JOINT MODULATION AND SPACE TIME BLOCK CODE CLASSIFICATION FOR MIMO SYSTEMS

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Abstract

In this thesis, the problems of modulation classification and space time block code (STBC) classification for MIMO systems are investigated. Two existing MIMO modulation type classification algorithms, an average likelihood ratio test, which is optimal in Bayesian sense, and a suboptimal Hybrid Likelihood ratio test, are investigated in detail. Subsequently, we have focused on improving these existing algorithms by using blind channel estimation methods with better performance, such as the Expectation–Maximization algorithm for spatial multiplexing which is known to converge to the maximum likelihood estimate, and a higher order statistic based estimation method in the case of signals which use space time block codes. Subsequently, we have proposed a novel approach for the task of modulation and STBC type classification, in which these two classification problems are considered as a single as joint classification problem, in contrast to the existing works in the literature. Based on this joint classification approach, we have proposed novel likelihood based joint STBC and modulation-type classification algorithms for 2 and 3 antenna cases.

ÇOK GİRDİLİ ÇOK ÇIKTILI SİSTEMLER İÇİN MODÜLASYON VE UZAY-ZAMAN BLOK KODUNUN ORTAKÇA KLASİFİKASYONU

Özet

Bu tezde çok girdili çok çıktılı (MIMO) sistemlerde modülasyon ve uzay-zaman blok kodu (STBC) klasifikasyonu problemleri incelenmiştir. Var olan iki adet MIMO modülasyon tipi klasifikasyonu algorithması, Bayesçi anlamda optimal olan ortalama olabilirlik oranı testi (ALRT) ve optimal altı olan melez olabilirlik oranı testi (HLRT) detaylıca incelenmiştir. Daha sonra, var olan bu algoritmaları en büyük olabilirlik kestirimine yakınsadığı bilinen uzaysal çoklamalı sinyaller için beklenti-büyütme (EM) ve uzay zaman kodlamaları kullanılan sinyaller için yüksek mertebeden istatistik tabanlı kestirim metodu gibi performansı daha yüksek gözü kapalı kanal kestirim yöntemleriyle geliştirmeye odaklandık. Daha sonra, literatürdeki var olan çalışmaların aksine, modülasyon ve uzay zaman kodlaması klasifikasyonu için alışılmışsın dışında bir yaklaşım önererek, bu iki klasifikasyon problemini ortakça tek bir problem olarak ele aldık. Ortakça klasifikasyon yaklaşımını temel alarak, alışılmışın dışında iki ve üç antenli durumlar için olabilirlik tabanlı ortakça uzay-zaman blok kodu tipi ve modülasyon tipi tanımlama algoritmaları önerdik.

Acknowledgements

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Dedication

To my parents, my sister, who supported during my study, at last SIMO …

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List of Abbreviations

ALRT – Average Likelihood Ratio Test

HLRT – Hybrid Likelihood Ratio Test

SM – Spatial Multiplexing

BSS – Blind Source Separation

M-PSK – M'ary Phase Shift Keying

M-QAM – M'ary Quadrature Amplitude Modulation

STBC – Space Time Block Code, Coding, Coder

J-ALRT – Joint Average Likelihood Ratio Test

J-HLRT – Joint Hybrid Likelihood Ratio Test

LF – Likelihood Function

LLF – Log Likelihood Function

RF – Radio Frequency

i.i.d. – Independent and Identical Distributed

MIMO – Multiple Input- Multiple Output

SISO – Single Input - Single Output

HOS – High Order Statistics

n_t – number of transmit antennas

n_r – number of receive antennas

Chapter 1

Introduction

With the advance of wireless communication systems in the last decades monitoring, controlling and surveillance of the radio spectrum and analysis of unknown or partially known transmitters became a popular research area. In this context, multiple applications of analysis methods can be seen in civilian and military areas. These analysis methods, commonly referred to as signal identification algorithms, are developed to identify the carrier frequency, bandwidth, frequency spreading methods, modulation type, coding type and any other transmission parameters specific to an unknown transmitter in a non-cooperative context.

Military, intelligence and security oriented applications are first application areas come to mind in the context of signal identification. Especially in military context, signal identification methods are commonly applied for jamming, tracking and intercepting signals with unknown transmission parameters. In civilian applications, signal identification algorithms mostly used for regulating and preventing unlicensed or illegal usage of frequency spectrum by authorities.

Furthermore, with increasing data processing capability of wireless communication terminals and increasing number of users and applications, a need for higher data rates have arisen. Thus, the efficient use of spectrum resources has become more crucial than before. The newly emerging paradigm of cognitive radio tackles this problem by allowing dynamic spectrum allocation, where spectral resources are assigned to users in a demand oriented manner. Cognitive radio systems, which employ flexible and reconfigurable software defined transceivers, make use of the available spectral resources in the most efficient manner possible, by taking into account such factors as the user needs, the requirements of the used applications and the types of the radio access technologies transmitting in its geographical location and their transmission modes. In this context, one of the most crucial differences between a conventional transceiver and a cognitive radio transceiver is need of cognitive radio to have situational awareness about sources in its frequency environment and their transmission parameters. Therefore, cognitive radio can be counted as one of the newest and most interesting application area of signal identification in civilian context.

Because of the increasing usage of digital wireless communication systems in both civilian and military areas, and the increasing complexity and diversity of the techniques used therein, the methods used in signal identification need to be constantly refined and updated to be able to identify the newly emerging transmission techniques. Each emerging transmission method presents to the signal identification systems new transmission parameters to identify and new challenges to overcome. The Multiple Input-Multiple Output (MIMO) systems, which became popular in last decade, can be counted as one of the most promising of those newly emerging transmission techniques in terms of the capacity increase and/or the robustness they offer. The main difference between the MIMO systems and conventional Single Input-Single Output (SISO) is that unlike SISO systems, MIMO systems employ multiple antennas for transmission and reception. By multiplexing the data symbols to multiple antennas and/or introducing redundancy to the signal by employing Space-Time codes, MIMO systems exhibit an advantage compared to SISO systems in terms of data rates and/or robustness in fading environments. Figure 1-1 shows a typical MIMO transmitter.

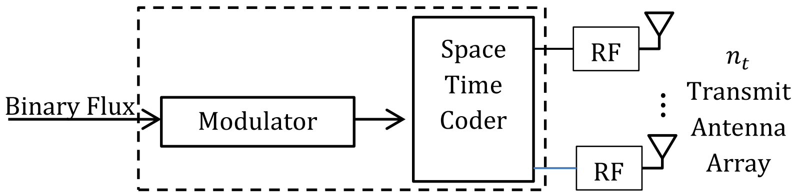

Figure 1-1 Typical MIMO transmitter

The complicated structure of MIMO transmitters pose new challenges to the signal identification systems. Although methods developed for SISO systems can also be adapted for identifying transmission parameters such as bandwidth, symbol rate and timing in MIMO systems, MIMO systems present new parameters such as the number of transmit antennas and employed Space-Time code, which do not exist in SISO systems and need to be identified. Furthermore, modulation type classification algorithms for SISO systems, that assume presence of a single modulated signal at the receiver are unable to classify MIMO signals, where multiple signals, one from each transmit antenna, is present at each antenna at the receiver. The structure of a signal identification system for an unknown MIMO system is given in Figure 1-2

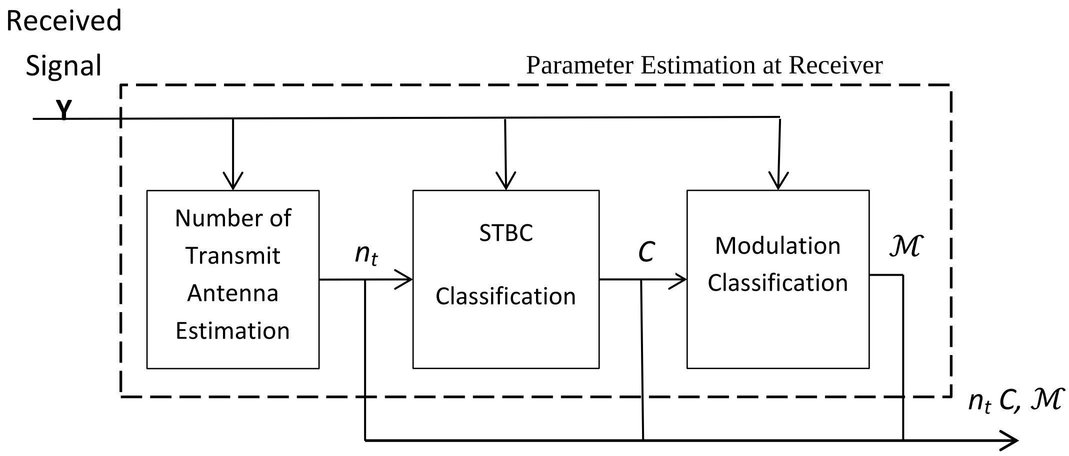

Figure 1-2 Structure of a MIMO signal identification system

In this thesis, we are going to focus on the problems of space-time code and modulation type classification in MIMO systems, and assume that the number of transmit antennas is known or estimated by the signal identification system before classification.

The family of linear space-time block codes (STBC) can be considered as the most popular of codes employed in MIMO system due to their simplicity. Thus, like all the works existing in the literature, we will focus on the STBC's, and leave other space-time code types for future study.

In the literature, the problems of space-time code classification and modulation type classification are usually handled separately. MIMO modulation type classification methods found in the literature (such as [1],[2],[3],[4]} usually make the assumption that the employed space time code is known by the receiver, whereas there exist space-time code classification algorithms that assume the knowledge of the employed modulation type (see, for example [5]), and some that do not depend on the employed modulation type at all ([6],[7],[8],[9]).

Two fundamental approaches exist for modulation type classification in the literature: Likelihood based and Feature based. Likelihood based methods make use of the likelihood function of the received signal and decide for the modulation type that maximizes it, whereas feature-based algorithms extract modulation–type specific features from the received signals and decide for modulation type, whose features are nearest to the estimated features using some distance metric.

In [1], Choqueuse has proposed an Average Likelihood Ratio based modulation type classification algorithm for Spatial- Multiplexing MIMO systems, which treats the transmit signals as random variables from a discrete alphabet, which is determined by the employed modulation type, and form the Average-Likelihood function by averaging over all possible transmit signals and assuming that the channel matrix and noise variance are perfectly known. The classification is performed by maximizing this average likelihood function over all possible modulation types. This classifier can be considered as optimal in the Bayesian sense, however, is impractical since it assumes that the channel matrix is perfectly known at the receiver. In the same work, Choqueuse also provided a more practical classification method, called HLRT, which uses a blind estimate of the channel matrix instead of exact value. In his dissertation [10], Choqueuse extended these algorithms to space time block coded MIMO signals by assuming that the employed STBC and the code timing (i.e. the beginning and the end of each code block) is known.

Feature based modulation type classification algorithms can be found in [2],[3] and [4] in which modulation type specific features based on cumulants are employed. In [2], a neural network based classifier is used for classification which requires prior training, whereas [4] derives the asymptotic likelihood function of the cumulant based feature vector for classification. It should be noted that feature based modulation classification methods may face difficulties if STBCs are used due to the fact that using STBCs may alter the signal alphabet, thus changing the modulation type specific features.

Similar to modulation type classification, STBC classification methods in the literature can be categorized into two subcategories: Likelihood and Feature based. In his PhD dissertation [10] Choqueuse presented ALRT and HLRT based STBC classification methods with the assumption of a-priori knowledge of the modulation type and code block timing (i.e. beginning and the end of each block).

For feature-based STBC classification, usually methods based on exploiting the cyclostationary characteristics of the received signal are used, which is induced by the space time block coding operation ([6],[7] and [8]). This approach has the added benefit of not requiring any a-priori information about the modulation type of the signal, however, has difficulties in discriminating between STBC's with similar cyclostationary characteristics (i.e. STBC's which exhibit cyclostationarity with the same cyclic frequency).

In this thesis, we first investigate the MIMO modulation type classification problem for spatial multiplexing (SM) signals and propose an HLRT algorithm, which uses the expectation maximization (EM) approach for blind channel compensation [11]. This HLRT based algorithm, which we refer to as the EM-HLRT, provides improvement in the classification performance compared to [1]. However, using EM algorithm for the case where STBC is used impractical due to the high computational complexity. For this case, we propose to use the Higher–Order Statistics (HOS) based blind channel compensation algorithm proposed in [12] prior to classification.

Subsequently, we show that, in contrast to methods found in the literature mentioned above, that handle the modulation type and STBC classification problems separately, these two problems can be tackled jointly, and propose a joint STBC and Modulation type classification algorithm, which we refer to as J-HLRT.

Finally, we show, via simulations, that the symbol timing parameter, which is assumed to be perfectly known in the proposed classification algorithms, can be blindly recovered by using the cyclostationary based approach in [13], which has originally been proposed for single-antenna systems.

The remainder of this thesis is organized as follows: In chapter 2, an overview of the MIMO communication systems is provided, along with our system model. In Chapter 3, we propose the EM-HLRT classifier for spatial multiplexing systems and compare its performance with ALRT and HLRT algorithms of Choqueuse in [1]. Furthermore, the HOS-HLRT algorithm is proposed for modulation type classification in space time block coded MIMO systems, with the assumption of the knowledge of the employed STBC.

The main contribution of this thesis can be found in chapter 4, where we propose the joint classification of the modulation type and STBC. The classification performance of the proposed algorithm, which we refer to J-HLRT, is investigated for using

Monte-Carlo simulations. Both codes designed for 2 and 3 transmit antennas are considered. The proposed algorithm does not require any a-priori information about the channel matrix and the noise variance. Finally, chapter 5 investigates the blind timing recovery problem.

Chapter 2

MIMO systems: An overview

This chapter presents a brief overview on the principles of MIMO systems considered for classification. The main difference between the MIMO and SISO systems is that the MIMO systems employ multiple antennas for transmission and reception. In this chapter we will examine the MIMO transmitter, the MIMO propagation environment and the MIMO receiver.

2.1 The MIMO Transmitter

Figure 2-1 presents a typical MIMO transmitter with n_t transmit antennas, which contains the modulator, a space-time coder and the RF block. First, the binary data symbols are converted to complex symbols by the modulator according to the constellation of the chosen modulation type. Subsequently, these symbols are multiplexed to the transmit antennas according to some coding rule by the space time block coder, and finally, the RF block performs the conversion of the discrete symbols into electromagnetic wave, and transmits the resulting signal. In the following subsections, each of these systems will be explained in detail.

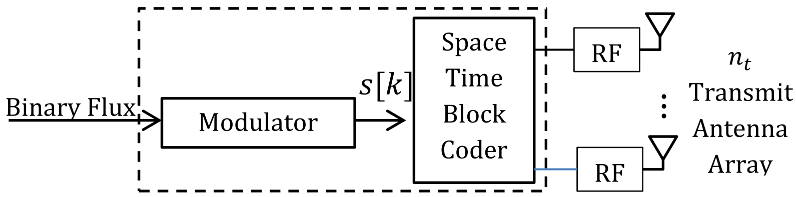

Figure 2-1 MIMO transmitter

2.1.1 Modulator

The modulator converts the binary data into complex symbols. In our thesis, we consider memoryless linear modulation types. A linear modulation converts blocks of $\log_2 M$ bits into complex valued symbols according to the constellation consisting of M elements. In our work, the modulation types we consider for classification are

BPSK, QPSK, 8PSK and 16QAM. The symbol constellations of these modulation types are given in Figure2-2.

Furthermore, we assume that the bits in binary data stream are independent and identically distributed (i.i.d.) random variables, with equal probabilities for 1 and 0. Thus, the modulated symbols stream also consists of i.i.d. complex valued random variables with each of the M states are equally probable.

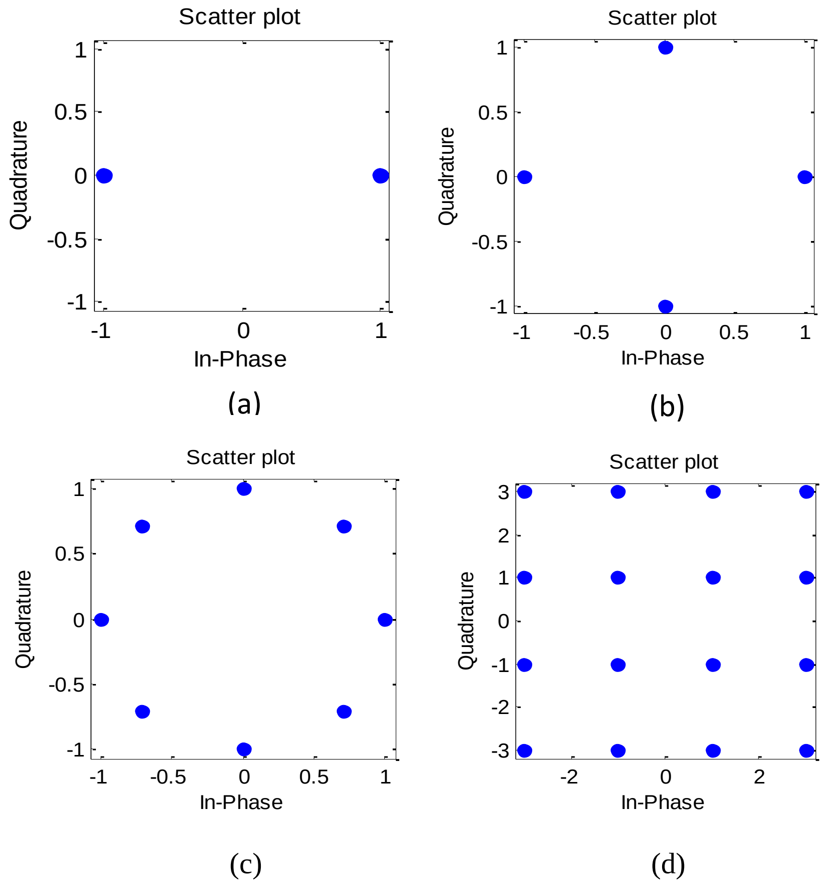

Figure 2-2 The symbols according to the constellations of (a)BPSK, (b)QPSK, (c)8PSK, (d)16QAM modulation types

2.1.2 Space Time Coder

The space-time coder multiplexes the modulated i.i.d. symbol stream onto n_t transmit antennas. The aim of the coding operation is to introduce space-time redundancies into the signal to increase the robustness of the transmission and/or increasing the data rates [14]. There exist multiple different of space-time coding techniques. The family of linear space-time block codes (STBC) can be considered as the most popular of codes employed in MIMO system due to their simplicity. Thus, like all the works existing in the literature, we will focus on the STBC's , and leave other space-time code types for future study.

In a MIMO system using STBC, the v'th transmit signal block $\boldsymbol{X}_v$ is generated by parsing the i.i.d. distributed modulated information bearing symbols $s[k]$ into blocks of length n_z, $\boldsymbol{s}[v] = \begin{bmatrix} s_1[v] \\ \vdots \\ s_{n_z}[v] \end{bmatrix}$ and mapping them to the transmit antennas according to a coding rule, which can be represented by a $n_t \times l_z$ code matrix, where l_z is the duration of code block, i.e. the number of time slots used for transmitting n_z information symbols. In the code matrix the i'th column represents the signal vector transmitted over n_t antennas in the i'th time slot. Thus, the v'th transmit signal block can be written as

$$\boldsymbol{X}_v = \boldsymbol{C}(\boldsymbol{s}[\boldsymbol{v}]), \tag{2.1}$$

where $\boldsymbol{C}(\,)$ represents the space time block coding operation.

STBC	n_t	Code Rate	$\boldsymbol{X}_v = C(\boldsymbol{s}[v])$
Spatial multiplexing (SM), $C^{(0)}$	2,3	n_t	$\begin{bmatrix} s_1[v] \\ s_2[v] \end{bmatrix}, \begin{bmatrix} s_1[v] \\ s_2[v] \\ s_3[v] \end{bmatrix}$
Alamouti $C^{(1)}$ [15]	2	1	$\begin{bmatrix} s_1[v] & -s_2^*[v] \\ s_2[v] & s_1^*[v] \end{bmatrix}$
$C^{(2)}$[16]	3	3/4	$\begin{bmatrix} s_1[v] & 0 & s_2[v] & -s_3^*[v] \\ 0 & s_1[v] & s_3^*[v] & s_2^*[v] \\ -s_2[v] & -s_3^*[v] & s_1^*[v] & 0 \end{bmatrix}$
$C^{(3)}$[17]	3	3/4	$\begin{bmatrix} s_1[v] & -s_2^*[v] & s_3^*[v] / \sqrt{2} & s_3^*[v] / \sqrt{2} \\ s_2[v] & s_1^*[v] & s_3^*[v] / \sqrt{2} & -s_3^*[v] / \sqrt{2} \\ s_3[v] / \sqrt{2} & s_3[v] / \sqrt{2} & \frac{-s_1[v] - s_1^*[v] + s_2[v] - s_2^*[v]}{2} & \frac{s_2[v] + s_2^*[v] + s_1[v] - s_1^*[v]}{2} \end{bmatrix}$

Table 1 List of STBCs considered and corresponding code matrices

For example in the Alamouti code [15] code given in Table 1 information symbols are transmitted in 2 time slots over 2 antennas. In the first time slot in the v'th transmitted signal block, the transmitted signal vector is $\begin{bmatrix} s_1[v] \\ s_2[v] \end{bmatrix}$ whereas in the second time slot the signal vector $\begin{bmatrix} -s_2^*[v] \\ s_1^*[v] \end{bmatrix}$ is transmitted. Table 1 provides a list of STBC considered in this work and corresponding code matrices. For 2 transmit antennas, we consider the Alamouti code, which is the first STBC proposed in the literature [15]. For 3 transmit antennas we consider 2 orthogonal STBC proposed in [16] and [17] respectively. Note that spatial multiplexing, where the modulated data is directly multiplexed into transmit antennas, is also considered as a special case of STBC.

2.1.3 The RF Block

After the space time block coding operation, the coded symbols undergo pulse shaping and are translated into passband in the RF block. This is illustrated in Figure 2-3 for one of the transmit antennas.

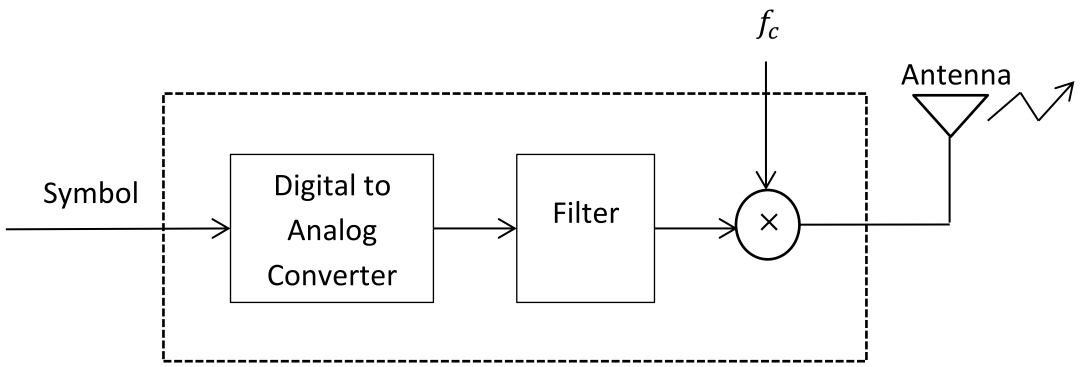

Figure 2-3 Structure of RF Block for one of the transmit antennas.

2.2 The MIMO Receiver and the Propagation Environment

In this thesis the following assumptions are made about the propagation environment and the MIMO receiver.

1. The MIMO receiver employs n_r receive antennas with $n_r > n_t$, i.e. the system is over determined.

2. The receiver and transmitter are synchronized w.r.t symbol timing, i.e. the sampling at the receiver after matched filtering has been performed at the optimal time instants. Although this assumption may be unrealistic in the context of signal identification, it can be shown that blind timing synchronization methods designed for SISO systems may be employed can be applied for MIMO systems (see chapter 5 for details).
3. The noise can be modeled as complex valued i.i.d. circular random process with variance σ^2 .
4. The bandwidth of the transmit signal is sufficiently narrow to justify the use of a frequency flat block fading Rayleigh distributed channel model.

Based on these assumptions, the structure of the non-cooperative MIMO receiver, which is considered in this work for modulation type and STBC classification, is illustrated in Figure 2.4.

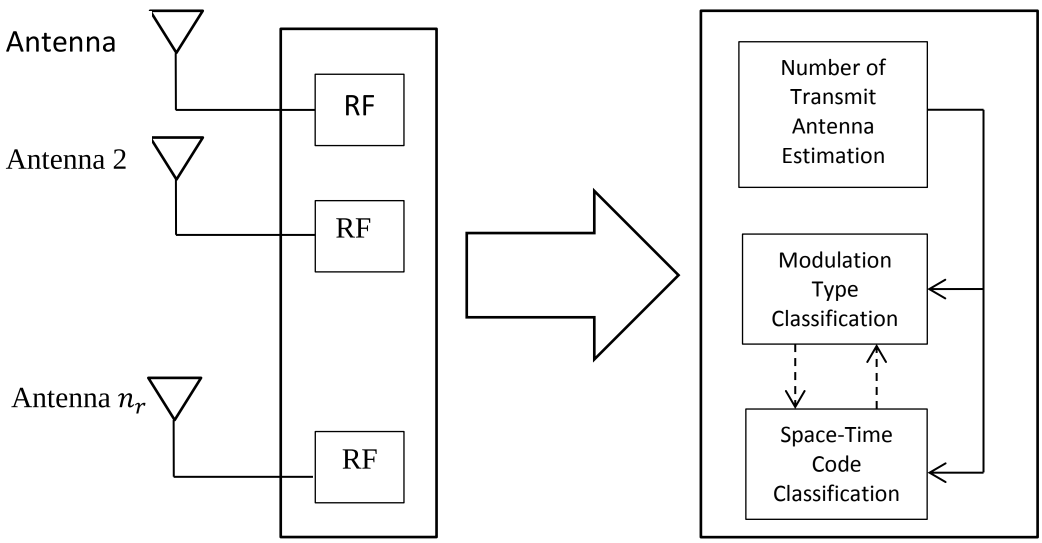

Figure 2-4 The structure of the non-cooperative MIMO receiver

Using these assumptions and the receiver model, the v'th $n_r \times l_z$ signal block received at the receiver can be expressed as

$$Y_v = HX_v + W_v \quad , \tag{2.2}$$

Where $\boldsymbol{W}_v$ represents additive white Gaussian noise matrix with i.i.d elements of variance σ^2, $\boldsymbol{X}_v = C(\boldsymbol{s}[v])$ is the v'th transmit signal block, $\boldsymbol{H}$ is the $n_r \times n_t$ channel matrix whose (i,j)'th element represents the channel coefficient between the i'th receive and the j'th transmit antenna, as illustrated in Figure 2-5. The elements of the channel matrix are modeled as complex Gaussian random variables with zero mean and unit variance. We assume a block fading channel model, i.e. the channel remains constant during an observation interval. Without loss of generality, the signal to noise ratio is defined as SNR=n_t/σ^2.

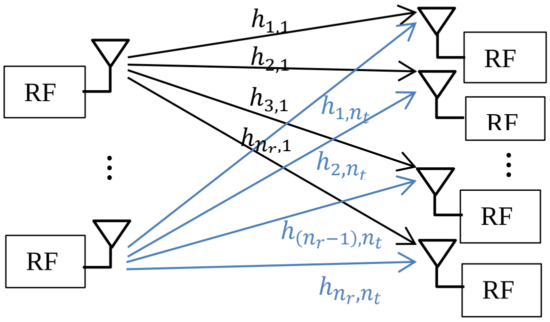

Figure 2-5 Channel coefficients of a $n_r \times n_t$ MIMO system

Chapter 3

Modulation Classification

The task of the modulation type classification can be seen as a multiple hypothesis testing problem, where the classifier has to determine which modulation, from the set of possible modulation types $\Theta_{(m)} = (\mathcal{M}_1, \dots, \mathcal{M}_u)$ is employed in the unknown transmit signal, using the received signal which is corrupted by MIMO fading channel and additive noise.

In this chapter, the Average Likelihood function for the general MIMO modulation type classification problem will be derived, and the modulation classification methods based on the Average Likelihood Ratio Test (ALRT) and its more practical version Hybrid Likelihood Ratio Test (HLRT) proposed in [1] for spatial multiplexing MIMO signals will be investigated in detail. Subsequently, we propose a novel modulation classification method, the EM-HLRT, which employs the expectation maximization (EM) approach (see [18] and [11]) for blind channel matrix estimation to improve the performance of the HLRT in [1] for spatial multiplexing signals. The use of EM is prohibitive in the case of space time block coded signals due to the high computational complexity. Therefore, in the final part of this chapter we propose the use of the Higher Order Statistics based blind channel matrix estimation method in [12] for modulation type classification for space time block coded signals assuming that the employed space time code is known at the receiver.

3.1 The Average Likelihood Function

Using the signal model given in Eq.2 The likelihood function of the received signal block v'th time instance can be given as [10]

$$\Delta\left[\boldsymbol{Y}_v \middle| \boldsymbol{H}, \sigma^2, C^{(z)}(\boldsymbol{s}[v])\right] = \frac{1}{(\pi\sigma^2)^{nr}} exp\left[-\frac{1}{\sigma^2}\left\|\boldsymbol{Y}_v - \boldsymbol{H}C^{(z)}(\boldsymbol{s}[v])\right\|_F^2\right], \qquad (3.1)$$

where $\|\quad\|$ denotes the Frobenius norm, $\boldsymbol{H}$ is the channel matrix, $C^{(z)}(\boldsymbol{s}[v])$ is the v'th space time coded signal block, $C^{(z)}$ represents the employed STBC operation. Since the symbol vector $\boldsymbol{s}[v]$ is not known to the receiver, except that it is drawn from a finite alphabet corresponding to its modulation type $\mathcal{M}_j$, which is an element of the set of all possible modulation types $\Theta_{(m)}$. The dependency on the particular transmit vector can be removed by averaging it over the distribution of modulation type. In this work, we assume that for a given modulation type, the occurrence of each symbol in the constellation is equally probable, thus, the probability of occurrence of each $\boldsymbol{s}^j$ is equal to $\frac{1}{M_j^{n_t}}$, where M_j is the number of symbols in the constellation of the j'th modulation type. Furthermore, assuming that $\boldsymbol{s}[v]$ is i.i.d. with respect to the time index v, The so called average likelihood function for the total received signal block $\boldsymbol{Y} = \left[\boldsymbol{Y}_0, \dots, \boldsymbol{Y}_{\left(\frac{N}{l_z}\right)-1}\right]$ can be written as,

$$\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(z)}, \boldsymbol{H}, \sigma^2\right] = \frac{1}{\left(M_j\right)^{\frac{Nn_z}{l_z}}(\pi\sigma^2)^{n_r}} \times$$

$$\prod_{v=0}^{\left(\frac{N}{l_z}\right)-1} \sum_{\boldsymbol{s}^j \in M_j^{n_t}} exp\left[-\frac{1}{\sigma^2}\left\|\boldsymbol{Y}_v - \boldsymbol{H}C^{(z)}\left(\boldsymbol{s}^j\right)\right\|_F^2\right] \quad (3.2)$$

where s^j denotes possible transmit symbol vector of the employed modulation type $\mathcal{M}_j$, N denotes length of the observation window and the log-Average likelihood function [10] ,

$$\log\left(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(z)}, \boldsymbol{H}, \sigma^2\right]\right) = -\frac{Nn_z}{l_z}\log\left(M_j\right) - n_r log(\pi\sigma^2)$$

$$+ \sum_{v=0}^{\left(\frac{N}{l_z}\right)-1} log\left(\sum_{\boldsymbol{s}^j \in M_j^{n_t}} exp\left[-\frac{\left\|\boldsymbol{Y}_v - \boldsymbol{H}C^{(z)}\left(\boldsymbol{s}^j\right)\right\|_F^2}{\sigma^2}\right]\right) \quad . \quad (3.3)$$

Equation (3.3) is the general form of Likelihood function that we will use in Chapter 3 and Chapter, 4 depending on assumptions, the function will have slight changes but general structure is going to be same.

3.2 The Average Likelihood Ratio Test for SM

In [1], an ALRT test for Spatial multiplexing MIMO signals has been proposed for modulation type classification. In the case of spatial multiplexing, the transmitted signal block can be written as

$$\boldsymbol{X_v} = \boldsymbol{C}(\boldsymbol{s}[v]) = \boldsymbol{s}[v] \tag{3.4}$$

Thus, the signal model for this case can be written as

$$\boldsymbol{y}[v] = \boldsymbol{Hs}[v] + \boldsymbol{w}[v] \tag{3.5}$$

Where $\boldsymbol{y}[v]$ is the received signal vector at time instant v. Hence, function given in Equation 3.1 is reduced to

$$\log\left(\Delta\left[\boldsymbol{Y}\middle|\boldsymbol{\mathcal{M}_j}, \boldsymbol{C}^{(0)}, \boldsymbol{H}, \boldsymbol{\sigma^2}\right]\right) = -\boldsymbol{N}.\boldsymbol{n_t}.\log\left(\boldsymbol{M_j}\right) - \boldsymbol{n_t}\boldsymbol{log}(\boldsymbol{\pi\sigma^2}) + \sum_{v=0}^{N-1} \boldsymbol{log}\left(\sum_{S^j \in M_j^{n_t}} \boldsymbol{exp}\left[-\frac{\left\|\boldsymbol{y}[v] - \boldsymbol{Hs}^j\right\|_F^2}{\boldsymbol{\sigma^2}}\right]\right). \tag{3.6}$$

The Hypothesis test proposed in [1], decides for the modulation type that maximizes this average likelihood function, i.e.

$$\widehat{\boldsymbol{\mathcal{M}}} = \arg\max_{\boldsymbol{\mathcal{M}_j \epsilon \Theta_{(m)}}} \boldsymbol{log}\left(\Delta\left[\boldsymbol{Y}\middle|\boldsymbol{\mathcal{M}_j}, \boldsymbol{C}^{(0)}, \boldsymbol{H}, \boldsymbol{\sigma^2}\right]\right) \tag{3.7}$$

This test can be considered as optimal in the Bayesian sense for SM signals, given that the channel matrix and the noise variance are known. However, especially the assumption of perfect knowledge of the channel matrix, which is unrealistic in the non-cooperative scenarios considered in this thesis, limits its use in practice. Nevertheless, the classification performance of this method can be regarded as an upper performance bound for the MIMO modulation type classification problem for spatial multiplexing systems.

3.2.1 The Hybrid Likelihood Ratio Test for SM

In practical scenarios involving modulation type classification, no cooperation between the transmitter and receiver is possible; thus the channel matrix is unknown to the receiver and needs to be estimated blindly. In the same work where ALRT has been proposed, a suboptimal hybrid likelihood ratio test (HLRT) is presented, which employs blind estimation of the channel matrix, and is therefore more practical [1].

The classification in this case is performed by maximizing the average likelihood function, with the channel matrix $\boldsymbol{H}$ replaced by its blind estimate $\widehat{\boldsymbol{H}}^{(j)}$ which is estimated with the assumption that the j'th modulation type is employed in the signal, i.e

$$\widehat{\mathcal{M}} = \arg\max_{\mathcal{M}_j \epsilon \Theta_{(m)}} log\left(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(0)}, \widehat{\boldsymbol{H}}^{(j)}, \sigma^2\right]\right). \quad (3.8)$$

3.2.2 The Blind Channel Estimation using JADE and phase correction for HLRT

In [1], Choqueuse has proposed to employ a blind channel estimation strategy consisting of two steps. First, an independent component analysis (ICA) method is used to estimate the channel matrix blindly up to a phase offset matrix. Then, the phase offset corresponding to each transmit signal component is estimated for each hypothesis.

The term ICA refers to a family of computational methods that are employed for blindly separating linear mixtures of statistically independent random processes under noise into their individual components [19]. In a SM system, the received signal consists of a linear mixture of independent transmit signals and the noise, therefore the methods used in ICA can also be used for blind estimation of the channel matrix in a spatial multiplexing system.

In [1], Choqueuse proposes to employ the joint approximate diagonalization of eigen-matrices (JADE) algorithm proposed in [20] for blind channel estimation required for the HLRT algorithm. Note that like many ICA algorithms, JADE is able to estimate the channel matrix and separate the independent signal components up to a phase rotation and permutation. Thus, the Channel matrix estimated by JADE, $\widetilde{\boldsymbol{H}}$ can be written as (ignoring the estimation errors):

$$\widetilde{\boldsymbol{H}} = \boldsymbol{HDP} \quad (3.9)$$

where $\boldsymbol{P}$ is a permutation matrix, and $\boldsymbol{D}$ is a unknown phase offset matrix which can be given as,

$$\boldsymbol{D} = \begin{bmatrix} e^{j\theta_1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & e^{j\theta_{nt}} \end{bmatrix} \tag{3.10}$$

Clearly, for an SM system, the presence of a permutation ambiguity is irrelevant. However, the phase offsets need to be estimated and compensated for in order to form the channel estimate $\widehat{\boldsymbol{H}}^{(j)}$.

3.2.3 Estimation of the Phase Offset

For the blind estimation of the phase offsets, Choquese proposed to use the phase estimation algorithm in [21]. First pre-estimates of a transmit vector $\boldsymbol{s}[v]$ are formed using $\widetilde{\boldsymbol{H}}$

$$\tilde{\boldsymbol{s}}[v] = \left(\widetilde{\boldsymbol{H}}^{\dagger}\widetilde{\boldsymbol{H}}\right)^{-\mathbf{1}}\widetilde{\boldsymbol{H}}^{\dagger}\mathbf{y}[v], \tag{3.11}$$

subsequently, the phase offsets are estimated for each component $\tilde{\boldsymbol{s}}[v]$ separately by using [21]. Under the assumption that j’th modulation type is transmitted, the phase offset estimate for the k’th component of $\tilde{\boldsymbol{s}}[v], \tilde{s}_k[v]$ is given as

$$\hat{\theta}_k^j = \frac{1}{q} arg\left(\mu_j^q \sum_{k=1}^{N} (\tilde{s}_k[v])^q\right) \tag{3.12}$$

Where $\mu_j^q = E[s^*[v]^q]$ given that the J’th modulation type has been employed [21]. The values of μ_j^q and q^j for i.i.d. symbol streams with different modulation types are given in Table 2.

Modulation Type, $\mathcal{M}_j$	BPSK	QPSK	8PSK	16QAM
q^j	2	4	8	4
μ_j^q	1	1	1	-0.68

Table 2 Values of μ_j^q and q^j for different modulation types $\mathcal{M}_j$

After estimating the phase offset for each component of $\tilde{\boldsymbol{s}}[v]$, the phase corrected channel estimate under the hypothesis j'th modulation type has been employed can be expressed as:

$$\widehat{\boldsymbol{H}}^{(j)} = \widetilde{\boldsymbol{H}}\widehat{\boldsymbol{D}}^{(j)}. \tag{3.13}$$

Where

$$\widehat{\boldsymbol{D}}^{(j)} = \begin{bmatrix} e^{j\hat{\theta}_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & e^{j\hat{\theta}_{nr}} \end{bmatrix}. \tag{3.14}$$

Figure 3-1 shows and example of the blind channel estimation method described above. In Figure 3-1-(a) scatter plot of the one component of $\boldsymbol{y}[v]$ is shown for a QPSK modulated transmit signal in a 2×4 MIMO system SNR=15 dB and N=500. In Figure 3-1-(b) one component of the output of the JADE algorithm $\tilde{s}_k$ is shown, which contains a phase offset. Finally, Figure 3-1-(c) shows the result of the phase correction algorithm described above [21].

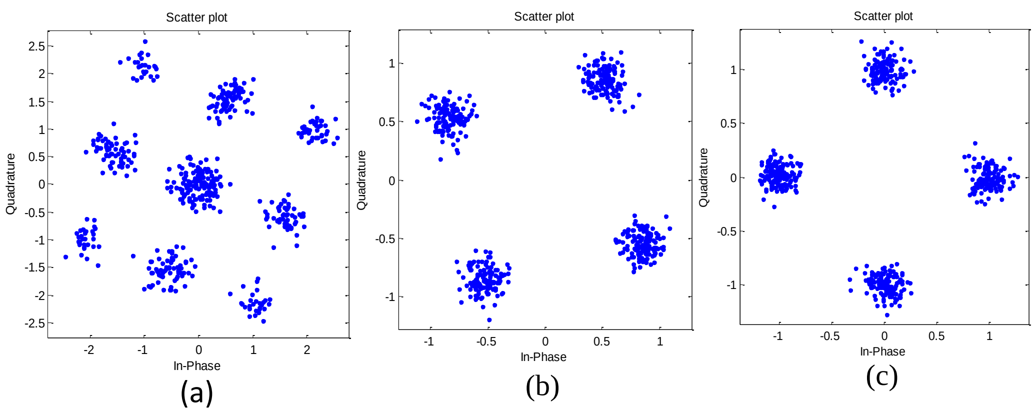

Figure 3-1 Example of the blind channel estimation for QPSK, blocksize 500 and SNR=15dB (a) Received signal Y_v (b) One component of the output of Jade with phase offset (c) One component of the output after channel estimation and phase correction.

The HLRT algorithm can be summarized as follows:

Algorithm of HLRT

1: **Input:** Receive signal **Y**, noise variance σ^2, transmit antenna number n_t , code type SMS

2: **Evaluate** channel matrix $\widetilde{\boldsymbol{H}}$ using JADE

3: **For** each Modulation type $\mathcal{M}_j \in \Theta_{(m)}$ **do**

4: **Evaluate** phase ambiguity matrix $\widehat{\boldsymbol{D}}^{(j)}$ using (3.12) and (3.14)

5: **Evaluate** $\widehat{H}^{(j)}$ using (3.13)

6: **Evaluate** $\log(\Delta[\boldsymbol{Y}|\mathcal{M}_j, C^{(0)}, \widehat{\boldsymbol{H}}^{(j)}, \sigma^2])$ using (3.6)

7: **End for**

8: **Output:** Choose $\widehat{\mathcal{M}} = \arg\max_{\mathcal{M}_j \epsilon \Theta_{(m)}} \log(\Delta[\boldsymbol{Y}|\mathcal{M}_j, C^{(0)}, \widehat{\boldsymbol{H}}^{(j)}, \sigma^2])$

3.2.4 Simulation results of the ALRT and HLRT

In Figure 3-2 and Figure 3-3 the classification performances of the ALRT and HLRT for spatial multiplexing are evaluated using Monte-Carlo simulations. In the simulations, we chose a modulation pool $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, 8\text{PSK}, 16\text{QAM}\}$. We use the average probability of correct classification P_{CC} as a performance measure, which is given as $\frac{1}{|\Theta_{(m)}|}\sum_{j=1}^{|\Theta_{(m)}|} P(\mathcal{M}_j|\mathcal{M}_j)$ where $|\Theta_{(m)}|$ is the cardinality of the set $\Theta_{(m)}$ and $P(\mathcal{M}_j|\mathcal{M}_j)$ is the probability of correct classification of j'th modulation type. For each SNR value and modulation type employed, 1000 Monte-Carlo trials are performed. During simulations of Figure 3-2 and Figure 3-3, MIMO models with 2 transmit and 4,6 receive antennas have been employed respectively and three different block sizes, *N=500,750* and *1000* are considered.

As seen on Figure 3-2, the ALRT algorithm with block size *N=500* achieves $P_{CC} = 0.9$ at about SNR=-3 dB, but the HLRT algorithm with *N=500* achieves the same correct classification performance near SNR=0 dB. Thus, use of the blind channel estimate instead of the exact value of the channel matrix leads to a performance loss of about 3 dB for *N=500*. For *N=1000*, the performance loss decrease to about 2.5 dB. This is due to the fact that the quality of the channel estimation gets better as the number of samples used for estimation increases.

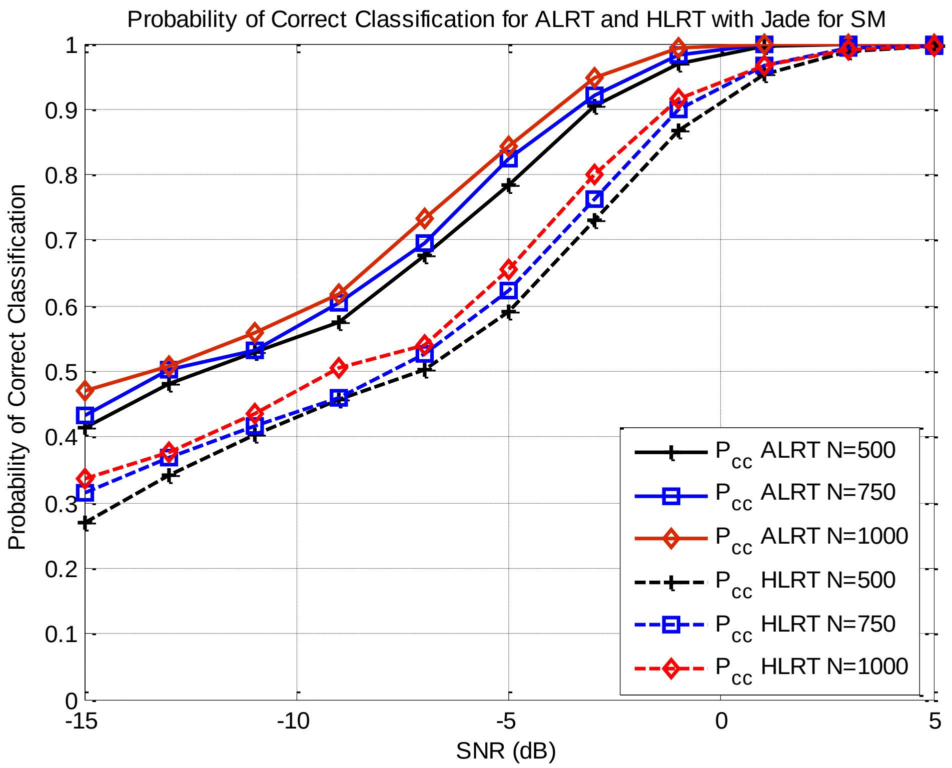

Figure 3-2 Classification performances of ALRT and HLRT for Spatial Multiplexing, n_t=2, n_r=4, N=500,750,1000

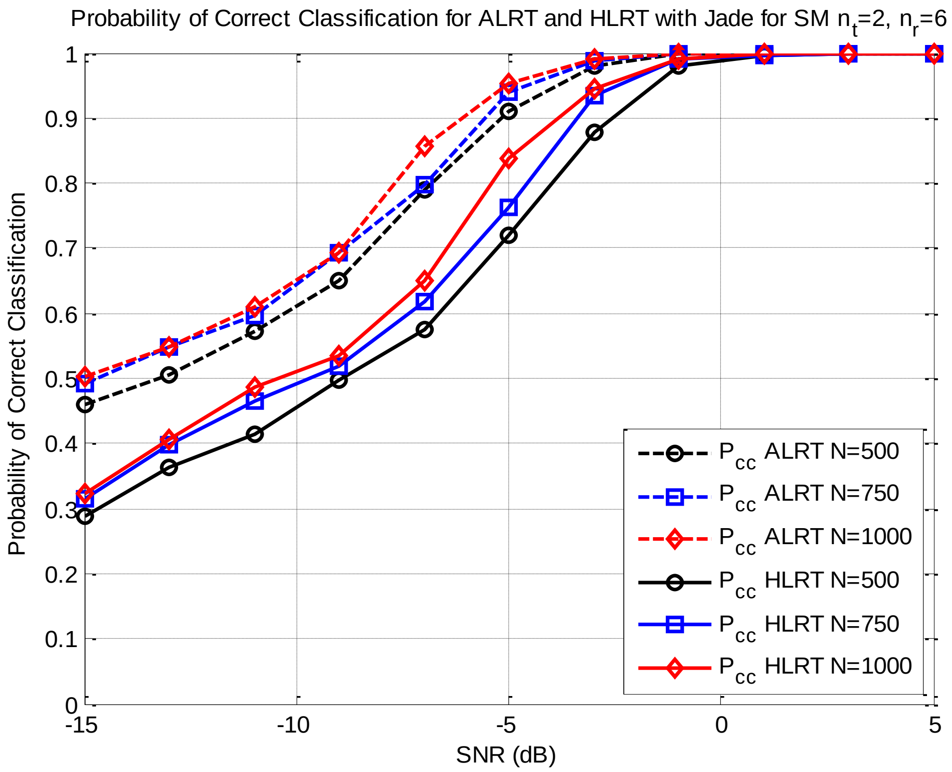

Figure 3-3 Classification performances of ALRT and HLRT for Spatial Multiplexing, n_t=2, n_r=6, N=500,750,1000

In Figure 3-3 performances of ALRT and HLRT with spatial multiplexing given in section 3.2 are evaluated with a MIMO system with 2 transmit and 6 receive antennas employed. *N=500,750* and *1000* are considered. ALRT algorithm with N=*500* achieves the P_{cc}=0.9 around SNR=-5 dB . HLRT algorithm with same block size achieves same P_{cc} above SNR=-2.5 dB. ALRT with N=*1000* achieves the correct classification performance of P_{cc}=0.9 near SNR=-6 dB, and HLRT with same N achieves same performance near SNR= -4 dB. Performance losses between ALRT and HLRT with N=*500,1000* are 2.5 dB and 2 dB respectively.

Clearly, the block size, denoted as N, is a critical parameter, which directly affects classification performance, i.e. ALRT with *N=500* achieves $P_{CC} = 0.9$ near SNR=3 dB. Increase of the N for the ALRT algorithm from 500 to 750, causes a performance improvement about 0.5 dB. Furthermore, HLRT algorithm with *N=500* achieves $P_{CC} = 0.9$ close to 0 dB and *N=750* achieves -1 dB.

3.3 The EM-HLRT Algorithm

It should be noted that the only difference between the ALRT and HLRT algorithms is in the use of blind estimation of the channel in HLRT, in contrast to ALRT, in which the channel is assumed to be known, and therefore the actual channel matrix is employed in the computation of the likelihood function for classification. Thus, the decrease in the classification performance in HLRT compared to ALRT occurs solely because of the estimation errors made when blindly estimating the channel. Thus, it is reasonable to expect an increase in the classification performance if the quality of the channel estimation could be increased. For this purpose, we propose the use of the expectation maximization (EM) method for the blind estimation of the channel matrix.

In [11], it has been shown that the expectation maximization (EM) method [18] can be used to estimate the channel matrix for discrete alphabet sources with the assumption that the probability distribution of the emitted symbols are known a-priori.

EM describes a family of iterative estimation techniques that can be used for finding the maximum likelihood estimates of parameters, especially when maximizing the likelihood function is intractable. For details of the general EM estimation, see [18]. It is well known that the EM estimates converge to the maximum likelihood estimate if the number of iterations are sufficiently high [11]. Thus, it is reasonable to expect that the use of the EM algorithm will increase the classification performance of the HLRT classifier.

In [11], the EM algorithm is derived for the channel matrix estimation in a MIMO context with i.i.d. sources and known discrete alphabet.The i'th step for this estimation algorithm with the assumption that the j'th modulation type $\mathcal{M}_j$ has been transmitted is given as

$$\boldsymbol{R}_{RS(j)}^{(i)} = \sum_{v=0}^{N-1} \sum_{p=1}^{m_q^{Nt}} \boldsymbol{y}[v]\,(\boldsymbol{s}_p^j)^H p\left(\boldsymbol{s}_p^j \mid \boldsymbol{y}[v], \widehat{\boldsymbol{H}}_{\mathbf{i}}^{(\mathrm{j})}, \sigma_w^2\right), \tag{3.15}$$

$$\boldsymbol{R}_{SS(j)}^{(i)} = \sum_{k=1}^{N-1} \sum_{p=1}^{m_q^{Nt}} \boldsymbol{s}_p^j (\boldsymbol{s}_p^j)^H p\left(\boldsymbol{s}_p^j \mid \boldsymbol{y}[v], \widehat{\boldsymbol{H}}_{\mathbf{i}}^{(\mathrm{j})}, \sigma_w^2\right), \tag{3.16}$$

$$\widehat{\boldsymbol{H}}_{\mathbf{i+1}}^{(\mathbf{j})} = \boldsymbol{R}_{RS(q)}^{(i)} \left(\boldsymbol{R}_{SS(q)}^{(i)}\right)^{-1} , \tag{3.17}$$

where $\widehat{\boldsymbol{H}}_{\mathbf{i}}^{(\mathrm{j})}$ denotes the estimate of the channel matrix in the i'th iteration and the conditional density $\mathrm{P}\left[\boldsymbol{Y} \middle| \mathcal{M}_j, C^{(z)}, \boldsymbol{H}, \sigma^2\right]$ can be derived using the likelihood function in (3.2). Note that the EM algorithm requires an initialization and a proper initialization is critical for the fast convergence of the algorithm. Thus, we initialize the EM algorithm using the blind channel estimation method, which employs JADE and phase correction described in the previous section which is already a good estimate of the channel.

The summary of the proposed novel classification algorithm with EM based blind channel matrix estimation which we will refer to as the EM-HLRT is given below. Note that the number of EM iterations in the algorithm is defined as $n_{iteration}$, and the algorithm reduces to the HLRT algorithm for $n_{iteration} = 0$.

Algorithm of EM-HLRT

1: Input: Input: Receive signal **Y**, noise variance σ^2, transmit antenna number n_t, code type SM

2: Estimate channel matrix $\widetilde{\boldsymbol{H}}$ using JADE

3: For each Modulation type $\mathcal{M}_j \in \Theta_{(m)}$ **do**

4: Estimate phase ambiguity matrix $\widehat{\boldsymbol{D}}^{(j)}$ using (3.12) and(3.14)

5: Initialize $\widehat{\boldsymbol{H}}_{(0)}^{(j)}$ using (3.13)

6: For i=1: $n_{iteration}$

7: Evaluate $\boldsymbol{R}_{RS(j)}^{(i)}$ at (3.15)

8: Evaluate $\boldsymbol{R}_{SS(j)}^{(i)}$ at (3.16)

9: Evaluate $\widehat{\boldsymbol{H}}_{\mathbf{i+1}}^{(\mathbf{j})}$ at (3.17)

10: End for

11: Evaluate $\log(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(0)}, \widehat{\boldsymbol{H}}_{n_{iteration}}^{(\mathbf{j})}, \sigma^2\right])$ using (3.6)

12: End for

13: Output: Choose $\widehat{\mathcal{M}} = \arg\max_{\mathcal{M}_j \epsilon \Theta_{(m)}} \log(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(0)}, \widehat{\boldsymbol{H}}_{n_{iteration}}^{(\mathbf{j})}, \sigma^2\right])$

3.3.1 Simulation Results of EM-HLRT

In Figure3-4, Figure 3-5 and Figure 3-6, the classification performance of the EM-HLRT for spatial multiplexing is evaluated using Monte-Carlo simulations. In the simulations, we chose a modulation pool $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, \text{8PSK}, \text{16QAM}\}$. For each SNR value and modulation type employed, 1000 Monte-Carlo trials are performed. During simulations, the MIMO model with 2 transmit and 4 receive antennas have been employed and three different blocksizes, N=500,1500 and 5000 are considered. At each case, the number of EM iterations $n_{iteration}$=0,1,2 and 3 is considered, where , as discussed above for $n_{iteration}$=0 the algorithm is identical to the HLRT algorithm of Choqueuse [1].

The simulation results show that show a performance increase in the classification as $n_{iteration}$ increases in each case, however, the amount of improvement in the performance decreases with each EM iteration, and comes eventually to as saturation. The highest improvement in performance is observed for N=500 between the case with $n_{iteration} = 0$ (i.e. the HLRT algorithm) and the first EM iteration and this improvement decreases as N increases.Thus, it can be concluded that the performance improvement in the channel estimation with EM is only significant for shorter N which is due to the fact that JADE-based channel estimation approaches the optimal estimate for high N.

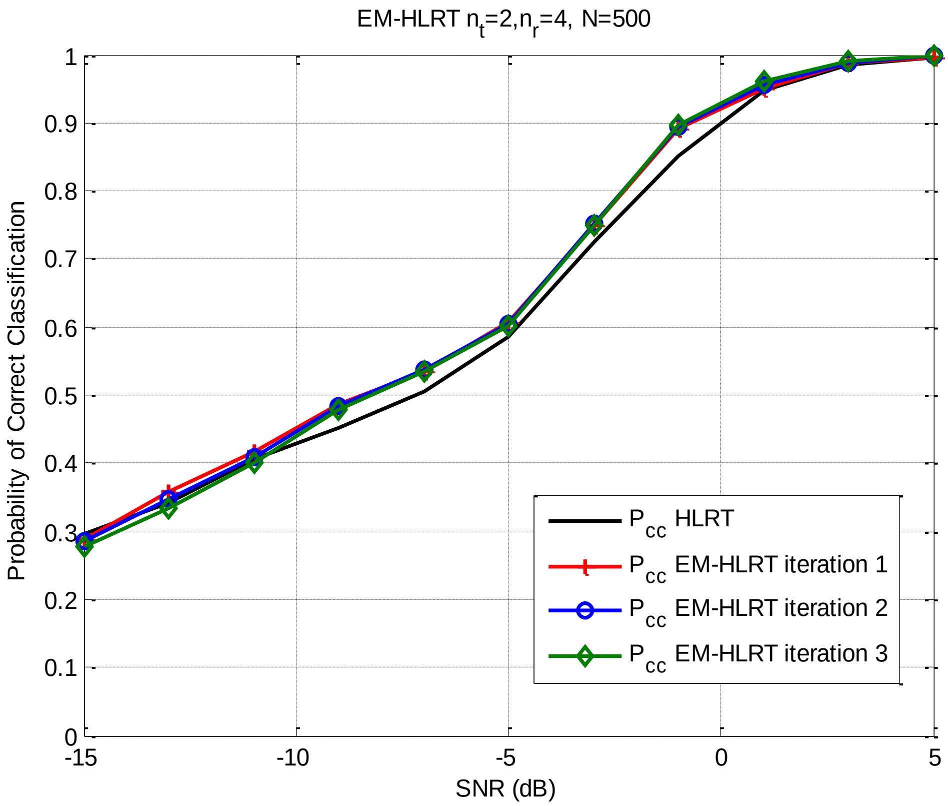

Figure 3-4 Classification performance of EM-HLRT, $n_{iteration}$=0,1,2, n_t=2, n_r=4, N=500

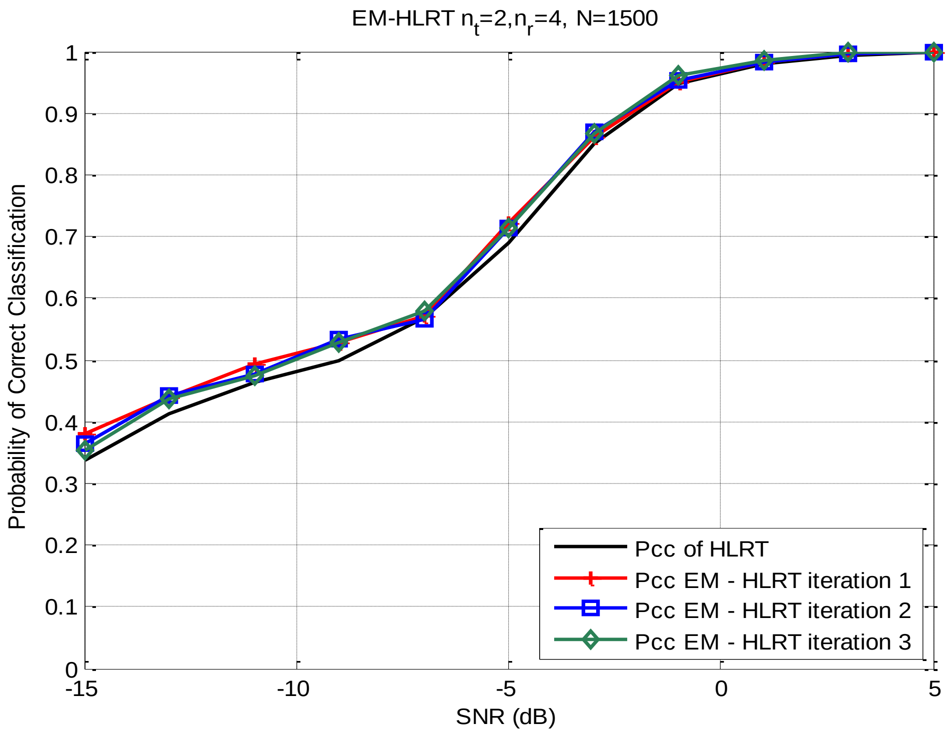

Figure 3-5 Classification performance of EM-HLRT, niteration=0,1,2, n_t=2, n_r=4, N=1500

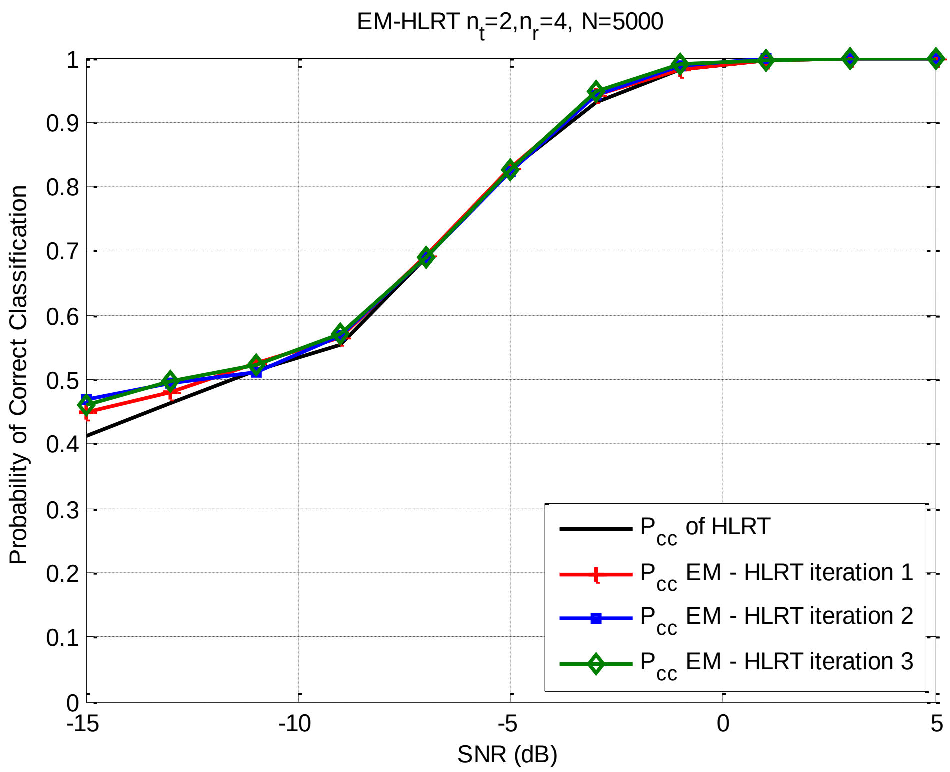

Figure 3-6 Classification performance of EM-HLRT, $n_{iteration}$=0,1,2, n_t=2, n_r=4, N=5000

3.4 Modulation Type Classification with a Known STBC

Modulation type classification with a known STBC in the case where a known space-time block code other than spatial multiplexing is used, the Average likelihood function can be written as

$$\log\left(\Delta\left[Y\middle|\mathcal{M}_j, C^{(z)}, H, \sigma^2\right]\right) = -\frac{Nn_z}{l_z}\log\left(M_j\right) - n_r log(\pi\sigma^2)$$

$$+\sum_{v=0}^{\left(\frac{N}{l_z}\right)-1} log\left(\sum_{S^j\in M_j^{n_t}} exp\left[-\frac{\left\|Y_v - HC^{(z)}\left(s^j\right)\right\|_F^2}{\sigma^2}\right]\right) \qquad (3.18)$$

In this case, the ALRT modulation classifier is given as

$$\widehat{\mathcal{M}} = \arg\max_{\mathcal{M}_j\epsilon\Theta_{(m)},} log\left(\Delta\left[Y\middle|\mathcal{M}_j, C^{(z)}, H, \sigma^2\right]\right). \qquad (3.19)$$

It should be noted that the received signal vectors contain statistical dependencies due to STBC operation. Thus the use of the JADE algorithm, which assumes statistical independence of source signals for the blind channel estimation for an HLRT classifier is not theoretically possible for this case. Instead, we propose to employ the high-order statistics based blind channel matrix estimation algorithm given in [12] for the HLRT based modulation classification algorithm for MIMO signals with known STBCs.

It should be noted that the blind channel estimation algorithm in [12] also contain ambiguities, which depend on the specific STBC employed. Table 3 lists the set of ambiguity matrices for the STBCs considered in this thesis. Note that amongst the considered STBC, only the cases of spatial multiplexing and Alamouti code lead to a phase ambiguity that needs to be resolved. There exist only sign ambiguities for the other two codes, which are irrelevant for the modulation type classification problem. For those cases where phase correction is required, we use phase correction algorithm in [21] described in section 3.2.3

Coding Technique	Set of Ambiguity Matrices After Channel Estimation
Spatial Multiplexing, $C^{(0)}$	$\widehat{\boldsymbol{D}}^{(0)} = \{PD\}$
Alamouti, $C^{(1)}$ [9]	$\widehat{\boldsymbol{D}}^{(1)} \in \{\begin{bmatrix} e^{j\theta} & 0 \\ 0 & e^{j\theta} \end{bmatrix}, \begin{bmatrix} 0 & e^{-j\theta} \\ e^{-j\theta} & 0 \end{bmatrix}\}$
Ganesan, $C^{(2)}$ [10]	$\widehat{\boldsymbol{D}}^{(2)} = \{\pm I_3\}$
Tarokh $C^{(3)}$ [11]	$\widehat{\boldsymbol{D}}^{(3)} = \{\pm I_3\}$

Table 3 Set of Ambiguity Matrices after Channel Estimation using HOS and corresponding Coding Techniques

The summary of the HLRT based modulation type classification algorithm for MIMO signals with known STBCs that uses higher order statistics (HOS) based estimation of the channel matrix, which we will refer to HOS-HLRT is given below.

Algorithm of HOS-HLRT

Input: Receive signal **Y**, noise variance σ^2, transmit antenna number n_t, code type $C^{(z)}$
Evaluate channel matrix $\widetilde{\boldsymbol{H}}^{(z)}$ using HOS [12]
For each Modulation type $\mathcal{M}_j \in \Theta_{(m)}$ **do**
If phase ambiguities exist according to Table 3
  Estimate phase ambiguity matrix $\widehat{\boldsymbol{D}}^{(j)}$ using (3.12) and(3.14)
  Evaluate $\widehat{\boldsymbol{H}}^{(j,z)}$ using (3.13)
Else
  $\widehat{\boldsymbol{H}}^{(j,z)} = \widetilde{\boldsymbol{H}}^{(z)}$
  Evaluate $\log(\Delta[\boldsymbol{Y} | \mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2])$ using (3.18)
End for
Output: Choose $\widehat{\mathcal{M}} = \arg\max_{\mathcal{M}_j \epsilon \Theta_{(m)}} \log(\Delta[\boldsymbol{Y} | \mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2])$

3.4.1 Simulation Results of HOS-HLRT

In this section, classification performances of the ALRT and HOS-HLRT for known STBCs are evaluated using Monte-Carlo simulations. In the simulations, we chose a modulation pool $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, 8\text{PSK}, 16\text{QAM}\}$. We use the average probability of correct classification P_{CC} as a performance measure, which is given as $P_{CC} = \frac{1}{|\Theta_{(m)}|}\sum_{j=1}^{|\Theta_{(m)}|} P(\mathcal{M}_j|\mathcal{M}_j)$ where $|\Theta_{(m)}|$ is the cardinality of the set $\Theta_{(m)}$ and $P(\mathcal{M}_j|\mathcal{M}_j)$ is the probability of correct classification of j'th modulation type. For each SNR value and modulation type employed, 1000 Monte-Carlo trials are performed.

For n_t=2, classifiers with both n_r= 4 and 6 have been employed, three different blocksizes, *N=500,750* and 1000 are considered, and spatial multiplexing and Alamouti codes are employed. For the case of n_t=3, a classifier with n_r= 6 has been employed and the codes Spatial Multiplexing, $C^{(2)}$, $C^{(3)}$ are considered from Table 1.

In Figures 3-7 and 3-8, modulation type classification performance of the ALRT and the HOS-HLRT are shown for an Alamouti-coded signal. As seen in Figure 3.7 ALRT algorithm with n_t= 2 and n_r= 4 and blocksize *N=500* achieves $P_{CC} = 0.9$ at about SNR=-5 dB, but the HLRT algorithm with *N=500* achieves the same correct classification performance around SNR=-1.5 dB. Thus, it can be easily noticed that use of the blind channel estimate instead of the exact value of the channel matrix leads to a performance loss of about 3.5 dB with N=500. For the cases of ALRT and HLRT with N=750 and N=1000, the performance loss is also about 3.5dB.

In Figure 3-8 the ALRT algorithm with n_t= 2, n_t= 6 and blocksizes *N=500* and *N=1000* achieve $P_{CC} = 0.9$ at about SNR=-7 dB and SNR= -8 dB respectively, but the HLRT algorithm with N=500 and N=1000 achieves the same correct classification performance around SNR=-4 dB and and SNR=-5 dB. Estimating channel with HOS algorithm as in section 3.4 results a performance loss around 3 dB in *N=500* and *N=1000*.

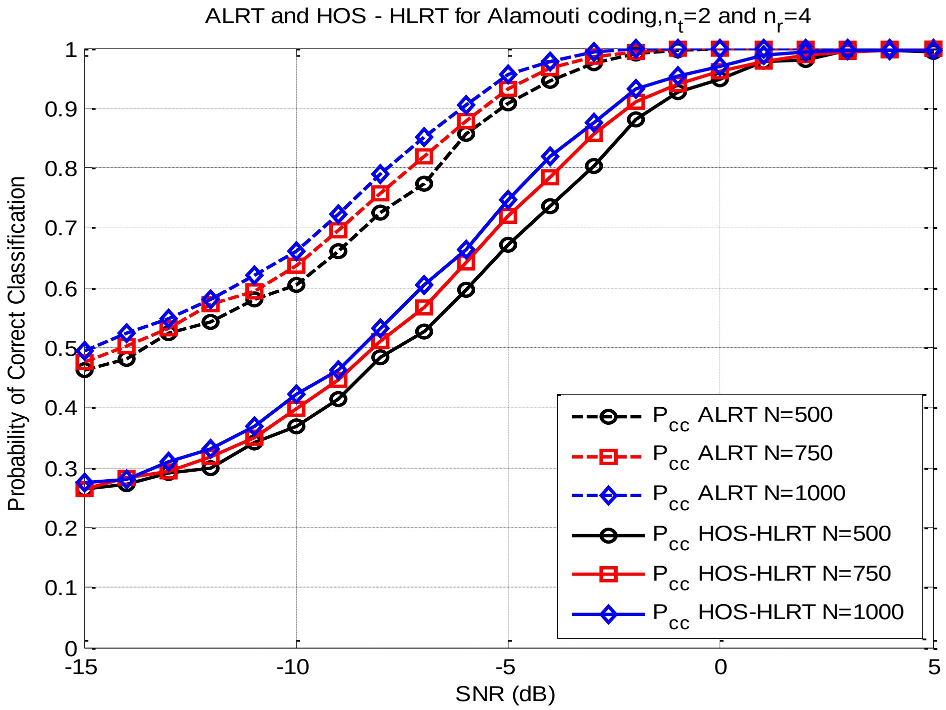

Figure 3-7 Classification performance of ALRT and HOS-HLRT for Alamouti ($C^{(1)}$) code, N=500, 750, 1000, 2x4 MIMO System

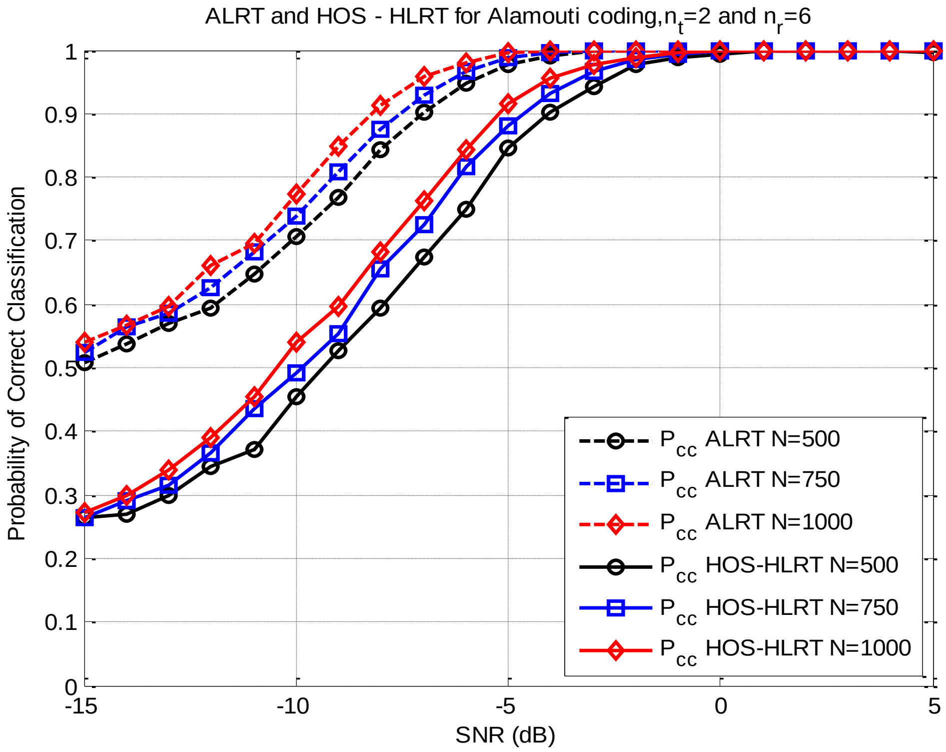

Figure 3-8 Classification performance of ALRT and HOS-HLRT for Alamouti ($C^{(1)}$) Code, N=500, 750, 1000, 2x6 MIMO System

Figure 3-9 shows the classification performance of ALRT and HOS-HLRT using equation (3.18) in given section 3.4.1. During the simulations of Figure 3-9 a MIMO system with 3 transmit and 6 receive antennas are considered (n_t= 3; n_r= 6) and the orthogonal space time block code $C^{(2)}$ from Table 1 is employed. ALRT with *N=500* achieves probability of correct classification of 0.9 near SNR=-8 dB and ALRT with *N=750* achieves same classification probability around SNR=-9. In the same figure, HOS-HLRT with *N=500* achieves P_{cc}=0.9 around SNR=-5dB and HOS-HLRT with blocksize achieves classification performance of 0.9 around-6 dB . In this case we can say that using the estimated channel matrix instead of exact value results a loss of 3 dB for both *N=500* and *N=750*.

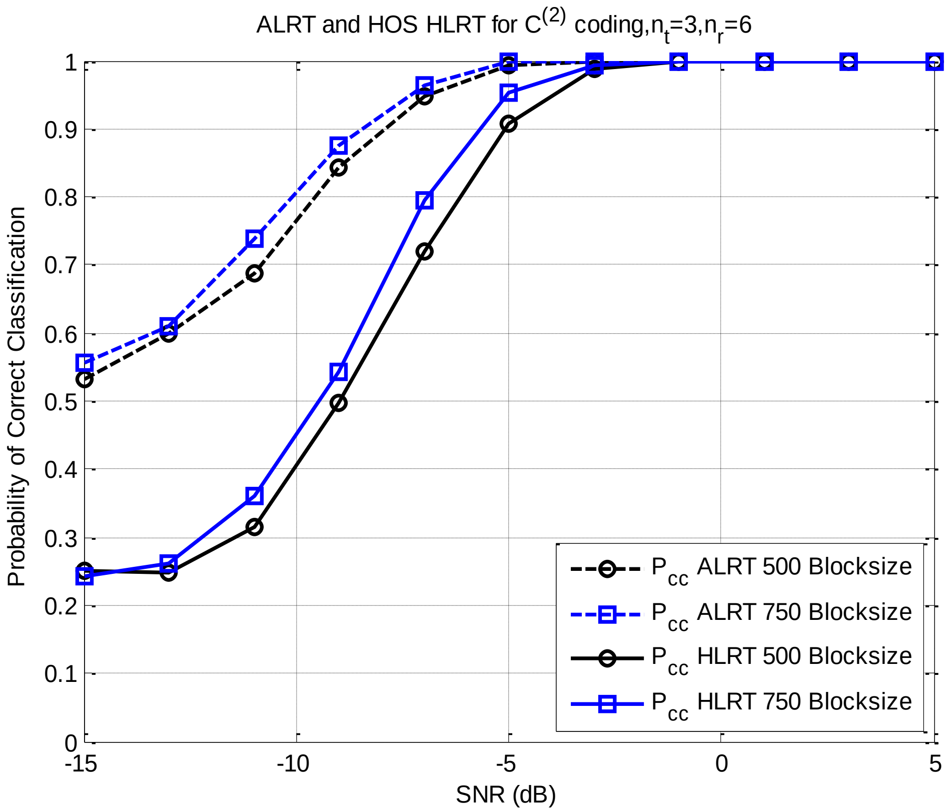

Figure 3-9 Classification performance of ALRT and HOS-HLRT for ($C^{(2)}$) Code(See Table 1), N=500, 750, 3x6 MIMO System

Chapter 4

Joint Classification of the Space Time Block Code and the Modulation Type

As discussed in Chapter 1, the modulation type and STBC classification problems are approached separately in the existing literature. However, the structure of the Average likelihood function

$$\log\left(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(z)}, \boldsymbol{H}, \sigma^2\right]\right) = -\frac{Nn_z}{l_z}\log\left(M_j\right) - n_r log(\pi\sigma^2) +$$

$$\sum_{v=0}^{\left(\frac{N}{l_z}\right)-1} log\left(\sum_{\boldsymbol{s}^j \in M_j^{n_t}} exp\left[-\frac{\left\|\boldsymbol{Y}_v - \boldsymbol{H}C^{(z)}\left(\boldsymbol{s}^j\right)\right\|_F^2}{\sigma^2}\right]\right) \tag{4.1}$$

allows a joint classification of the both simultaneously.

In this thesis, we propose a joint classification of the modulation type and STBC in MIMO systems based on the likelihood function of the received signal. Using this novel approach to the MIMO signal identification problem, we propose joint ALRT and HLRT tests for the joint classification. We also consider more practical cases, where the noise variance and the code block timing (i.e. the beginning and the end of each code block) are unknown to the receiver.

4.1 An ALRT test for Joint STBC and Modulation Type Classification

Using the average likelihood function of the received signal in a MIMO system using an STBC, the Joint ALRT classifier, which we refer to as J-ALRT, for the modulation type and the STBC employed can be given as,

$$\left(\widehat{\mathcal{M}}, \hat{C}\right) = \arg \max_{\mathcal{M}_j \epsilon \Theta_{(m)}, C^{(Z)} \epsilon \Theta_{(c)}} log\left(\Delta\left[\boldsymbol{Y}\middle|\mathcal{M}_j, C^{(z)}, \boldsymbol{H}, \sigma^2\right]\right) \tag{4.2}$$

Note that in this case, the number of hypotheses to be tested is equal to $|\Theta_{(m)}||\Theta_{(c)}|$, where $\Theta_{(c)}$ is the set of all possible STBC's and $|\Theta_{(c)}|$ is the cardinality of the set $\Theta_{(c)}$. Here , the classification is performed by maximizing the average likelihood function jointly with respect to the modulation type and the STBC. Clearly, as in the case of the ALRT in chapter 3, this test is impractical due to the fact that it assumes the perfect knowledge of the channel matrix, noise variance and the code block timing, however, assuming the existence of this a-priori information at the receiver, this test can be considered as optimal in the Bayesian sense, thus, the classification performance of this method can be regarded as an upper performance bound for the joint modulation type and STBC classification problem.

4.2 HLRT tests for Joint STBC and Modulation Type Classification

A Hybrid likelihood ratio test for this joint classification problem can be derived by replacing the true value of the channel matrix H in Equation 4.1 with its estimate $\widehat{\boldsymbol{H}}^{(j,z)}$ which has been estimated by assuming that the j'th modulation type and z'th STBC has been employed. As in section 3.4 we propose to use the higher order statistics based blind channel estimation strategy proposed in [12] for generating $\widehat{\boldsymbol{H}}^{(j,z)}$. The algorithm which we refer to as J-HLRT is summarized below.

Algorithm of J-HLRT

1: **Input:** Receive signal **Y** and noise variance σ^2,transmit antenna number n_t
2: **For** each code type $C^{(z)} \in \Theta_{(c)}$ **do**
3: **Evaluate** channel matrix $\widetilde{\boldsymbol{H}}^{(z)}$ using HOS
4: **For** each Modulation type $\mathcal{M}_j \in \Theta_{(m)}$ **do**
5: **If** phase ambiguities exist according to Table 3
6: **Estimate** phase ambiguity matrix $\widehat{\boldsymbol{D}}^{(j)}$ using (3.12) and(3.14)
7: **Evaluate** $\widehat{\boldsymbol{H}}^{(j,z)}$ using (3.13)
8: **Else**
9: $\widehat{\boldsymbol{H}}^{(j,z)} = \widetilde{\boldsymbol{H}}^{(z)}$
10: **Evaluate** $\log(\Delta[\boldsymbol{Y}|\mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2])$ using (3.18)
11: **End for**
12: **End for**
13: **Output:** Choose $(\widehat{\mathcal{M}}, \hat{C}) = \arg\max_{\mathcal{M}_j\epsilon\Theta_{(m)}, C^Z\epsilon\Theta_{(c)}} log\left(\Delta[\boldsymbol{Y}|\mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2]\right)$

4.2.1 J-HLRT with Noise Variance Estimation

Both in the ALRT and HLRT algorithms proposed by Choquesue in [1], and the algorithms that we propose in this thesis, it has been assumed that the noise variance σ^2 is known at receiver. However, usually a-priori information about the noise variance doesn't exist at receiver and therefore, σ^2 has to be estimated. Fortunately, both the JADE and HOS based blind channel estimation algorithms ([20] and [12], respectively) make the assumption that the signal components in the transmit signal vector have unit power and this assumption as a constraint in solving the optimization problem. Therefore, it is straightforward to show that, a method-of-moments estimator for the noise variance can be given as

$$\hat{\sigma}^{2(j,z)} = \frac{1}{n_t} trace\left(\left(\widehat{\boldsymbol{H}}^{(j,z)}\right)^H \widehat{\boldsymbol{H}}^{(j,z)}\left(\widehat{\boldsymbol{\Sigma}}_y - I\right)\right) \quad , \tag{4.3}$$

where $\widehat{\Sigma}_y$ is the sample covariance matrix of the received signal:

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{N}\boldsymbol{Y}\boldsymbol{Y}^H \quad . \tag{4.4}$$

Using the estimate in the HLRT function in equation (4.1) instead of its true value leads to a classifier that is more practical in the sense that it does not require any a-priori information for the classification except perfect symbol timing and code block timing synchronization.

4.2.2 J-HLRT with Unknown Code Block Timing

In all the cases with space-time block coding discussed above, it has been assumed that the code-block timing, i.e. the beginning and the end of each code block is known to the receiver, which is an unrealistic assumption in a non-cooperative environment. However, the J-HLRT algorithm given in section 4.2 can be easily extended for this case by treating the code timing as an unknown parameter and maximizing the average likelihood function over the unknown timing parameter τ. The classification in this case can be, performed as follows:

Define $\boldsymbol{Y}^{(\tau)}$ as the received signal block with code timing error τ, i.e. the beginning and the end of each code block is shifted by τ time instants. The J-HLRT classifier for this case can be

$$(\widehat{\mathcal{M}}, \hat{C}) = \arg\max_{\mathcal{M}_j \epsilon \Theta_{(m)}, C^{(Z)} \epsilon \Theta_{(c)}, 0 \leq \tau_i < l_z} \left(\Delta\left[\boldsymbol{Y}^{(\tau-\tau_i)} \middle| \mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2\right]\right), \quad (4.5)$$

where the likelihood function can be written as

$$\log\left(\Delta\left[\boldsymbol{Y} \middle| \mathcal{M}_j, C^{(z)}, \widehat{\boldsymbol{H}}^{(j,z)}, \sigma^2, \tau_i\right]\right) = -\frac{Nn_z}{l_z}\log(M_j) - nrlog(\pi\sigma^2)$$
$$+ \sum_{v=0}^{\left(\frac{N}{l_z}\right)-1} log\left(\sum_{\boldsymbol{S}^j} exp\left[-\frac{\left\|\boldsymbol{Y}_v^{(\tau-\tau_i)} - \widehat{\boldsymbol{H}}^{(j,z)} C^{(z)}(\boldsymbol{S}^j)\right\|_F^2}{\sigma^2}\right]\right), \quad (4.6)$$

where $\boldsymbol{Y}_v^{(\tau)}$ defined as the v'th code block cropped with timing error τ as shown in the Figure 4-1

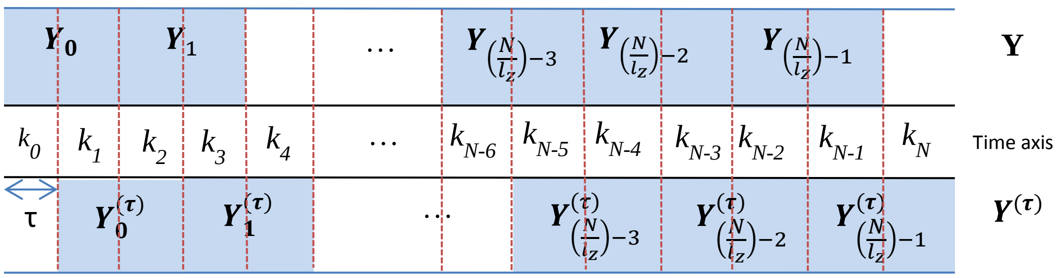

Figure 4-1 $\boldsymbol{Y}$ represents the signal without timing error and $\boldsymbol{Y}^{(\tau)}$ with a timing error of τ for Alamouti Code

In the Figure 4.1, $\boldsymbol{Y}$ represents the signal without timing error, where each of the parsed signal blocks $\boldsymbol{Y}_v$ corresponds exactly to the code block, whereas $\boldsymbol{Y}^{(\tau)}$ where the signal blocks $\boldsymbol{Y}_v^{(\tau)}$ are parsed with a timing error of τ, i.e. each block $\boldsymbol{Y}_v^{(\tau)}$ contain symbols from two consecutive code blocks.

4.3 Simulation Results of J-ALRT and the proposed J-HLRT algorithms

In the following simulations, the joint classification performance of the proposed J-ALRT and J-HLRT algorithms are investigated in practice. As a performance measure we use the Joint average of correct classification which is given as

$$P_{cc-j} = \frac{1}{|\Theta_{(c)}||\Theta_{(m)}|}\sum_{j}\sum_{z} P\big[(\mathcal{M}_j, C^{(z)})|(\mathcal{M}_j, C^{(z)})\big] \ , \tag{4.7}$$

where $P\big[(\mathcal{M}_j, C^{(z)})|(\mathcal{M}_j, C^{(z)})\big]$ denotes the probability of correct classification of both the STBC and the modulation type used in the transmit signal. In all the simulations, we chose a modulation pool $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, 8\text{PSK}, 16\text{QAM}\}$. Both cases with n_t=2 and n_t=3 are considered. The classification performance of the both J-ALRT and J-HLRT are evaluated using Monte-Carlo simulations. For each SNR value, modulation type and STBC employed, 1000 Monte-Carlo trials are performed, except in J-HLRT with unknown code block timing case 1000 Monte-Carlo trials are performed for each SNR value, modulation type, STBC employed and timing error τ. For n_t=2 case, the set of code type $\Theta_{(c)} = \{\text{SM}, \text{Alamouti}\}$ has been considered, since the Alamouti code is the most widely (almost exclusively) used STBC for MIMO systems with 2 transmit antennas. For n_t=3, the STBC set considered $\Theta_{(c)} = \{\text{SM}, C^{(2)}, C^{(3)}\}$ see Table 1 for the code matrices of the STBC considered in this work.

4.3.1 J-ALRT and J-HLRT

Figures 4-2, 4-3 and 4-4, demonstrate the classification performance P_{cc-j} of J-ALRT and J-HLRT, proposed for joint classification of STCB and modulation type, using equation (4.1) as described in section 4.1 and 4.2 respectively. Figures 4-2 and 4-3 present the simulation results for n_t=2 and n_r=4 and 6 respectively, where the STBC set considered is $\Theta_{(c)} = \{\text{SM}, \text{Alamouti}\}$. In both cases N=*500, 750, 1000* are considered.

In Figure 4-2 J-ALRT with N=500 achieves the performance of P_{cc-j}=0.9 around SNR=-4 dB. The same classification performance can be achieved by J-ALRT with N=1000 near SNR=-5 dB. J-HLRT with N=500 and 1000 achieves P_{cc-j}=0.9 about SNR=-1 dB and -2 dB respectively. At last, performance gap between J-ALRT and J-HLRT algorithm for *N=500* is about 3 dB and for the J-ALRT and J-HLRT algorithms with N=1000 is also 3 dB, where those performance losses are caused by the use of channel estimation using HOS instead of the exact value of channel matrix ***H***.

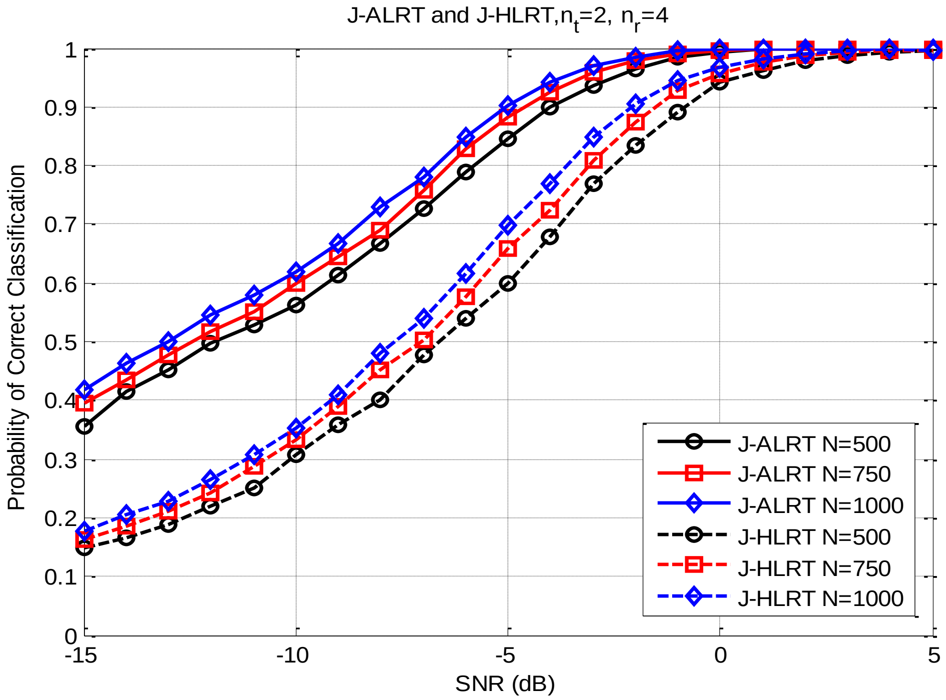

Figure 4-2 Joint classification performances of J-ALRT and J-HLRT,N=500,750,1000,nt=2 nr=4

In Figure 4-3, where the case with 6 receive antennas is considered (n_r=*6*) the J-ALRT algorithm with N=500 achieves the classification performance of $P_{cc-j} = 0.9$ about SNR=-6 dB and same algorithm with block size N=*1000* achieves same classification performance near SNR=-7 dB. On the other hand, performance loss between the algorithms J-ALRT and J-HLRT with N=500 is around 2,5 dB and for the lengths of *N=750* and *1000* the gap between corresponding J-ALRT and J-HLRT is also same same with value of 2,5 dB. As explained above, these performance losses arisen for the same N values of J-ALRT and J-HLRT because of using estimated channel matrix as a substitute for exact value of channel matrix H.

Combining the results given in figures 4-2 and 4-3, it can be easily seen that the joint classification performances P_{cc-j} of both J-ALRT and J-HLRT algorithms is directly affected by the number of receive antenna n_r, i.e.in Figure 4-2, the J-ALRT algorithm, where a receiver with 4 antennas is employed, achieves the performance $P_{cc-j} = 0.9$ near SNR=-4 dB for *N=500*, however, the same algorithm given in Figure 4-3, with a 6 antenna receiver and blocksize *N=500* achieves the same performance result near SNR=-6.5 dB, thus, increasing the number of receive antennas by 2 results in 2.5 dB improvement in this case. A similar observation can be made S for the J-HLRT case. In Figure 4-2, J-HLRT algorithm where a 4-antenna receiver is employed with *N=500* achieves the performance $P_{cc-j} = 0.9$ near -1 dB and in Figure 4-3 J-HLR with a 6 antenna receiver with same N achieves the same performance near SNR=-4.5 dB, which shows an improvement of about 3.5 dB.

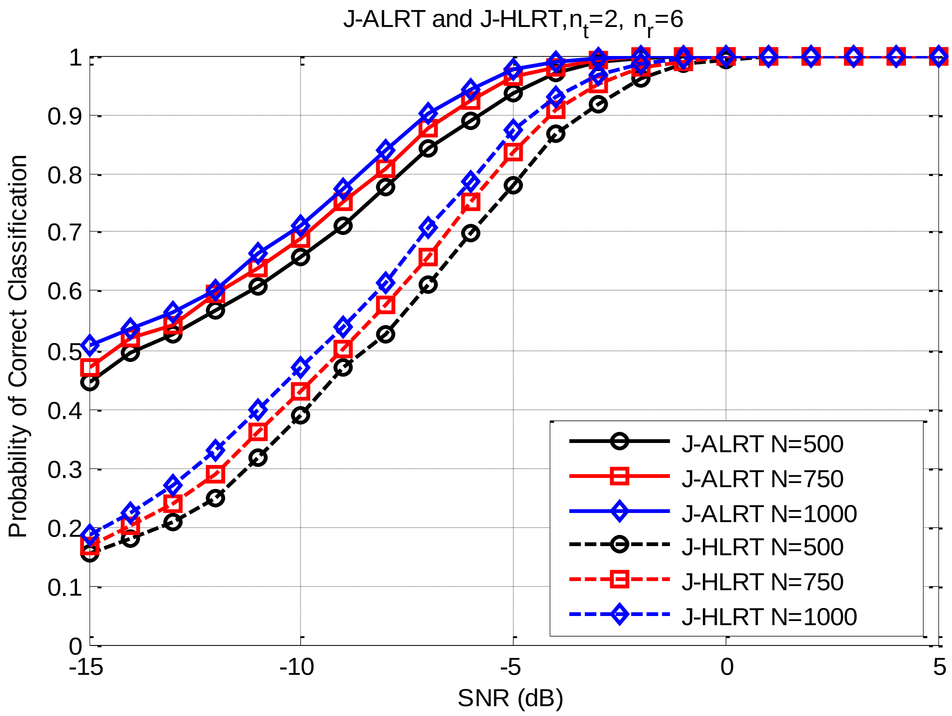

Figure 4-3 Joint classification performance of J-ALRT and J-HLRT. $n_t = 2$ and $n_t = 6$, N=500,750,1000

In Figure 4-4, classification performances P_{cc-j} J-ALRT and J-HLRT algorithms, given section 4.1 and 4.2, are shown for the MIMO system with 3 transmit and 6 receive antennas. Values of blocksize are considered as *N=500,750*. During the simulations of Figure 4-4 the STBC pool is considered as $\Theta_{(c)} = \{\mathrm{SM}, C^{(2)}, C^{(3)}\}$. J-ALRT algorithm with *N=500* achieves the classification performance of $P_{cc-j} = 0.9$ about SNR=-6 dB and same algorithm with N=750 achieves same classification performance near SNR=-7 dB. On the other hand, performance loss between the algorithms J-ALRT and J-HLRT with N=500 is around 2,5 dB and for the lengths of *N=750*,the gap between corresponding J-ALRT and J-HLRT is about same.

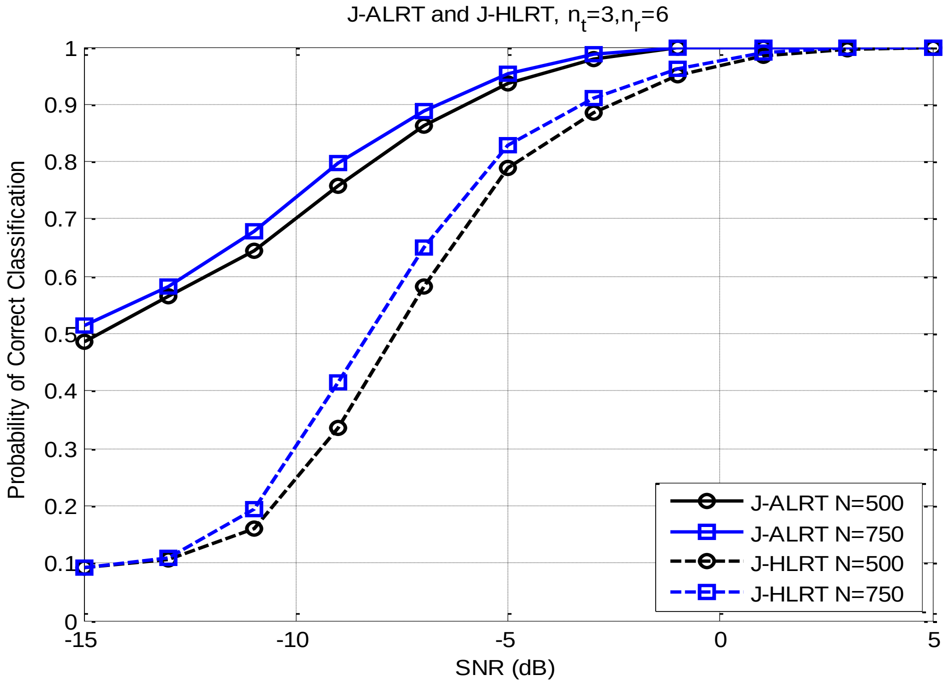

Figure 4-4 J-ALRT and J-HLRT. $n_t = 3$ and $n_t = 6$, N=500,750

Figure 4-5 and Figure 4-6 provide a comparison between the classification performances of the HOS-HLRT algorithm proposed in chapter 3, where modulation type classification is performed with the knowledge of the employed space-time block code, and the J-HLRT proposed in section 4.2 where joint classification of the code and the modulation is performed. In Figure 4-5 the case for $n_t = 2$ and $n_r = 6$ with code pools $\Theta_{(c)} = \{SM, Alamouti\}$ is considered. As expected, the classification performance of the J-HLRT is somewhat lower for low SNRs, however, the performance gap is almost closed for SNR>-5 dB due to the fact that the J-HLRT successfully recognizes the employed type of STBC at those SNRs. A similar observation can be made in the case of $n_t = 3$ and $n_r = 3$ considered in Figure 4-6, with the STBC pool $\Theta_{(c)} = \{\text{SM}, C^{(2)}, C^{(3)}\}$, where the classification performances of both cases become almost equal for SNR>-3 dB.

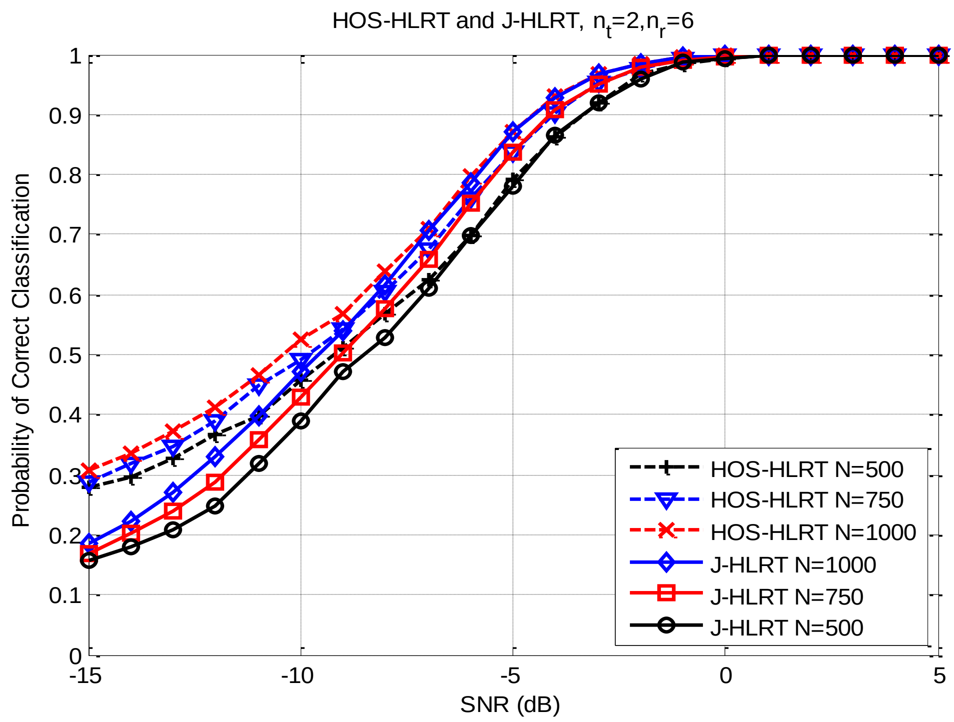

Figure 4-5 HOS-HLRT and J-HLRT, $n_t = 2$ and $n_r = 6$, N=500,750,1000

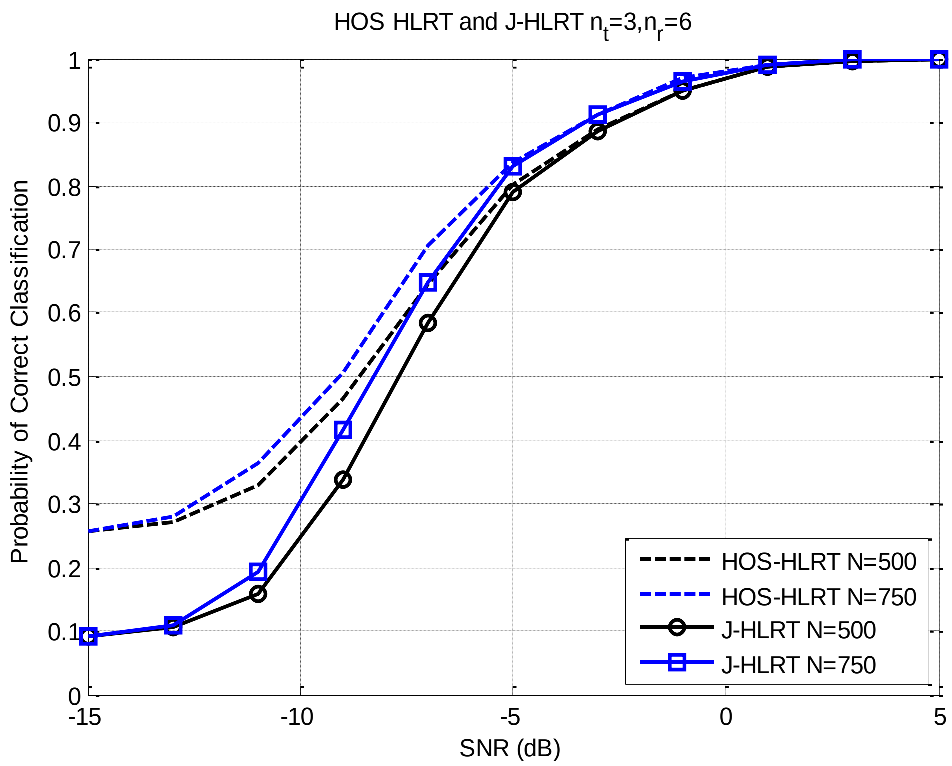

Figure 4-6 HOS-HLRT and J-HLRT, $n_t = 2$ =2 and $n_r = 6$, N=500,750

4.3.2 J-HLRT with Noise variance Estimation

Figure 4-7 and Figure 4-8 show the effect of using the estimate of the noise variance $\hat{\sigma}^{2(j,z)}$ for j'th modulation type and z'th STBC in the average likelihood function for classification as described in the section 4.2.1 instead of using the true value of the noise variance σ^2. In Figure 4-7 the cases for $n_t = 2$ and $n_r = 4$ and 6 is considered with $\Theta_{(c)} = \{\text{SM}, \text{Alamouti}\}$. In Fıgure 4-9 $n_t = 3$ and $n_r = 6$ is considered with $\Theta_{(c)}$={SM, $C^{(2}$, $C^{(3)}$}. In both cases, the performance drop due to using the variance estimate in the classification is very small, and almost zero for SNR>-3 dB. Clearly, the use of noise variance estimation, which increases the practical applicability of the system, has only a negligible effect on the joint classification algorithm.

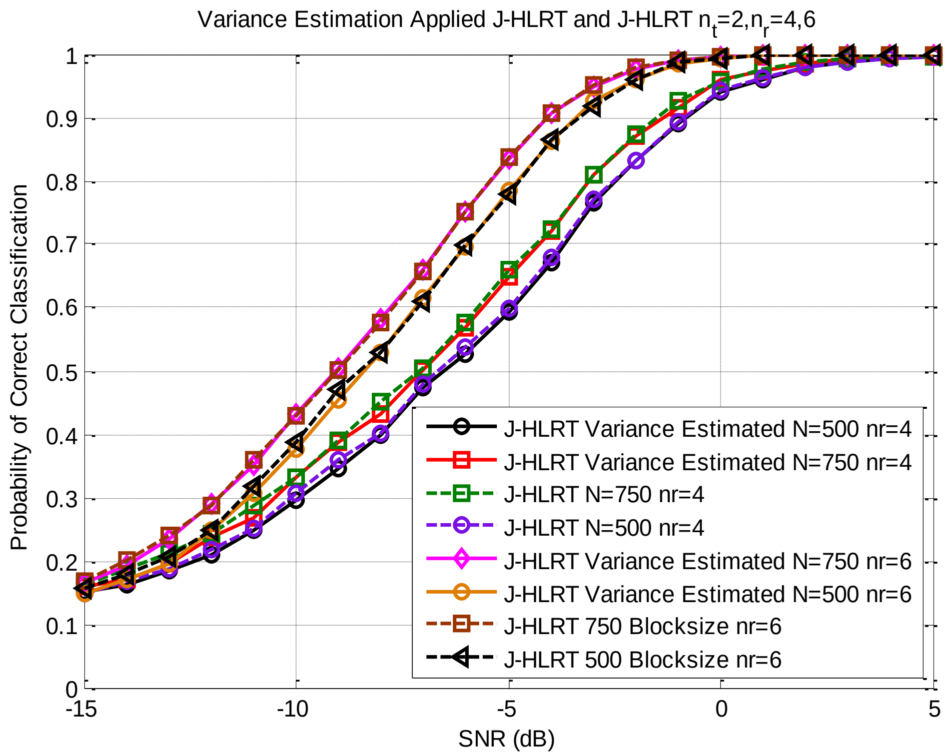

Figure 4-7 Joint classification performance of J-HLRT with and without noise variance estimation. $n_t = 2$ and $n_r = 4, 6$, N=500,750.

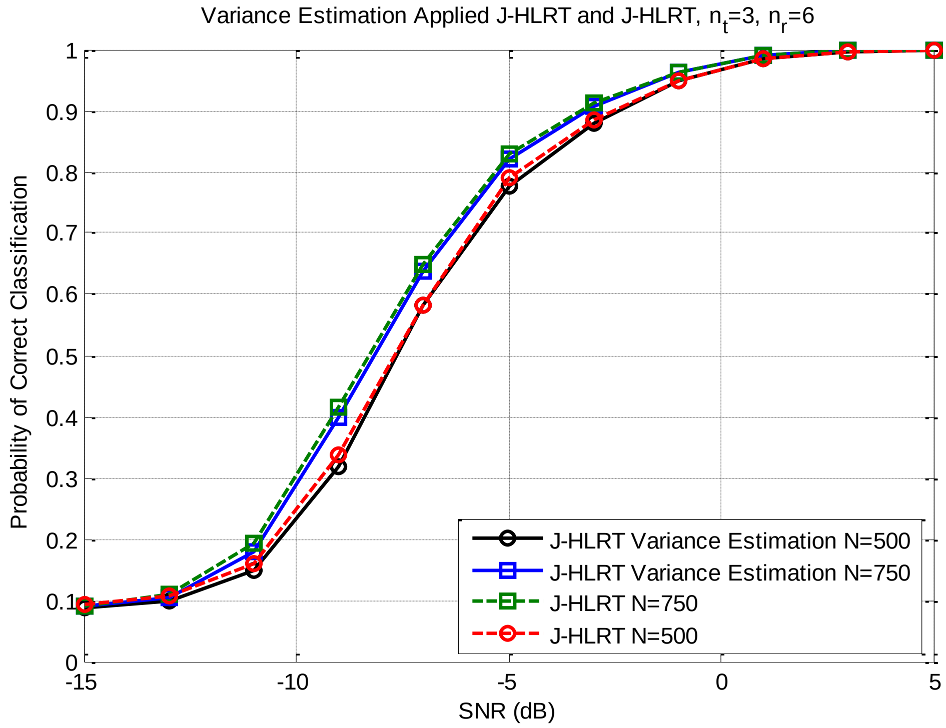

Figure 4-8 Joint classification performance of J-HLRT with and without noise variance estimation, $n_t = 3$ and $n_r = 6$, N=500,750

4.3.3 J-HLRT with Unknown Code Block Timing

The simulation results provided in Figure 4-9and Figure 4-10 investigate the performance of the J-HLRT algorithm with unknown code block timing as described in section 4.2.2 and equation (4.6) comparing J-HLRT given in section 4.2. Here MIMO systems with $n_t = 2$ with $\Theta_{(c)} = \{\text{SM}, \text{Alamouti}\}$ and $n_r = 4{,}6$ are considered in Figure 4-9 and Figure4-10 respectively. In both figures and for both algorithms N=500,750 are considered. The modulation pool, as in all the simulations, is set to $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, \text{8PSK}, \text{16QAM}\}$.

As seen in both Figure 4-9 and, Figure 4-10 treating the code timing as an unknown parameter and maximizing the average likelihood function over the unknown timing parameter τ as described in section 4.2.2, does not have critical affect the classification performance of J-HLRT. However, the need for maximizing over the unknown delay parameter increases the computational complexity of the algorithm considerably, especially for STBC's with large code block lengths.

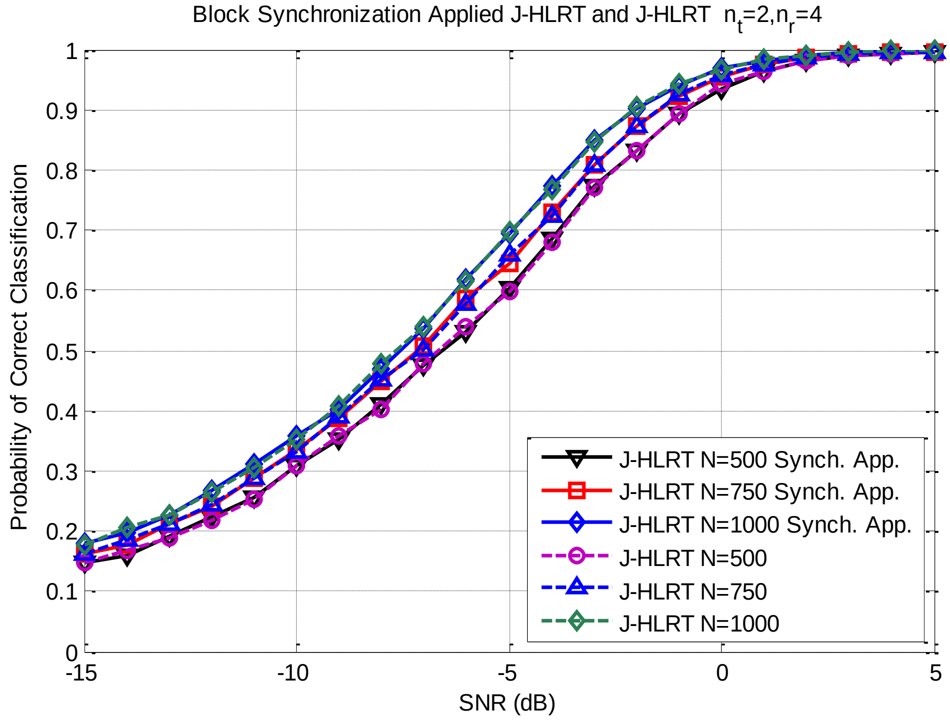

Figure 4-9 Joint classification performance of J-HLRT with and without unknown code block timing $n_t = 2$ and $n_t = 4$, N=500,750,1000

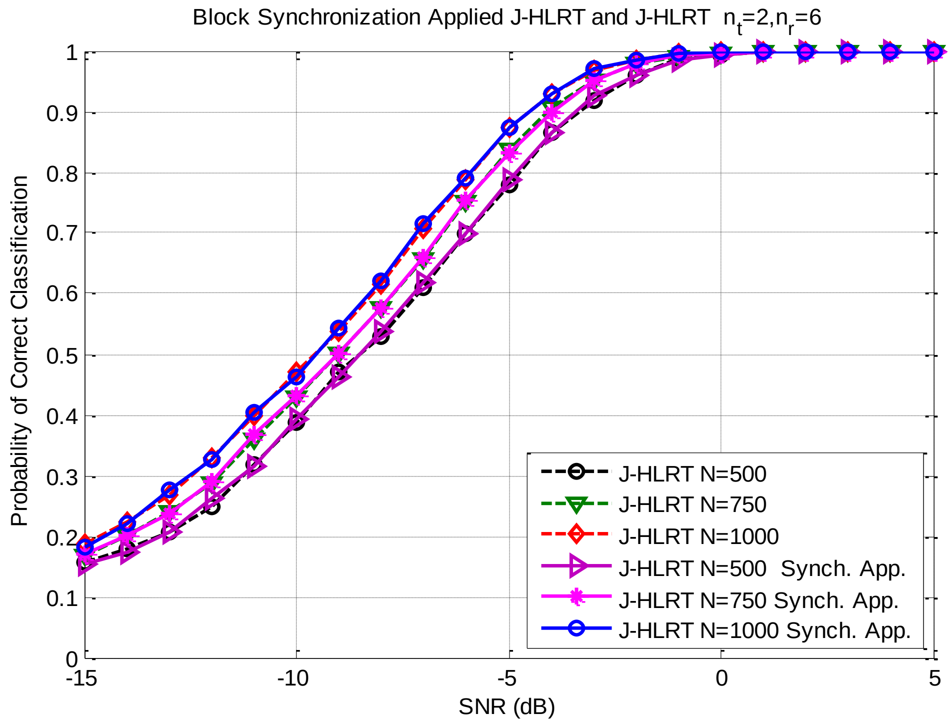

Figure 4-10 Joint classification performance of J-HLRT with and without unknown code block timing, $n_t = 2$ and $n_r = 6$, N=500,750,1000

4.3.4 J-HLRT with Noise Variance Estimation and Unknown Code Block Timing

Figure 4-11 investigates the J–HLRT case where both the noise variance and code block timing are unknown to the receiver, i.e. the classification is performed by maximizing equation (4.5) with the noise variance replaced by its estimate as given in equation (4.4).Since, combining those algorithms in one hybrid likelihood ratio function eliminates all a-priori information requirements except transmit antenna number n_t, this classifier is the practically most applicable approach in this thesis.

In the simulations for this case, a MIMO system with $n_t = 2$ and $n_r = 4,6$ is employed with coding pool $\Theta_{(c)} = \{\text{SM}, \text{Alamouti}\}$. For each SNR value, modulation type, STBC employed and timing τ_i, 1000 Monte-Carlo trials are performed during simulations. The modulation set is $\Theta_{(m)} = \{\text{BPSK}, \text{QPSK}, \text{8PSK}, \text{16QAM}\}$ with N=500 and 750 are considered for blocksize.

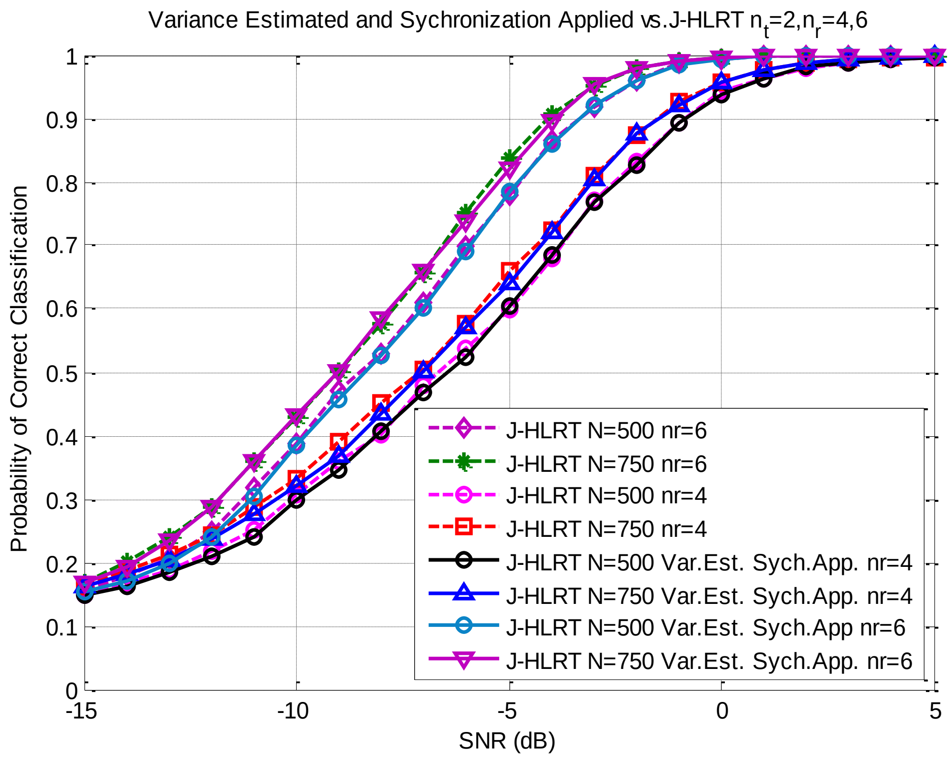

Figure 4-11 Joint classification performance of J-HLRT with and without unknown code block timing and Noise variance estimation $n_t = 2$ and $n_t = 4,6$, N=500,750

Figure 4-11 shows that the combined effect of the unknown code block timing and noise variance leads to small performance drop for SNR<-3 dB. For the SNR values of SNR>-3 dB the error between corresponding cases performance loss can be accepted as negligible.

Chapter 5

Blind Recovery of Symbol Timing

In all the classification algorithms given above, it has been assumed that the unknown MIMO transmitter and the MIMO Receiver are perfectly synchronized in time, i.e. that the receiver knows the perfect symbol timing instants for the matched filtering. Clearly, for the non-cooperative scenarios considered for signal identification, this assumption is not realistic. Thus, the receiver needs to estimate the symbol timing blindly before classification.

In this chapter, we investigate the use of the blind, feed forward symbol timing algorithm in [13] proposed for SISO systems, in multiple input multiple output systems.

5.1 Preliminaires

In [13], Gini and Giannakis have proposed a blind symbol timing estimation algorithm for flat fading channels which exploits the cyclostationary nature of the oversampled received signal y[n].

A discrete time random process is referred to as wide-sense cyclostationary, if its time varying autocorrelation function $R_y(n,k) = E\{y[n]y^*[n+k]\}$ is periodic in the time index n with a period P [22]. In such case, $R_y(n,k)$ can be expressed as a Fourier series

$$R_y(n,k) = \sum_{l=0}^{P-1} R_{(k)}^{ß=\frac{2\pi l}{P}} e^{j\frac{2\pi}{P}ln} \tag{5.1}$$

where the Fourier series coefficients $R_y^{ß}$(k) which depend on the cycle frequency parameter ß and the lag k, are referred to as the cyclic autocorrelation function of y[n].The cyclic autocorrelation function of y[n] can be estimated from the signal as

$$\hat{R}_y^{ß}(k) = \frac{1}{N}\sum_{n=0}^{N-k-1} y[n]y^*[n+k]e^{-jßn} \qquad (5.2).$$

It is straightforward that to show that $R_y^{ß}(k)$ is nonzero only for ß which are integer multiples of $\frac{2\pi}{P}$,i.e $ß = \frac{2\pi l}{P}$, $l = 0,1, \dots . P-1$

5.2 Symbol Timing Recovery Exploiting Cyclostationarity

In [13] it has been shown that the symbol timing of a linearly modulated signal under AWGN and flat fading channel can be estimated using its cyclic autocorrelation function. In this case the received signal with a sampling rate P/T can be given as

$$y[n] = h \sum_{j=-\infty}^{\infty} a_j g_\varepsilon[n - jP] \tag{5.3}$$

with $g_\varepsilon[n] = g(t - \varepsilon T)$ where T is the symbol duration and ε is the timing to be estimated and $g(t)$ is the combined pulse shape of the transmitter and receiver and h is the channel coefficient. The symbol timing estimator in [13] for SISO systems can be given as

$$\hat{\varepsilon} = -\frac{1}{4\pi(L_g + 1)} \sum_{k=0}^{L_g} \arg\left\{\hat{R}^{ß=\frac{2\pi}{P}}(k)\right\} - \arg\left\{\hat{R}^{ß=-\frac{2\pi}{P}}(k)\right\} \tag{5.4}$$

Where L_g is the number of lag parameter over which the averaging is performed.

In a MIMO system, the received signal at each transmit antenna is a linear combination of the signals transmitted from each transmit antenna. Assuming the symbol timing of each transmit antenna are identical and the cross-correlation function between the signal components $x_i[n]$ and $x_j[n]$ are zero, i.e $R_{x_i x_j}(n, k) = E[x_i[n] x_i^*[n + k]] = 0$ (as in spatial multiplexing, Alamouti and Orthogonal STBCs). The Gini-Giannakis estimator [13] can be used for the symbol estimation, due to the fact that the cyclic autocorrelation of uncorrelated components are additive. Since in the MIMO case, we have n_r receive antennas, the estimation of $\hat{\varepsilon}$ is performed by individually estimating the timing at each receive antenna, and subsequently averaging all the n_r estimates.

5.3 Simulation Results

In Figure 5-1, the simulation results for the estimation of the unknown symbol timing ε is displayed for spatial multiplexing QPSK modulated signal, with $n_t = 2$ and $n_r = 6$ in a flat fading channel environment. *N=500* considered and 20000 Monte-Carlo trials are performed for each n_r antennas and SNR. The pulse shape has been chosen as raised root cosine with roll-off factor 0.5. The mean squared error (MSE) of the estimator vs. SNR has been chosen as the performance criterion of the estimator. The MSE results are given for $\varepsilon = \frac{1}{8}, \frac{1}{4}, \frac{3}{8}$, and $\frac{1}{2}$.

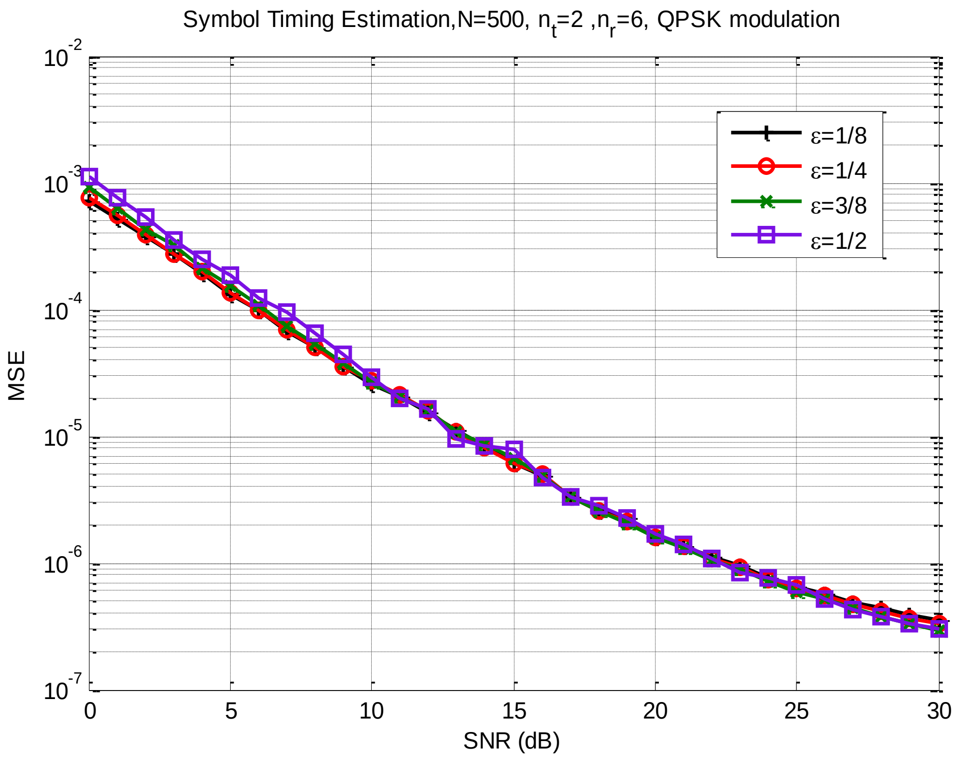

Figure 5-1 MSE of Symbol Timing recovery estimator vs. SNR, $\boldsymbol{\varepsilon = \frac{1}{8}, \frac{1}{4}, \frac{3}{8}, \frac{1}{2}}$, QPSK modulation, N=500

The simulation results show that the timing estimation algorithm of [13], although originally designed for SISO systems, provides a good estimation performance for MIMO systems. Thus, the assumption of known symbol timing in the proposed modulation type and joint STBC and modulation type classification algorithms can be relaxed by applying this algorithm for blind timing estimation prior to classification.

Chapter 6

Conclusion

The emergence of multiple input multiple output (MIMO) systems, which, in contrast to the conventional single input single output (SISO) systems, employ multiple antennas for transmission, presents new challenges to signal identification systems. In this thesis, we have focused on two of these challenges: Modulation type classification and the space time block code classification.

In the first part of the thesis, we have focused on improving existing likelihood based modulation-type classification algorithms (with the assumption of known STBCs), by using blind channel estimation algorithms with higher performance, such as the Expectation–Maximization algorithm for spatial multiplexing which is known to converge to the maximum likelihood estimate. It has been shown that, although some performance improvement can be achieved using the EM algorithm, especially for short data lengths, the performance gain is not satisfactory, considering the high computational complexity required by the EM based channel estimation algorithm. A novel modulation-type classification algorithm for MIMO signals with known STBC’s other than spatial multiplexing is also proposed, which uses a higher order statistic based channel estimation algorithm proposed in [12].

In the second part of the thesis, which contains the main contribution of our work to the literature, we have employed a novel approach to the modulation type-and STBC classification problems, by considering these two problems as a joint classification problem, in contrast to the existing works, where these two problems are handled separately. We have proposed likelihood based joint STBC and modulation-type classification algorithms for 2 and 3 antenna cases and investigated their performances using simulations. We have considered the channel matrix, the noise variance and the code block timing (i.e. the beginning and the ending of each code block) as parameters, the values of which may be known or unknown at the classifier, and each case, i.e. the case with all of them known, the case where only the channel matrix is unknown, the case where the channel matrix and the noise variance are unknown and finally, where all three parameters are unknown, are investigated separately. Our simulation results show that the joint classification of the modulation type and the STBC can be achieved with high accuracy for quite low values of the signal-to-noise–ratio; even when all of the parameters are unknown and need to be estimated blindly.

In all the classification algorithms in this thesis, it has been assumed that the receiver has the perfect knowledge of the symbol timing, which is unrealistic. In chapter 5, we have shown, using simulations that the symbol timing can be blindly estimated with high accuracy for MIMO systems, using the cyclostationary based blind symbol timing estimation approach proposed in [13] originally for SISO systems.

Similar estimation strategies may be employed for blind carrier frequency estimation for the MIMO signals, which can be considered as a direction for further research. Furthermore, signal identification for MIMO signals which use multicarrier transmission, such as orthogonal frequency division multiplexing (OFDM) presents new challenges, thus, extension of the methodologies developed in this thesis to the OFDM case may also be seen as an interesting research area for further studies.

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