m\} = \underline{\boldsymbol{H}}\,\mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\}$ and the *augmented covariance* of $\boldsymbol{y}|\mathcal{H}_m$ is given in closed form as:

$$\boldsymbol{\Sigma}_{\underline{\boldsymbol{y}}|\mathcal{H}_m} = \underline{\boldsymbol{H}}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\underline{\boldsymbol{H}}^{\dagger} + \sigma_w^2\,\boldsymbol{I}_{2N} \,. \tag{3.18}$$

Chapter 4

Numerical Results

In this chapter, the general execution of different fusion rules which utilized at the DFC in the WSN system model is tested. Moreover, the rapprochement of performance for different fusion rules is executed over numerical analysis so as to get ROC curves for different fusion rules with different hypothesis. Moreover, we studied the influence of different factors that may influence the performance of a fusion rule such as the average SNR values for communication channel, number of local detectors in the network (i.e. K), the number of antenna at the DFC (i.e. N), number of hypothesis (i.e. M) and the local detectors information (i.e. $P_{D,k}$ and $P_{F,k}$).

4.1 Comparison of Performance Among Different Fusion Rules Utilized at the WSN System Model

In this subsection, the general execution of different fusion rules which utilized at the DFC in the WSN system model is tested. Moreover, the rapprochement of performance for different fusion rules is executed over numerical analysis so as to get ROC curves for different fusion rules with different hypothesis. Moreover, we studied the influence of different factors that may influence the performance of a fusion rule such as the average SNR values for communication channel, number of local detectors in the network (i.e. K), the number of antenna at the DFC (i.e. N), number of hypothesis (i.e. M) and the local detectors information (i.e. $P_{F,k}$ and $P_{F,k}$).

ROC: We show, for the derived rules, in Figure 4.1 and Figure 4.2 we show the ROC (i.e. P_D vs P_F), for different fusion rules with $K = 8$ local detectors and $N = 2$ antennas at the DFC, the a channel $(SNR) = 15$ dB for different number of hypothesis.

The recognized detection performance shown in Figure 4.1 and Figure 4.2 and we conclude that the optimum map fusion rule extends the best performance among the other fusion rules among number of different hypothesis.

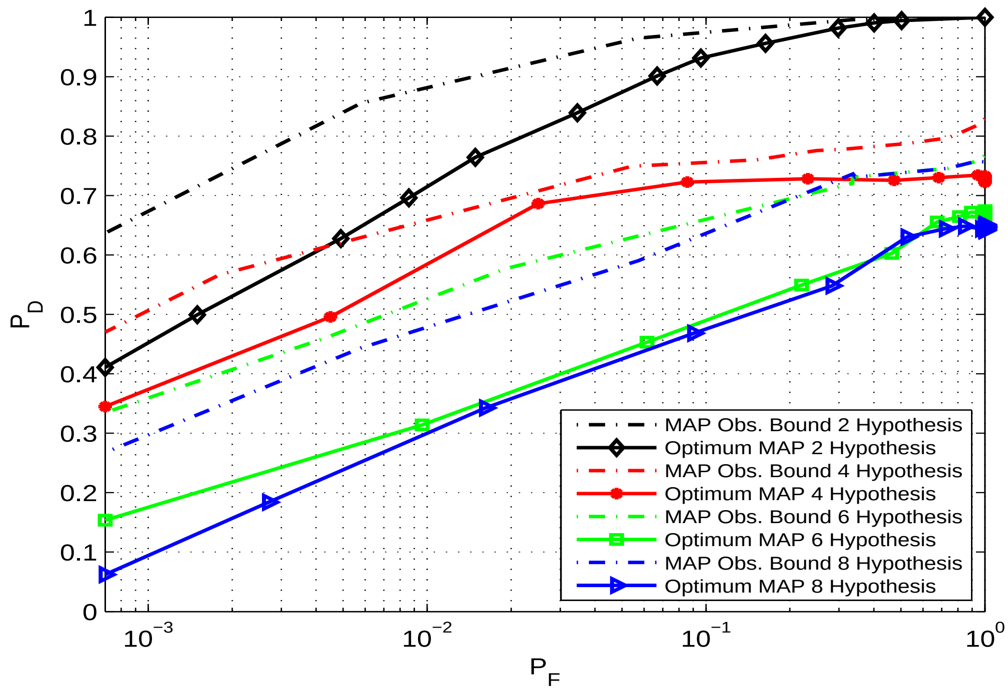


Figure 4.1: ROC for the optimum MAP and observation bound rules. Channel $SNR = 15$ dB, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of local detectors K=8 and number of antenna $N = 2$.

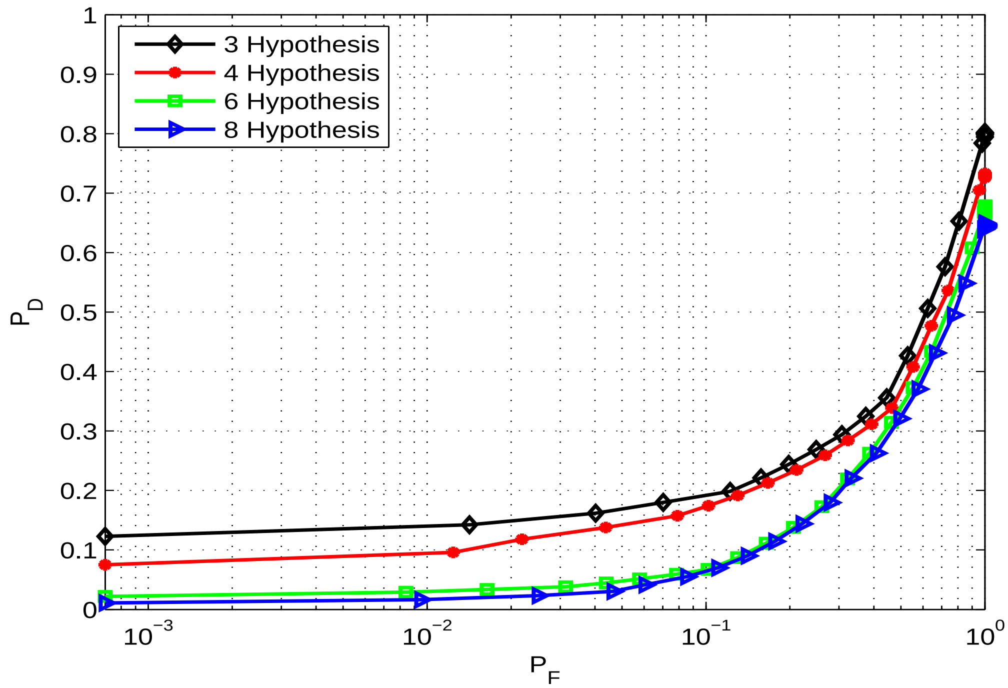


Figure 4.2: ROC for the A-QDA rule. Channel SNR = 15 dB, $P_{D,k}$ = (0.5), $P_{F,k}$ = (0.05), number of local detectors K=8 and number of antenna $N = 2$.

4.2 The Effect of the Channel SNR Between the Sensors and the DFC

In this scenario we consider that the local detector indices are identical under the same value of channel SNR between the sensors and the DFC. However, the channels SNR to the DFC in this scenario are not Fixed and we study the effect of the channels quality for a wide rage of SNRs.

In Figure 4.3 and Figure 4.4, a comparison in terms of the performance of detection versus the average channel SNR between different fusion rules utilized at the WSN system model.

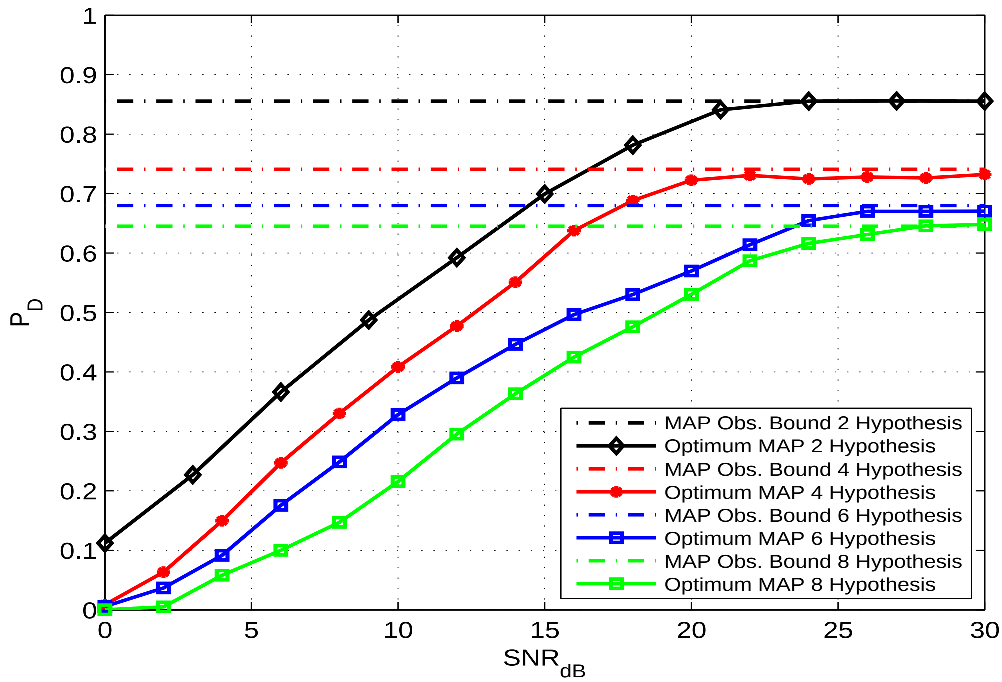


Figure 4.3: P_D vs channel (SNR) dB for the optimum MAP and observation bound rules, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of local detectors K=8 and number of antenna $N = 2$.

P_D vs. (SNR) dB: In Figure 4.3 and Figure 4.4 , we simulate, for the derived rules, P_D as a function of the average channel (SNR) dB for different hypothesis, we consider WSN with fixed number of sensors and antennas at $K = 8$ and $N = 2$ respectively, we plot the cases $\mathcal{H} \in \{H_2, H_4, H_6, H_8\}$ in Figure 4.5 while in Figure 4.6 we plot the cases $\mathcal{H} \in \{H_3, H_4, H_6, H_8\}$. We plot these scenario to investigate the effect on performances when different hypothesis are exist. It can be noticed from Figure 4.3 and Figure 4.6 that at higher channel SNR we can achieve higher performance. In Addition, the optimum map rule is better performance than other AQDA rule for different hypothesis scenarios. However, in Figure 4.6 we shows that

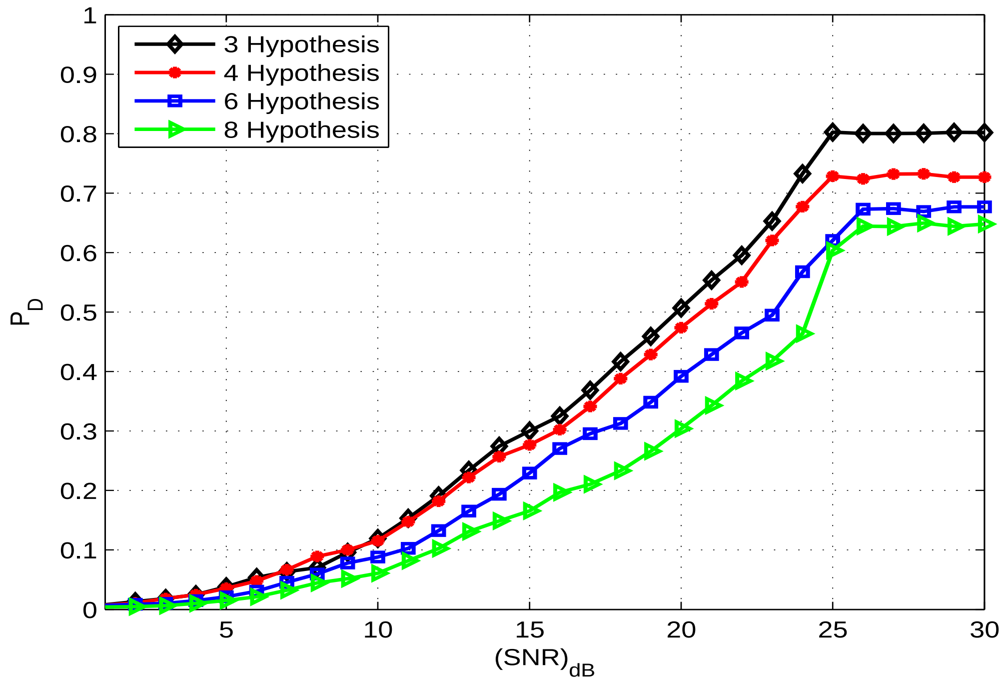


Figure 4.4: P_D vs channel (SNR) dB for the A-QDA rule, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of local detectors K=8 and number of antenna $N = 2$.

the WSN system model could significantly raise the performance of A-QDA fusion rule for higher SNR values for different hypothesis scenarios.

All the presented rules significantly benefit from the presence of two antennas at DFC with lower number of hypothesis.When we have 2 or 4 hypothesis, the optimum map has the best range of improvement in the $[5, 20]$ dB and reaches the observation bound at $(SNR) \approx 20$ dB, While that the $(SNR) \approx 25$ dB when there is 6 or 8 hypothesis. The A-QDA needs higher value of SNR to gain acceptable performances, but the case 3 or 4 hypothesis as yet needs less power to reach the observation bound. Finally decreasing number of hypothesis not only increase the detection performances for the presented rules at low-medium SNR, but also give better limiting performances.

4.3 The Effect of the Number of Antenna Used at the DFC

Performance comparison between different fusion rules as a function of number of antenna N at the DFC is shown in Figure 4.5 and in Figure 4.6. We consider fixed values of SNR at 15 dB, system probability of false alarm $P(_{fo}) = 0.01$, the local detectors have a performance indices of $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$.

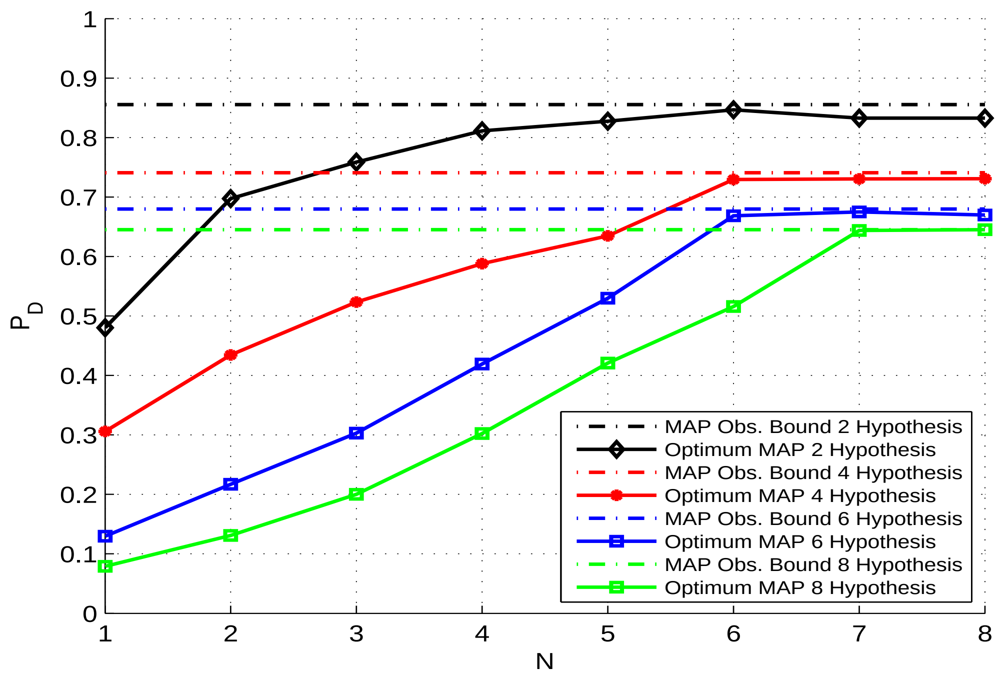


Figure 4.5: P_D vs N for the optimum MAP and observation bound rules, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of local detectors K=8 and $(SNR) = 15$ dB.

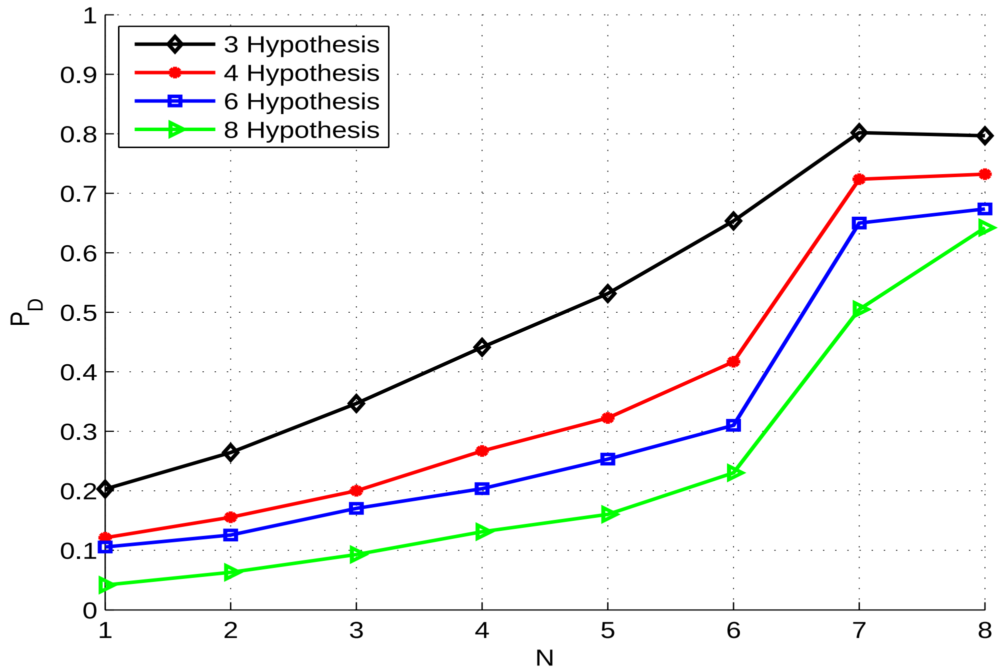


Figure 4.6: P_D vs N for the A-QDA rule, $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, number of local detectors K=8 and $(SNR) = 15$ dB.

P_D vs. N: In Figure 4.5 and Figure 4.6, we simulate, for the derived fusion rules, the P_D as a function of the number of antenna N for different hypothesis, we plot the case $P_{D,k} = (0.5)$, $P_{F,k} = (0.05)$, we consider wireless system with $K = 8$ local detector and the value of channel $(SNR) \approx 15$ dB, also we plot the cases $\mathcal{H} \in \{H_2, H_4, H_6, H_8\}$ in Figure 4.5 while in Figure 4.6 we plot the cases $\mathcal{H} \in \{H_3, H_4, H_6, H_8\}$ to investigate the effect of number of antenna N at the DFC under realistic channel SNR value in the proposed WSN system model for the various fusion rules with different hypothesis. It is apparent that adding more antennas at the DFC is more beneficial for the presented rules, however, a saturation effect is present. The effect of saturation depends on the channel SNR and the chosen rule of fusion, but also number of hypothesis. In addition, it can be noticed that when the number of hypothesis increasing the performance detection will decreasing, so we get better performance when increasing the number of antenna and decreasing number of hypothesis. In particular, specific configurations achieve the observation bound (e.g. optimum map with $N = 4$ at $(SNR) = 15$ dB) while others (e.g. A-QDA with $N = 7$ at $(SNR) = 15$ dB). Moreover, an increase in number of antennas N and decrease the number of hypothesis gives a increase in performance detection.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

In this thesis, the problem of fusion of decisions for distributed classification in MIMO wireless sensor networks is studied. Many decision fusion rules proposed in literature, these fusion rules are mainly applied at the DFC and they have different performance and require a variety of information so as to get a final decision with respect to a certain phenomena. In addition these fusion rules solve the issues about fixed point implementations and present a wide spectrum of choices for reduced complexity and lower system knowledge.

The comparison has been outright through MATLAB simulation for three different fusion rules, optimum (MAP), MAP observation bound, A-QDA applied at MIMO WSN system model. We investigate the effect of the system parameters on the overall system performance at the DFC. We study the effect of the local sensing elements information are assumed identical, also investigating the effect of the total number of antenna at the DFC, the number of sensing elements, the number of hypothesis and the effect of the value of the SNR between the sensing elements category and the DFC. Numerical results show that the derived system model provide a relatively better execution when increasing the number of antenna at the DFC with lower number of hypothesis for the applied fusion rules (i.e. that the optimum (MAP) has the best performance than A-QDA rule).

5.2 Future Work

Several research problems exist and may extend the current work presented in this thesis and they are listed as below:

1. In this thesis, we extending the mathematical analysis of optimum and observation bound rules, however, we may extend the analysis of other rules which discuss in Section 2.2.

2. In this work, we get the numerical result for 8 hypothesis, however, we can get the numerical results for hypothesis greater than 8.

3. In this work, we assume that the channel between the sensors layer and the DFC is Rayleigh channel. However, in some scenarios there may exist a line of sight between the sensors and the DFC, thus another fading distribution may be considered such as rician fading distribution. We could investigate to combine the decisions that is sending through rician fading channels and the ability to apply the proposed WSN model in the case of rician and other fading channels.

Notations

u_o	final decision fusion center
u_k	local decision made by the sensing element
x_k	received noisy by sensing element
K	total number of local detectors
N	total number of antenna
$\mathbb{E}\{\cdot\}$	the expectation value
$\mathrm{var}\{\cdot\}$	the variance value
$(\cdot)^T$	the matrix transpose
$(\cdot)^\dagger$	the matrix conjugate transpose
$\|\cdot\|$	Euclidean norm operators
$\det(\boldsymbol{A})$	the determinant of $\boldsymbol{A}$
$\mathrm{Re}\,(\cdot)$	real part
$\mathrm{Im}(\cdot)$	imaginary part
$\mathcal{A}^K$	the k-ary Cartesian power of $\mathcal{A}$
$\mathbf{0}_N$	the null vector of length N
$\boldsymbol{O}_{N\times K}$	the $N \times K$ null matrix
P_{d_k}	sensing element probability of detection

P_{f_k}	sensing element probability of false alarm
Λ	fusion statisic
σ^2	variance of white Gaussian noise
T	decision threshold
$P(\cdot)$	the probability of mass function (pmf)
$p(\cdot)$	the probability of density function (pdf)
$\mathrm{diag}(\boldsymbol{A})$	the diagonal matrix extracted from $\boldsymbol{A}$
$\boldsymbol{\Sigma}_{\boldsymbol{x}}$	the covariance matrix of the complex-valued random vector $\boldsymbol{x}$
$\mathcal{N}_{\mathbb{C}}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$	complex normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$
$\propto$	statistically equivalent to
$\sim$	distributed as

Appendix A

$Second-order characterization of \boldsymbol{y}|\mathcal{H}_m$

In this appendix we provide a second-order characterization for $\boldsymbol{y}|\mathcal{H}_m$. First, We recall that the exact pdf is

$$\boldsymbol{y}|\mathcal{H}_m \sim \sum_{\boldsymbol{d}\in\mathcal{X}^K} P(\boldsymbol{d}|\mathcal{H}_m)\,\mathcal{N}_{\mathbb{C}}(\,\boldsymbol{H}\boldsymbol{d},\,\sigma_w^2\,\boldsymbol{I}_N), \tag{5.1}$$

which is recognized as a mixture of 2^K *proper* complex-valued Gaussian vectors. Then, we evaluate the mean vector of $\boldsymbol{y}|\mathcal{H}_m$ as follows:

$$\mathbb{E}\{\boldsymbol{y}|\mathcal{H}_m\} = \sum_{\boldsymbol{d}\in\mathcal{X}^K} \mathbb{E}\{\boldsymbol{y}|\boldsymbol{d}\}\,P(\boldsymbol{d}|\mathcal{H}_m) = \tag{5.2}$$

$$\boldsymbol{H}\sum_{\boldsymbol{d}\in\mathcal{X}^K} \boldsymbol{d}\,P(\boldsymbol{d}|\mathcal{H}_m) = \boldsymbol{H}\,\mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\} \tag{5.3}$$

It is worth remarking that (5.3) was obtained by exploiting $\mathbb{E}\{\boldsymbol{w}\} = \boldsymbol{0}_N$. Differently, the covariance matrix is evaluated as

$$
\begin{aligned}
\boldsymbol{\Sigma}_{\boldsymbol{y}|\mathcal{H}_m} = \mathbb{E}\{&[\boldsymbol{H}\,(\boldsymbol{d} - \mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\}) + \boldsymbol{w}] \\
&[\boldsymbol{H}\,(\boldsymbol{d} - \mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\}) + \boldsymbol{w}]^{\dagger}\,|\mathcal{H}_m\Big\} = \qquad (5.4)\\
&\boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\boldsymbol{H}^{\dagger} + \mathbb{E}\{\boldsymbol{w}\boldsymbol{w}^{\dagger}\} = \qquad (5.5)\\
&\boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\boldsymbol{H}^{\dagger} + \sigma_w^2\,\boldsymbol{I}_N \qquad (5.6)
\end{aligned}
$$

since: (i) $\boldsymbol{x}$ and $\boldsymbol{w}$ are *mutually independent* and (iii) $\mathbb{E}\{\boldsymbol{w}\} = \boldsymbol{0}_N$. Similarly, we obtain the *complementary covariance* [43] as

$$
\begin{aligned}
\bar{\boldsymbol{\Sigma}}_{\boldsymbol{y}|\mathcal{H}_m} = \mathbb{E}\{&[\boldsymbol{H}\,(\boldsymbol{d} - \mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\}) + \boldsymbol{w}] \\
&[\boldsymbol{H}\,(\boldsymbol{d} - \mathbb{E}\{\boldsymbol{d}|\mathcal{H}_m\}) + \boldsymbol{w}]^{T}\,|\mathcal{H}_m\Big\} = \qquad (5.7)\\
&\boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\boldsymbol{H}^{T} + \mathbb{E}\{\boldsymbol{w}\boldsymbol{w}^{T}\} = \qquad (5.8)\\
&\boldsymbol{H}\,\boldsymbol{\Sigma}_{\boldsymbol{d}|\mathcal{H}_m}\,\boldsymbol{H}^{T} \qquad (5.9)
\end{aligned}
$$

where the last equality follows from $\mathbb{E}\{\boldsymbol{w}\boldsymbol{w}^T\} = \boldsymbol{O}_{N\times N}$ (indeed $\boldsymbol{w}$ is a *proper* random vector). Therefore, we conclude that $\boldsymbol{y}|\mathcal{H}_m$ is an *improper random vector*, since its complementary covariance matrix does not vanish, thus motivating the potential for WL processing.

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