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Exploration of Spatial Diversity in Multi-Antenna Wireless Communication Systems

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Exploration of Spatial Diversity in Multi-Antenna Wireless Communication Systems

by

Shichuan Ma

A DISSERTATION

Presented to the Faculty of
The Graduate College at the University of Nebraska
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Exploration of Spatial Diversity in Multi-Antenna Wireless Communication Systems

Shichuan Ma, Ph.D.

University of Nebraska, 2011

Advisor: Yaoqing (Lamar) Yang

With increasing demand on wireless internet and personal multimedia, the data rate of wireless communications is expected to increase dramatically. Future wireless networks face challenges of supporting data rates higher than one gigabits per second. Among various technologies, multi-antennas, also known as multiple-input multiple-output (MIMO), are undoubtedly the most promising to enable higher data rates. By employing the extra degrees of freedom in the spatial domain, multi-antenna techniques enhance the wireless communication systems through array gain, spatial diversity, and spatial multiplexing. Although multi-antenna systems have been utilized for more than ten years, a thorough analysis of various aspects of multi-antenna systems and the potential applications of MIMO technology need to be explored.

In this dissertation, we explore some new features of multi-antenna systems. After introducing the fundamentals of radio propagations, we first study long-range channel prediction and the I/Q imbalance compensation in MIMO-OFDM systems. A novel multi-block linear channel predictor is proposed for limited feedback precoded spatial multiplexing MIMO-OFDM systems, and a new virtual channel method is proposed to analyze the I/Q imbalances in a MIMO-OFDM wireless communication system over multipath fading channels. We then provide a detailed study of recent advances in distributed MIMO technologies in cooperative wireless networks. We also utilize the MIMO technique to enhance the self-encoded spread spectrum (SESS) systems, resulting in a robust MIMO-SESS system. Finally, we present a novel physical-layer technique to secure wireless communications by transmitting artificially generated jamming noise signals that can deteriorate the signal quality at the eavesdroppers.
This dissertation would not be possible without the contributions of many people. First, I would like to express my genuine gratitude to my advisor, Prof. Yaoqing (Lamar) Yang, for his excellent supervision and encouraging discussions. His extensive expertise and experience, combined with great enthusiasm in research, have made working on this dissertation a wonderful experience. I also value his influence on my professional and personal development.

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Finally, this dissertation is dedicated to my wife and parents for their love, sacrifice, and support.
To my wife Xin and my parents
for their love and support
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Chapter 1

Introduction

1.1 Background

Since the invention of the radio telegraph by Marconi in 1895, wireless communication has attracted great interest and is now one of the most rapidly developing technologies. From narrow-band voice communications to broadband multimedia communications, the data rate of the wireless communications has been increased dramatically, from kilobits per second to megabits per second. However, with increasing demand on wireless internet and personal multimedia, the data rate of wireless communications needs be further expanded. Future wireless networks face challenges of supporting data rates higher than one gigabits per second [1].

Among numerous factors that limit the data rate of wireless communications, multipath propagation plays an important role [2]. In wireless communications, the radio signals may arrive at the receiver through multiple paths because of reflection, diffraction, and scattering. This phenomena is called multipath propagation, which causes constructive and destructive effects due to signal phase shifting. Channels with multipath fading fluctuate randomly, resulting in significant degradation of signal quality. When the bandwidth of the signal is greater than the coherence bandwidth of the fading channel, different frequency components of the signals experience different fading. This frequency-selective fading may further limit the data rate of wireless communications.

To combat multipath fading, code division multiple access (CDMA) and orthogonal frequency-division multiplexing (OFDM) were developed [3,4]. As a spread spectrum modulation, CDMA overcomes multipath fading by transmitting signals which occupy a wider bandwidth. Even though a small portion of this wideband channel undergoes deep fading,
the overall channel could be in good condition. The loss of the signals can be recovered by using the Rake receiver and/or maximum-ratio combining [5]. On the other hand, the OFDM scheme splits the channel into many small bandwidth carriers, each of which occupies a narrowband channel. The information in the carriers under deep fading can be recovered if forward error correction is applied [6].

Although CDMA and OFDM are effective in combating against multipath fading, they cannot provide a higher data rate compared to other techniques. In multiple access systems, all users have to share the available bandwidth. Users in a CDMA system share the same bandwidth by using different spreading codes, while in an OFDM system, each user is assigned to a subset of the carriers, a frequency division multiple access system (FDMA) in essence. In general, these traditional wireless communication schemes employ time, frequency, and code dimensions for multiple access. Given a bandwidth and a number of users, other dimensions of freedom are expected to increase data rates.

During the past decade, multi-antenna systems, which are also referred to as multiple-input multiple-output (MIMO) systems, have attracted significant interest. The benefits of multiple antennas arise from the use of extra spatial dimension. By employing multiple antennas at the transmitter and/or receiver in a wireless system, the rich scattering channel can be exploited to create a multiplicity of parallel links over the same radio band. This novel property provides MIMO with several advantages, including array gain, spatial diversity gain, and spatial multiplexing gain [7].

Array gain refers to the average increase in the signal-to-noise ratio (SNR) that results from a coherent combining of signals from multiple transmit-receive antenna pairs. The coherent combining may be achieved at the receiver by beamforming; if the channel state information (CSI) is known to the transmitter, the coherent combining may also be realized at the transmitter by weighting the transmission signals into multiple antennas, known as transmit beamforming. Array gain improves the system robustness to the noise, thereby improving the coverage of the system.
By providing the receiver with multiple copies of the transmitted signal in space, MIMO systems achieve spatial diversity and effectively mitigate multipath fading, thereby improves the quality and reliability of the reception. The achieved spatial diversity order depends on the channel environment, specifically, the channel coherence.

In a rich scattering environment, a transmitter with an antenna array may transmit multiple independent data streams within the bandwidth of operation, and the receiver with an antenna array can successfully separate the data streams. MIMO systems, therefore, offer an increase in data rate through spatial multiplexing.

Multipath scattering is commonly seen as detrimental to wireless communications. However, with the emergence of MIMO systems, multipaths have been effectively converted into a benefit for wireless communications. Due to this advantage, MIMO technology is considered key to future gigabit wireless communications [1]. MIMO can also be integrated with various modulation schemes to enhance the system performance. For example, MIMO has been employed in wideband CDMA (WCDMA) systems and the long term evaluation (LTE) to enhance CDMA and OFDM systems, respectively [8,9].

1.2 Motivation and Dissertation Outline

Although multi-antennas have presented various advantages and have been utilized for more than ten years, a theoretical analysis of some aspects in multi-antenna systems and the potential applications of MIMO technology remain unexplored. Studies of MIMO are still ongoing in both academia and industry. New concepts and methodologies such as distributed MIMO, cooperative MIMO, network MIMO, coordinated multi-point, and physical layer security have been proposed in recent years [10–13]. These studies will undoubtedly enhance wireless communications in the near future.

This dissertation explores the spatial diversities provided by multi-antenna transmission. Solutions to two existing problems in MIMO-OFDM systems are presented, a spread spectrum system is enhanced by using the multi-antenna technique, and a novel applica-
tion of the multi-antenna system is explored for securing wireless communications. The rest of the dissertation is organized as follows: Chapter 2 introduces the fundamentals of multi-antenna wireless communications. Chapter 3 investigates the BER performance of the limited feedback precoded spatial multiplexing MIMO-OFDM system with channel prediction at the receiver. A virtual channel based approach is proposed to analyze the I/Q imbalances in MIMO-OFDM systems in Chapter 4. In Chapter 5, a detailed investigation of the recent advances in distributed MIMO technologies in cooperative wireless networks is presented. In Chapter 6, the multi-antenna technique is incorporated into self-encoded spread spectrum (SESS) systems to improve the system performance. Chapter 7 proposes a novel physical layer method to secure wireless communications by taking advantages of the extra dimensions of freedom provided by multi-antenna transmission. Finally, Chapter 8 concludes this dissertation.

1.3 Nomenclature

3GPP 3rd Generation Partnership Project
AF Amplify-and-Forward
AOA Angle of Arrival
AOD Angle of Departure
AR Autoregressive
AWGN Additive White Gaussian Noise
BER Bit-Error Rate
BPSK Binary Phase Shift Keying
CDF Cumulative Distribution Function
CDMA Code Division Multiple Access
CP Cyclic Prefix
CSI Channel State Information
DF Decode-and-Forward
<table>
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<tr>
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<th>Description</th>
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<tr>
<td><strong>DFT</strong></td>
<td>Discrete Fourier Transform</td>
</tr>
<tr>
<td><strong>DOA</strong></td>
<td>Direction Of Arrival</td>
</tr>
<tr>
<td><strong>DSTC</strong></td>
<td>Distributed Space-Time Coding</td>
</tr>
<tr>
<td><strong>EV</strong></td>
<td>Eigenvector</td>
</tr>
<tr>
<td><strong>FDMA</strong></td>
<td>Frequency Division Multiple Access</td>
</tr>
<tr>
<td><strong>FFT</strong></td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td><strong>i.i.d.</strong></td>
<td>Independent Identically Distributed</td>
</tr>
<tr>
<td><strong>I/Q</strong></td>
<td>In-Phase/Quadrature-Phase</td>
</tr>
<tr>
<td><strong>ICI</strong></td>
<td>Intercarrier Interference</td>
</tr>
<tr>
<td><strong>IDFT</strong></td>
<td>Inverse Discrete Fourier Transform</td>
</tr>
<tr>
<td><strong>LOS</strong></td>
<td>Line-of-Sight</td>
</tr>
<tr>
<td><strong>LS</strong></td>
<td>Least Square</td>
</tr>
<tr>
<td><strong>LTE</strong></td>
<td>Long Term Evolution</td>
</tr>
<tr>
<td><strong>MIMO</strong></td>
<td>Multiple-Input Multiple-Output</td>
</tr>
<tr>
<td><strong>MISO</strong></td>
<td>Multiple-Input Single-Output</td>
</tr>
<tr>
<td><strong>ML</strong></td>
<td>Maximum Likelihood</td>
</tr>
<tr>
<td><strong>MMSE</strong></td>
<td>Minimum Mean Square Error</td>
</tr>
<tr>
<td><strong>MRC</strong></td>
<td>Maximum Ratio Combining</td>
</tr>
<tr>
<td><strong>MRT</strong></td>
<td>Maximum-Ratio Transmission</td>
</tr>
<tr>
<td><strong>MU-MIMO</strong></td>
<td>Multi-User MIMO</td>
</tr>
<tr>
<td><strong>MUSIC</strong></td>
<td>Multiple Signal Classification</td>
</tr>
<tr>
<td><strong>NS</strong></td>
<td>Null Space</td>
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<tr>
<td><strong>OFDM</strong></td>
<td>Orthogonal Frequency-Division Multiplexing</td>
</tr>
<tr>
<td><strong>PDF</strong></td>
<td>Probability Density Function</td>
</tr>
<tr>
<td><strong>PLS</strong></td>
<td>Physical Layer Security</td>
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<tr>
<td><strong>PN</strong></td>
<td>Pseudo-Noise</td>
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QAM Quadrature Amplitude Modulation
RF Radio Frequency
RX Receiver
SCM Spatial Channel Model
SDMA Space-Division Multiple Access
SESS Self-Encoded Spread Spectrum
SIMO Single-Input Multiple-Output
SINR Signal-to-Interference plus Noise Ratio
SISO Single-Input Single-Output
SM Spatial Multiplexing
SNR Signal-to-Noise Ratio
STBC Space-Time Block Code
STC Space-Time Coding
SU-MIMO Single-User MIMO
SVD Singular Value Decomposition
TRD Transmit-Receive Diversity
TX Transmitter

1.4 Notations

In this dissertation, the following notations are used. A small (capital) letter represents a variable in time (frequency) domain, and a bold small (capital) letter represents a vector (matrix). The superscripts $*$, $T$, $H$, and $-1$ represent the conjugate, the transpose, the Hermitian transpose, and the matrix inverse operations, respectively. $|\cdot|$ and $\|\cdot\|$ denote the absolute value of a scalar and the Euclidean norm of a vector. $\mathbb{C}^{M \times N}$ denotes complex-valued $M \times N$ matrices. The $\mathbf{I}_k$ and $\mathbf{0}_k$ represent a $k \times k$ identity matrix and a vector with $k$ zero elements, respectively. The vec{$\cdot$} and $E\{\cdot\}$ represent the vectorization operation and
the expectation operation, respectively. The symbol $\perp$ denotes the orthogonality between two vectors. Operation $(a)^+$ is to find the maximum value between the real number $a$ and zero. The minimum singular value of matrix $A$ is denoted by $\lambda_{\text{min}}\{A\}$. $\text{diag}(\cdot)$ denotes the diagonal vector of a matrix. $\otimes$ denotes convolution. The Dirac delta function, Q-function, gamma function, and incomplete gamma function are denoted by $\delta\{\cdot\}$, $Q(\cdot)$, $\Gamma(a)$, and $\Gamma(a,x)$, respectively.
Chapter 2

Fundamentals of Multi-Antenna Wireless Communications

This chapter introduces basic concepts in multi-antenna wireless systems that are related to this dissertation research. Radio propagation presents some unique characteristics, including large-scale pass loss and small-scale fading. The study of a point-to-point wireless link helps understand the performance of radio systems. When multiple antennas are employed, space-time channel models should be constructed, upon which the multi-antenna system can be modeled. The three basic architectures of the multi-antenna systems are beamforming, spatial multiplexing, and space-time coding. Multi-user MIMO and distributed MIMO are the extended schemes. When the channel experiences frequency-selective fading, OFDM modulation can be used in a multi-antenna system to mitigate the fading effects.

2.1 Radio Propagation

Unlike wired channels, the radio channels are extremely random because of the reflection, diffraction, and scattering of the electromagnetic wave propagation [2]. In order to analyze wireless communication systems, it is important to study the statistical characteristics of radio channels. Large-scale path loss and small scale fading are two important characteristics of the radio channel. The commonly used methodology to study these characteristics is to create propagation models.

2.1.1 Large-Scale Path Loss

Radio wave power decays along the propagation path. A large-scale model determines the average received signal strength at a long distance from the transmitter. It is useful in estimating the radio coverage area of a transmitter. Free-space propagation model is an
important theoretical large-scale model [2]. According to this model, the power received by a receiver antenna at a distance $d$ from the transmitter is given by

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L},$$

(2.1)

where $P_t$ is the transmitted power, $P_r(d)$ is the received power, $G_t$ is the transmit antenna gain, $G_r$ is the receive antenna gain, $\lambda$ is the wavelength in meters, and $L$ is the system loss factor.

The difference in dB between the transmitted power and the received power is defined as path loss. For the free-space model, the path loss is given by

$$PL(dB) = 10 \log \frac{P_t}{P_r} = -10 \log \left[ \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \right].$$

(2.2)

In practice, the free-space model may not be accurate because of the presence of trees, buildings, and other obstacles. Different terrain profiles may cause very different propagation models. The most widely used propagation models in practice include the Okumura model and the Hata model. The Okumura model is used for urban cellular communications with base station antenna heights ranging from 30 m to 1000 m, cell radius of 1 km to 100 km, and application frequencies from 150 MHz to 1920 Mhz. This model is expressed as

$$L_{50}(dB) = L_F + A_{mu}(f,d) - G(h_{te}) - G(gre) - G_{AREA},$$

(2.3)

where $L_{50}$ is the 50th percentile value of propagation path loss, $L_F$ is the free space propagation loss, $A_{mu}$ is the median attenuation relative to free space, $f$ is the carrier frequency, $G(h_{te})$ is the base station antenna height gain factor, $G(h_{re})$ is the mobile antenna height gain factor, and $G_{AREA}$ is the gain due to the type of environment.

The Hata model is an empirical formulation of the graphical path loss data provided by Okumura, and is valid from 150 MHz to 1500 MHz. According to this model, the median path loss in urban areas is given by

$$L_{50}(urban)(dB) = 69.55 + 26.16 \log f_c - 13.82 \log h_{te} - a(h_{re}) + (44.9 - 6.55 \log h_{te}) \log d,$$

(2.4)
where $f_c$ is the frequency in MHz and $a(h_{re})$ is the correction factor for effective mobile antenna height, which is a function of the size of the coverage area.

### 2.1.2 Small-Scale Fading

Small-scale fading describes the rapid fluctuations of the amplitude and phases of a radio signal over a short period of time or propagation distance. This rapid signal fluctuation is caused by the constructive and destructive combination of the signals arriving at the receiver through multiple paths with different delays. In other words, multipath in the radio channel creates small-scale fading effects.

The time-dispersive properties of multipath channels are quantified by multipath delay spread. If the delay spread is small, the radio channel has a constant gain and linear phase response over the bandwidth of the transmitted signal. In this situation, the received signal undergoes flat fading. Otherwise, the received signal may undergo frequency-selective fading.

In wireless communications, the statistical time-varying nature of the received envelope of a flat fading signal is commonly modeled by the Rayleigh distribution [14], whose probability density function (pdf) is given by

$$p(r) = \begin{cases} 
\frac{r}{\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right), & (0 \leq r \leq \infty) \\
0, & (r < 0) 
\end{cases}$$

where $\sigma$ is the rms value of the received voltage signal before envelope detection.
2.2 Space-Time Channel Models

Consider a MIMO system with \(N_t\) transmit antennas and \(N_r\) receiver antennas. The space-time channel is given by the \(N_r \times N_t\) matrix

\[
H(\tau, t) = \begin{bmatrix}
h_{1,1}(\tau, t) & h_{1,2}(\tau, t) & \cdots & h_{1,N_t}(\tau, t) \\
h_{2,1}(\tau, t) & h_{2,2}(\tau, t) & \cdots & h_{2,N_t}(\tau, t) \\
\vdots & \vdots & \ddots & \vdots \\
h_{N_r,1}(\tau, t) & h_{N_r,2}(\tau, t) & \cdots & h_{N_r,N_t}(\tau, t)
\end{bmatrix}, \tag{2.6}
\]

where \(h_{i,j}\) denotes the impulse response between the \(j\)th transmit antenna and the \(i\)th receive antenna from time \(t\) to time \(t - \tau\). If the transmitted signal from the \(j\)th transmit antenna is denoted by \(s_j(t)\), the signal received at the \(i\)th receive antenna is given by

\[
y_i(t) = \sum_{j=1}^{N_r} h_{i,j} \times s_j(t), \quad i = 1, 2, \ldots, N_r. \tag{2.7}
\]

When the channel is flat fading, the delay \(\tau\) can be dropped from the channel matrix expression. When the channel is frequency-selective fading, the channel may be expressed in the frequency domain via a Fourier transform. By applying orthogonal frequency-division multiplexing (OFDM), the frequency-selective channel can be divided into a number of narrow-band subchannels that are considered as flat fading. Due to this reason, the channels used in this dissertation are considered as flat-fading channels unless noted otherwise.

2.2.1 i.i.d. Model

In the classic independent identically distributed (i.i.d.) channel model, the elements of \(H\) are independent zero mean circularly symmetric complex Gaussian (ZMCSCG) random variables with unit variance. The i.i.d. channel matrix is denoted by \(H_w\). Some properties of \(H_w\) are summarized below:

\[
\mathbb{E}\left\{[H_w]_{i,j}\right\} = 0, \tag{2.8}
\]

\[
\mathbb{E}\left\{|[H_w]_{i,j}|^2\right\} = 1, \tag{2.9}
\]
\[ \mathcal{E} \left\{ [H_w]_{i,j} [H_w]^*_{m,n} \right\} = 0, \text{ if } i \neq m \text{ or } j \neq n. \]  

\section*{2.2.2 3GPP Spatial Channel Model}

In 2003, the 3rd Generation Partnership Project (3GPP) standards body developed a spatial channel model (SCM) [15]. SCM is a type of statistics channel model. It adopts a sum-of-sinusoids method to describe channel spatial characteristics.

Figure 2.1 illustrates the SCM model. There are M=20 MPCs (also called sub-paths) that are grouped into one cluster with certain powers, delays, angle of arrivals (AoAs) and angle of departures (AoDs), which are randomly selected according to specific probability density functions (PDF) and their cross-correlations. All sub-paths in one cluster have identical powers and delays but different angle offsets for both AoA and AoD. These offsets are chosen from fixed tables in order to meet the desired per-path angle spread [15]. A fixed number of \( N = 6 \) clusters is defined in this model. Scatters related to the clusters are placed randomly and are determined by the AoAs and AoDs of the sub-paths.

SCM is designed for a bandwidth up to 5 MHz, which is not sufficient for high-speed data service requirements. By introducing intra-cluster delay spread, SCME supports higher bandwidth. The targeted bandwidth of SCME is 100 MHz. Because both SCM and SCME were intended for cellular environments [16], only three scenarios are defined, including suburban macro, urban macro, and urban micro. This drawback limits their applications in outdoor-to-indoor environments. In [17], SCM is extended into a three-dimensional channel which is suitable for outdoor-to-indoor environments.

\section*{2.3 Multi-Antenna System Model}

According to the number of the antennas used at the transmitter and the receiver, multi-antenna systems are divided into four schemes: single-input single-output (SISO), single-input multiple-output (SIMO), multiple-input single-output (MISO), and MIMO [7]. SISO, SIMO, and MISO can be treated as special cases of MIMO. Figure 2.2 shows a typical block
Figure 2.1: 3GPP spatial channel model

diagram of the MIMO system with $N_t$ transmit antennas and $N_r$ receive antennas. The input information stream $s$ is assumed to be symbols that have been coded and mapped onto constellations. The input symbols are first divided into $N_s$ data streams denoted by $s$, and then are pre-processed in space (and in time) domain into $N_t \times K$ blocks $X$, which are transmitted via the radio channel. Here $K$ is the length of the space-time codewords. If no space-time coding is applied, $K = 1$. The transmitted signal can be expressed as

$$X = f(s),$$ (2.11)

where $f$ denotes the operation of the space(-time) pre-processing.

Under the narrow-band flat fading assumption, the channel is represented by a $N_r \times N_t$ matrix $H$, where $H_{ij}$ denotes the channel coefficient between the $i$th receive antenna and the $j$th transmit antenna. Thus, the received signals are given as

$$Y = HX + n,$$ (2.12)

where $n$ is the complex white Gaussian noise vector. The received signals are then post-processed in space(-time) domain to obtain the estimated signal.
2.4 Basic Multi-Antenna Schemes

The choice of $N_s$ and $K$ not only determines the data rate of the system, but also implies the architecture of the MIMO systems. Based on different configurations, there are three basic multi-antenna schemes: beamforming, spatial multiplexing (SM), and space-time coding (STC).

2.4.1 Beamforming

Beamforming is a powerful technique which can increase the link signal-to-noise ratio (SNR) by focusing the energy into desired directions. In this scheme, $N_s = 1$ and $K = 1$, resulting in the data rate $R = 1$. To enable beamforming, the number of transmit antennas and/or the number of the receive antennas should be greater than one.
Figure 2.3 : Illustration of a receive beamforming system.

**Receive Beamforming**

With a single transmit antenna ($N_t = 1$) and multiple receive antennas ($N_r > 1$), beamforming can be realized at the receiver. Figure 2.3 illustrates the receive beamforming scheme. The source symbol $s$ arrives at the antenna array at the receiver side through the wireless channel. The received signals from the multiple antennas are first weighted by a beamforming vector $w$ and then are combined.

After the receiver has acquired a channel estimate, it can set the beamforming vector $w$ to its optimal value to maximize the received SNR. This is done by aligning the beamforming vector with the channel via the so-called maximum ratio combining (MRC) $w = H^H$, which can be viewed as a spatial version of the well-known matched filter [18].

Another method for selecting the beamforming vector is to maximize the receive signal energy by steering the radiation pattern of the antenna array to the direction of arrival (DOA). This technique is known as smart antenna [19]. DOA can be estimated by using MUSIC (multiple signal classification) [20] and ESPRIT (estimation of signals parameters via rotational invariance technique) [21] algorithms.

Although the matched beamforming maximizes the SNR in AWGN channels, it is not
optimal when there is co-channel interference. In this case, null-steering beamformer can be used to cancel the interference from other interference sources. By selecting the beamforming vector to be orthogonal to the channel from the interference sources, cancelation of up to \( N_r - 1 \) interfering signals is theoretically feasible.

**Transmit Beamforming**

Beamforming can also be realized at the transmitter [18]. Similar to the receive beamforming scheme, the transmitting signal is precoded by a beamforming vector and then transmitted via multiple transmit antennas. The beamforming vector is selected based on the channel state information (CSI) to maximize the receive SNR of the received signal. To enable the vector selection, the CSI must be known at the transmitter. This requires CSI feedback from the receiver, where the CSI is estimated, to the transmitter. A transmit beamforming system is used in Section 7 to enable physical layer security.

**2.4.2 Spatial Multiplexing**

With beamforming, a multi-antenna system can only transmit one symbol at a time. However, the multiple transmit-receive paths provide extra degrees of freedom. More than one symbol could be transmitted via the MIMO channel simultaneously. Spatial dimension may be utilized to increase the system throughput. With \( N_t > 1 \) transmit antennas and \( N_r > 1 \) receive antennas, up to \( \min(N_t, N_r) \) streams can be multiplexed in space dimension. Therefore, in a spatial multiplexing multi-antenna system, \( N_s > 1 \) and \( K = 1 \), leading to the data rate \( R > 1 \).

In spatial multiplexing, a precoding matrix \( \mathbf{W} \), also called precoder, is used to precode the symbols in the vector \( \mathbf{s} \) as

\[
\mathbf{X} = \mathbf{W}s.
\]  

(2.14)

The precoder has two effects: decoupling the input signal into orthogonal spatial modes in the form of eigen-beams, and allocating power over these beams, based on the CSI at the
transmitter. If the precoded orthogonal spatial modes match the channel eigen-directions, there will be no interference among signals sent on these modes, creating parallel channels and allowing transmission of independent signal streams. Moreover, the precoder allocates power on these beams. For orthogonal eigen-beams, if the beam powers are different, the overall transmit radiation pattern will have a specific shape. The precoder effectively creates a radiation shape matching to the channel based on the CSI, so that more power is sent in the directions where the channel is strong and less or no power where it is weak. More transmit antennas will increase the ability to finely shape the radiation pattern and therefore are likely to deliver more precoding gain. At the receiver, the signals can be recovered by linear detection algorithms.

2.4.3 Space-Time Coding

In beamforming and spatial multiplexing schemes, $K$ is chosen to be 1, which means no modulation or coding are involved in time domain. However, joint coding in space and time domains could lead to full spatial diversity with no CSI required at the transmitter. This technique is called space-time coding (STC) [22].

In a space-time coding system, the $N_s$ information symbols are coded into a $N_t \times K$ block, where $K$ is the length of the codewords. To successfully decode the symbols at the receiver, it is usually required that $K$ be greater than or equal to the number of symbols $N_s$. Hence, the data rate of a STC system is $R <= 1$. When $R = 1$, the system is called a full-rate system.

The most common used STC is space-time block codes (STBC). Alamouti first proposed the code for two transmit antennas [23]. In this scheme, the input symbols are grouped into blocks. Each block consists of two consecutive symbols, denoted by $s = [s_1, s_2]$. The blocks are coded into $2 \times 2$ blocks by using the codeword

$$\mathcal{G}_2 = \begin{pmatrix} s_1 & s_2 \\ -s_2^* & s_1^* \end{pmatrix} \quad (2.15)$$
This $2 \times 2$ block information is transmitted through two antennas and in two time slots: in the first time slot, $s_1$ and $-s_2^*$ are transmitted, and in the second time slot, $s_2$ and $s_1^*$ are transmitted. Alamouti code is the only STBC with full rate. For more than two transmit antennas, no full-rate STBC exists, but it has been proven that for any number of transmit antennas, orthogonal STBCs with data rate less than one can be found [24].

2.4.4 Single-User vs Multiple-User MIMO

In the aforementioned three basic schemes, the information transmitted via the multi-antenna channels is limited to one user. These schemes are called single-user MIMO (SU-MIMO). Because the multiple antennas provide extra spatial dimension, it is possible to transmit information of multiple users simultaneously in the same bandwidth, while the users are differentiated in the spatial domain. The technology that implement this scheme is called multi-user MIMO (MU-MIMO) [25]. It is an attractive approach to increase spectral efficiency in wireless links.

MU-MIMO is an extended concept of space-division multiple access (SDMA), which allows a terminal to transmit (or receive) signal to (or from) multiple users in the same band simultaneously. MU-MIMO can also be thought of as an extension of MIMO applied in various ways as a multiple access strategy. The performance of MU-MIMO relies on precoding capability. Its performance advantages are not achievable if the transmitter does not use precoding. The precoding matrix is generated from the CSI, which means that the feedback of CSI from the receiver to the transmitter is inevitable.

Per-User Unitary Rate Control (PU²RC) is a practical MU-MIMO scheme [26]. It utilizes the concept of both pre-coding matrices and scheduling to enhance the system performance of multi-antenna wireless networks. Recently, PU²RC has been adopted in the IEEE 802.16m system [27] and the concept of this scheme was included in the 3GPP LTE standard [9].
2.4.5 Distributed MIMO

Traditionally, spatial diversity is achieved by using multiple antennas at the transmitter and/or receiver, where the antennas are packed together with spacing of the order of wavelength, referred to as co-located MIMO. However, the benefits of the co-located MIMO technique are limited in practical systems. The reasons for this limitation are two-fold. First, spatial correlation causes performance degradation. In a co-located MIMO system, antennas at each node have to be placed close to each other. Thus, radio signals at the co-located antennas experience a similar scattering environment, and the channels may be correlated, especially when a line-of-sight (LOS) channel between the transmitter and receiver dominates. The channel matrices could be ill-conditioned, resulting in significant capacity decrease. Second, due to the terminal size limitation, the node cannot be equipped with many antennas. Since the diversity gain is proportional to the number of antennas, a co-located MIMO system with few antennas cannot produce the expected performance.

To mitigate the aforementioned drawbacks in co-located MIMO systems, a new technique named “distributed MIMO” was proposed and has attracted much attention [28]. The major difference between the distributed MIMO and the co-located MIMO is that multiple antennas at the front-end of wireless networks are distributed among widely-separated radio nodes. In a distributed MIMO system, each node may be only equipped with one antenna. Many nodes at different locations transmit the same information to the receiver. In this manner, multiple nodes form a virtual antenna array that achieves higher spatial diversity gain. This kind of spatial diversity is referred to as user cooperation diversity [28], or simply cooperative diversity [29]. Distributed MIMO can provide full user cooperation diversity, and the data rate in the cooperative networks can be significantly increased by using distributed space-time coding [10].
2.5 OFDM and Broadband Communications

OFDM is an attractive modulation scheme used in broadband wireless systems with large delay spread. By converting the frequency-selective fading channel into a parallel collection of flat-fading subchannels, OFDM can mitigate multi-path dispersion and provide high data-rate transmissions [30]. The high spectral efficiency and the efficient implementation by using fast Fourier transform (FFT) also make OFDM an popular modulation scheme. OFDM-based physical layers have been selected for a number of wireless applications including digital broadcast systems [31], wireless local area networks (LANs) [32] [33], and broadband wireless access systems [34].

A block diagram of an OFDM system is shown in Figure 2.4. The transmitted block of the modulated symbols is denoted by

$$\mathbf{s} = [s(1) \, s(2) \, \cdots \, s(N)]^T$$

where $N$ is the number of the sub-carriers. Each block is transformed to the time domain by the inverse discrete Fourier transform (IDFT):

$$\mathbf{s} = \mathbf{F}^* \mathbf{s}$$

where $\mathbf{F}$ is the unitary discrete Fourier transform (DFT) matrix of size $N$ defined by

$$F_{ik} = \frac{1}{\sqrt{N}} e^{-j\frac{2\pi ik}{N}}, \quad i, k = 0, 1, \ldots, N - 1$$
A cyclic prefix (CP) of length $P$ is added to the head of each transformed block. The time-domain blocks are then serially transmitted over the time-varying Rayleigh fading channel. A finite impulse response (FIR) model with $L + 1$ taps is assumed for the channel, i.e.,

$$\mathbf{h} = [h_0 \ h_1 \ \cdots \ h_L]^T$$

(2.19)

with $L \leq P$ in order to preserve the orthogonality between tones.

At the receiver, the signal corresponding to the transmitted block $\bar{s}$ is sampled into a vector. After discarding the CP, the received block of data can be written as [35]

$$\bar{y} = \mathbf{H}\bar{s} + \bar{v}$$

(2.20)

where

$$\mathbf{H} = \begin{bmatrix}
h_0 & h_1 & \cdots & h_{L-1} & h_L \\
h_0 & h_1 & \cdots & h_{L-1} & h_L \\
\vdots & \ddots & \ddots & \ddots & \ddots \\
h_L & h_0 & h_1 & \cdots & h_{L-1} \\
h_2 & \cdots & h_L & h_0 & h_1 \\
h_1 & h_2 & \cdots & h_L & h_0
\end{bmatrix}$$

(2.21)

is an $N \times N$ matrix, and $\bar{v}$ is additive white noise at the receiver. $\mathbf{H}$ presents the form of a circulant matrix due to the existence of the CP. It is well known that $\mathbf{H}$ can be diagonalized by the DFT matrix as

$$\mathbf{H} = \mathbf{F}^*\text{diag}\{\lambda\}\mathbf{F}$$

(2.22)

where the vector $\lambda$ is related to $\mathbf{h}$ via

$$\lambda = \sqrt{N}\mathbf{F}^* \begin{bmatrix} \mathbf{h} \\ \mathbf{0}_{N-(L+1)\times 1} \end{bmatrix}$$

(2.23)

and $\text{diag}\{\lambda\}$ is an $N \times N$ matrix with $\lambda$ as its main diagonal.
Then, substituting (2.22) into (2.20), the received block of data can be expressed as

$$\bar{y} = F^* diag\{\lambda\} \bar{F} \bar{s} + \bar{v}$$  

(2.24)

Applying DFT, the received frequency-domain data is given by

$$z = F\bar{y}$$  

(2.25)

Substituting (2.24) into (2.25), the received data is given by

$$z = diag\{\lambda\} s + v$$  

(2.26)

where $v$ is a transformed version of the original noise vector $\bar{v}$.

Although OFDM is a type of advanced modulation technique, it suffers from degradations resulting from the imbalances between the In-phase and the Quadrature-phase (IQ) branches. IQ imbalance is caused by the analog front-end imperfections. It may lead to inter-carrier interference in an OFDM system, resulting in limited operating SNR.

2.6 Summary

This chapter introduces the fundamentals of multi-antenna wireless systems. The concepts and the system models will be extended in the following chapters.
Chapter 3

Long-Range Channel Prediction in Spatial Multiplexing
MIMO-OFDM Systems

3.1 Introduction

With ever increasing demands for multimedia services and web-related contents, high data throughput is becoming one of the major features in the next generation of wireless communication systems. Among the existing techniques, spatial multiplexing (SM) MIMO-OFDM is considered as one of the most promising physical-layer architectures to provide high-speed communications [36].

In a less-severe scattering environment, the channel matrix could become ill-conditioned, resulting in the performance degradation of a spatial multiplexing MIMO-OFDM system. However, a precoding technique can be used to improve the robustness of spatial multiplexing to the rank deficiencies of the MIMO channel matrix [37,38]. According to this method, the transmitted data streams are customized to the eigenstructure of the channel matrix by being multiplied with a precoding matrix, which is generated based on the channel state information (CSI). This implies that the transmitter requires some sort of knowledge of the CSI.

In most communication systems, the CSI at the transmitter is acquired from a low data-rate feedback channel where the receiver provides information about the forward link condition to the transmitter [26,39]. In an OFDM system, the CSI of all subchannels should be fed back. However, it is usually unrealistic to feed back very much information to the transmitter due to the bandwidth efficiency. Recently, an alternative way was proposed for precoded systems to select the codewords for each subchannel at the receiver and feed the indices back to the transmitter [40–43]. With this method, the total feedback bits for each
Another concern in the feedback systems is feedback delay. Due to the reverse propagation delay and the processing and queuing time at the transceiver, the feedback delay may last for several milliseconds, or tens of the OFDM symbol time [44, 45]. The feedback CSI at the transmitter may become outdated and hence cause a significant performance degradation. As an effective countermeasure against feedback delay, channel prediction has been used in many systems. An adaptive channel predictor based on linear minimum mean square error (MMSE) estimation was proposed in a single antenna single carrier system [46]. By using this adaptive algorithm, this predictor can successfully predict the channel variation within a longer range. Linear channel predictors were also used in transmit-beamforming systems [43,47–49]. So far, only Kalman filter-based methods have been employed to predict the fading channel for spatial multiplexing MIMO systems [41,42]. However, the pilot-based linear channel estimates cannot be utilized to improve the adaptive performance of the Kalman filter, resulting in a relatively short prediction period which cannot cover the long-range delay.

In this chapter, a multi-block autoregressive (AR) model-based linear MMSE predictor is proposed to predict the time-varying fading channel in the limited feedback precoded SM-MIMO-OFDM systems [50]. Instead of using an adaptive algorithm, multi-block prediction is utilized to iteratively predict the long-range channel variation. Codewords for precoding the future blocks are selected at the receiver based on the predicted CSI, and the indices of the codewords are fed back to the transmitter. The bit-error rate (BER) performance of the system is investigated. Simulation results show that the proposed approach can accurately predict long-range channel variation and almost completely compensate for the error performance degradation.
3.2 System Model

The block diagram of a limited feedback precoded spatial multiplexing MIMO-OFDM system with channel prediction is depicted in Figure 3.1, where $N_t$ transmit antennas and $N_r$ receive antennas are deployed for MIMO architecture. OFDM utilizes $N_f$ subcarriers, wherein $N_d$ and $N_p$ subcarriers are allocated for user data and pilot symbols, respectively.

In Figure 3.1, the input data are first divided into $N_d$ groups of $N_s$ substreams, $s_k(n) \in \mathbb{C}^{N_s \times 1}$, where $k \in \{1, 2, \cdots, N_d\}$ is the index of the subcarriers and $n$ is the index of the OFDM symbols. It is assumed that the input data is chosen independently from the CSI and $E\{s_k(n)s_k^H(n)\} = (E_s/N_s)I_{N_s}$, where $E_s$ is the total transmit power. Each group of the $N_s$ substreams is then multiplied by a precoding matrix $F_k(n) \in \mathbb{C}^{N_t \times N_s}$, which is selected from a codebook $\mathcal{F} = \{F_1, F_2, \cdots, F_{2^{N_b}}\}$ according to the $N_b$-bit indices fed back from the receiver over an delayed error-free feedback channel. The precoded data $x_k(n) \in \mathbb{C}^{N_t \times 1}$
can be expressed as

\[ x_k(n) = F_k(n)s_k(n). \] (3.1)

These coded data are then modulated after OFDM modulation, including pilot insertion, inverse discrete Fourier transform (IDFT), adding cyclic prefix (CP), and serial-parallel conversion. Finally, the OFDM modulated signal is transmitted over a time-varying fading channel. It is assumed that the channel length \( N_l \) is shorter than the CP length \( N_{cp} \), leading to a flat fading over each subcarrier.

At the receiver, the received signal is demodulated in term of OFDM demodulation, including CP remove, discrete Fourier transform (DFT), and separation between user data and pilot symbols. According to [51], the received symbol vector can be written as

\[ y_k(n) = H_k(n)x_k(n) + w_k(n) \]

\[ = H_k(n)F_k(n)s_k(n) + w_k(n), \] (3.2)

where \( H_k(n) \in \mathbb{C}^{N_r \times N_t} \) is the channel matrix of the \( k \)th subchannel during the \( n \)th OFDM symbol, and \( w_k(n) \in \mathbb{C}^{N_r \times 1} \) is a noise vector whose entries consist of the independent and identically distributed (i.i.d.) complex Gaussian distribution with zero mean and variance \( N_0 \).

### 3.2.1 Channel Estimation

After OFDM demodulation, the pilot symbols are extracted from the received data and are used to estimate the current CSI at the pilot subcarriers. The CSI at all subcarriers is obtained by linear interpolation at the receiver [52]. It is assumed that the CSI is correctly estimated and is denoted by \( \hat{H}_k(n) \).

### 3.2.2 Linear Receiver

Although the maximum likelihood (ML) receiver outperforms with linear receiver, its computation complexity increases exponentially with the number of substreams. A linear
MMSE receiver may also provide good performance. The received data are estimated by using linear decoding matrices, $G_k(n) \in \mathbb{C}^{N_s \times N_r}$, defined as follows:

$$\hat{s}_k(n) = G_k(n)y_k(n),$$  \hspace{1cm} (3.3)

where the decoding matrix $G_k(n)$ for the MMSE criterion is given as \[51,53\]

$$G_k(n) = \left[ \frac{N_s N_0 I_{N_s}}{\xi_d} + F_k^H(n) \hat{H}_k^H(n) \hat{H}_k(n) F_k(n) \right]^{-1} F_k^H(n) \hat{H}_k^H(n).$$  \hspace{1cm} (3.4)

### 3.2.3 Codeword Selection Criteria

Many criteria have been used to select the optimal precoding matrix from a given codebook for linear receivers, such as minimum singular value selection criterion (MSV-SC), mean square error selection criterion (MSE-SC), and capacity selection criterion (Capacity-SC) \[54\]. MSV-SC is chosen as the selection criterion because it provides a close approximation to maximize the minimum signal-to-noise ratio (SNR) for dense constellations. Based on MSV-SC, the optimal codeword $F_{opt}$ is selected from the codebook $\mathcal{F}$ given a channel realization $H$ as follows \[54\]:

$$F_{opt} = \arg\max_{F_i \in \mathcal{F}} \lambda_{\min}\{HF_i\}. \hspace{1cm} (3.5)$$

### 3.2.4 Codebook Design

Codebook design has attracted much attention recently. An excellent overview of the development of codebook design is found in \[26\]. Generally, the codebook should be designed according to the codeword selection criteria. For MSV-SC, the codebook is designed by maximizing the minimum projection norm-2 distance between any pair of codeword matrix column spaces, which is known as Grassmannian subspace packing \[54\]. This designed codebook is also known as the best codebook \[55\].
3.3 Proposed Multi-Block Linear Predictor

Wireless channels usually demonstrate time-varying characteristics. In some environments, the channel is fast fading, e.g., the terminal user is moving around quickly. According to the Jakes model [56], the autocorrelation of a fading channel is given as

$$r(t) = J_0(2\pi f_d t), \quad (3.6)$$

where $J_0(\cdot)$ is the zero-order Bessel function of the first kind, and $f_d$ is the maximum Doppler shift, which is given by the terminal’s moving speed $v$ as

$$f_d = \frac{v}{c} f_c, \quad (3.7)$$

where $c$ and $f_c$ are the light speed and the carrier frequency, respectively.

The autoregressive (AR) model-based linear predictor is the most commonly used method to predict time-varying fading channels. Usually, the channel prediction is given by a AR($M$) model as

$$\hat{h}_k(n+1) = \sum_{m=1}^{M} a_m \hat{h}_k(n-m+1), \quad (3.8)$$

where $M$ is the order of the AR model, $a_m$ is the $m$th AR model coefficient, and $\hat{h}_k(n) = \text{vec}\{\hat{H}_k(n)\}$, where vec{·} means of stacking all columns of $\hat{H}$ into one column vector. This
implies that the predictor can only predict one OFDM symbol ahead. However, the feedback delay may last for several milliseconds, or tens of time slots of the OFDM symbol [44,45]. To enable a long-range prediction, a multi-block linear predictor is proposed, shown in Figure 3.2, where a 2-block prediction procedure is illustrated.

The proposed predictor first utilizes $M$ previous channel estimates, which are separated from each other by one block of $D$ OFDM symbols, to predict the $D$th next channel matrix as follows:

$$\tilde{h}_k(n + D) = \sum_{m=1}^{M} a_m \hat{h}_k(n - mD + D).$$  \hspace{1cm} (3.9)

The AR model coefficients are determined by the MMSE criterion as [46]:

$$a_k = R^{-1}r,$$  \hspace{1cm} (3.10)

where $a_k = [a_1 \ a_2 \ \cdots \ a_M]^T$, $R \in \mathbb{C}^{M \times M}$ is the autocorrelation matrix with elements $R_{ij}(n) = r(D|i - j|)$, and $r \in \mathbb{C}^{M \times 1}$ is the autocorrelation vector with elements $r_i(n) = r(Di)$.

It should be noted that the autocorrelation matrix and vector, and thereby the AR model coefficients, are slow fading. They can be calculated by using the measured Doppler frequency. As a matter of convention, these parameters are assumed to be time invariant and their time indices are dropped.

Using Equation (3.9), the prediction range is the period of $D$ OFDM symbols. If the OFDM symbol time is $T$, the prediction range is $DT$. The intuitive sense is that this method can predict infinity delay by increasing the block size $D$. However, the channel estimates used in (3.9) must be sampled at least at the Nyquist rate given by twice of the maximum Doppler shift $f_d$. This requirement limits the prediction range. For example, if the maximum Doppler shift is 200 Hz, the channel matrix has to be taken every 2.5 ms, i.e., the largest prediction delay must be limited within 2.5 ms. In practice, the channel sampling frequency has to be set higher than the Nyquist rate in order to achieve an accurate estimation. As shown in Section 3.4, when the maximum Doppler shift is 200
Hz, the channel estimates should be selected every 1 ms to guarantee the accuracy of the channel prediction.

In order to increase the prediction range, an iterative method is further utilized to predict a few more blocks ahead. For a $Q$-block predictor, the $QD$th next channel prediction is given as

$$\tilde{h}_k(n + QD) = \sum_{q=1}^{Q-1} a_q \tilde{h}_k(n + QD - qD) + \sum_{m=Q}^{M} a_m \hat{h}_k(n - mD + QD).$$

(3.11)

The multi-block prediction exploits the previous channel estimate and previously predicted channel matrices. Although the iterative procedure introduces error propagation, this multi-block predictor can effectively predict a few blocks of data stream ahead of the channel variation. The performance improvement can be validated by the numerical simulation in the next section.

### 3.4 Simulation Results

In this section, we present the Monte Carlo simulation results of the BER performance in a limited feedback precoded spatial multiplexing MIMO-OFDM system with multi-block channel prediction. The system parameters are listed in Table 3.1. A $4 \times 4$ MIMO architecture is employed and 512 subcarriers are allocated for OFDM scheme. No pilot symbols are used *. Two substreams are transmitted over each subchannel. ITU Vehicular A channel model [57] is adopted to simulate the multipath channel, and the channel time-varying characteristic is modeled as a Jakes model [56]. It is assumed that the terminal user moves with a fixed speed of 108 km/h, leading to a fixed maximum Doppler shift of 200 Hz. As the sampling frequency is set as 5 MHz, one OFDM symbol time is 108.8 $\mu$s. If the block size is set to 10, the channel matrix used in the linear predictor is taken as a sampling rate.

*Channel estimation is not evaluated in the simulation; It is assumed that the channel is estimated at the receiver without error.
Table 3.1: System Parameters for Simulation

<table>
<thead>
<tr>
<th>Parameters</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antenna configuration ((N_t \times N_r))</td>
<td>4 × 4</td>
</tr>
<tr>
<td>FFT size ((N_f))</td>
<td>512</td>
</tr>
<tr>
<td>CP length ((N_{cp}))</td>
<td>32</td>
</tr>
<tr>
<td>Channel model</td>
<td>ITU Vehicular A model</td>
</tr>
<tr>
<td>Channel correlation</td>
<td>Jake’s model</td>
</tr>
<tr>
<td>Carrier frequency ((f_c))</td>
<td>2.0 GHz</td>
</tr>
<tr>
<td>Sampling frequency ((f_s))</td>
<td>5 MHz</td>
</tr>
<tr>
<td>Sampling time ((T_s))</td>
<td>0.2 µs</td>
</tr>
<tr>
<td>OFDM symbol time ((T))</td>
<td>108.8 µs</td>
</tr>
<tr>
<td>Terminal speed ((v))</td>
<td>108 km/h</td>
</tr>
<tr>
<td>Maximum Doppler spread ((f_d))</td>
<td>200 Hz</td>
</tr>
<tr>
<td>Block size ((D))</td>
<td>10 ~ 30</td>
</tr>
<tr>
<td>Predictor order ((M))</td>
<td>1, 2, 5, 10</td>
</tr>
<tr>
<td>Modulation</td>
<td>64 QAM</td>
</tr>
<tr>
<td>Codebook length</td>
<td>(2^2, 2^3, 2^4, 2^6)</td>
</tr>
</tbody>
</table>

919 Hz, which is greater than twice the maximum Doppler frequency. For easy comparison, the 6-bit codebook listed in [55] and an AR(10) model are employed.

Figure 3.3 shows the BER performance of a precoded SM-MIMO-OFDM system with different feedback delay without channel prediction \((Q = 0)\). It is observed that the BER performance is exacerbated with the increase of the feedback delay. When the delay is over 10 OFDM symbols, the degradation is almost 6 dB at \(10^{-4}\) BER. The BER performance of the system with randomly selected precoding matrices is also shown in Figure 3.3, labeled as “Random PM”. If the delay is long enough so that the autocorrelation is close to zero,
Figure 3.3: BER performance of a precoded SM-MIMO-OFDM system with different feedback delay but without channel prediction.

Figure 3.4: BER performance of a precoded SM-MIMO-OFDM system with different feedback delay and 1-block prediction, AR(10).
the precoding matrices can be considered to be randomly selected. Therefore, the curves labeled as “Random PM” and “No Delay” can be treated as the performance upper bound and lower bound, and are shown in the following figures for comparison.

The system performance with different feedback delay and 1-block prediction is shown in Figure 3.4. It is observed that with 1-block prediction, the performance degradation can be successfully mitigated if the feedback delay is less than the period of 12 OFDM symbols. If the feedback delay is longer, performance degradation occurs due to the low sampling rate of the channel matrix. \( D = 10 \) is used in the following simulations to ensure accuracy of one-block prediction.

Figure 3.5 compares the BER performance of the system with fixed channel sampling rate, \( D = 10 \), but with different feedback delays. It is shown that using proposed multi-block iterative prediction, long feedback delay can be well compensated and the enhanced BER performance is close to the lower bound. With 3-block prediction, the BER degradation at
Figure 3.6: BER performance comparison under different orders of AR model, $D=10$.

Figure 3.7: BER performance comparison for different size of codebook, $D=10$, AR(10).
$10^{-4}$ is less than 1 dB, resulting of 5 dB more improvement.

The effect of the AR-model order is also evaluated by using 1-block channel predictor, shown in Figure 3.6. The performance is improved with the increase of the order number of the AR-model. When the order number is greater than 5, the BER performance approximates to the lower bound. This demonstrates that the AR model is very effective in modeling channel variation.

Finally, the BER performance with different codebook sizes is compared in Figure 3.7. It shows that the proposed channel predictor can effectively compensate for the performance degradation of systems using any sizes of codebooks. The improved BER performance is very close to the performance of system without delay.

### 3.5 Summary

In this chapter, a novel multi-block linear channel predictor is proposed to compensate for performance degradation caused by feedback delay in the limited feedback precoded spatial multiplexing MIMO-OFDM systems [50]. The time-varying channel is modeled by an autoregressive (AR) model, whose coefficients are obtained by the linear minimum mean square error algorithm. Long-range prediction is enabled by using an iterative prediction of multiple blocks. Simulation results show that 1) performance degradation can be effectively compensated for by using the proposed multi-block predictor; 2) the higher-order AR model is capable of accurately predicting channel variation; and 3) the proposed prediction-feedback mechanism can be utilized with any size of codebooks.
Chapter 4

Virtual Channel-Based I/Q Imbalance Compensation in MIMO-OFDM Systems

4.1 Introduction

Although OFDM presents numerous advantages, it suffers from performance degradation due to the hardware component flaws in the analog front-ends of the transceivers. The in-phase/quadrature-phase (I/Q) imbalance is a major factor resulting in performance degradation [58, 59]. When the received radio-frequency (RF) signal is downconverted to baseband, the analog front-end imperfections cause imbalances between the I and Q branches, which introduces intercarrier interference (ICI) and frequency-dependent distortion to the received data. This leads to a decrease in the operating signal-to-noise ratios (SNRs) and low data rates. Because the effect of the I/Q imbalances on the system is mixed with the signal distortion from the fading channel, the estimation and compensation of the I/Q imbalances from the received data are critical and challenging in OFDM-based systems.

Frequency-independent and frequency-dependent I/Q imbalance models are reported in [58] and [59], respectively. Based on these models, the effects of I/Q imbalances are studied in OFDM systems [60–65] and in MIMO-OFDM systems [66–70]. In [66], the input-output relation of a MIMO-OFDM system with frequency-independent I/Q imbalances at the receiver is derived. Based on this result, an adaptive method is introduced to compensate for the received data. In [68], the effect of frequency-dependent I/Q imbalances on MIMO-OFDM system is studied, using a pilot-based compensation scheme. In both studies, however, the received signals are diversity combined using inaccurate channel state information (CSI) estimated under I/Q imbalances, leading to system performance degradation. We have proposed a method to deal with this problem in [70]. By jointly esti-
mating and compensating for multipath fading channels and I/Q imbalances, this method can effectively mitigate the I/Q effects.

In this chapter, a novel approach is proposed to analyze MIMO-OFDM wireless communication systems with I/Q imbalances over multipath fading channels \[65, 70, 71\]. A virtual channel is proposed to bypass the channel estimation under I/Q influence. Based on this approach, the TX and RX I/Q imbalances are treated as parts of the fading channels. The effects of both the fading channels and I/Q imbalances on the system can be jointly estimated before diversity combining and are then employed for diversity combining and signal compensation. A minimum mean square error (MMSE) estimator and a least square (LS) estimator are used to estimate the joint coefficients of the virtual channel. A signal compensation approach based on a zero-forcing algorithm is also provided. The system performance is theoretically analyzed, and the bit error rate (BER) is expressed in closed-form. Extensive simulation results verified that the I/Q imbalances at both transmitter and receiver sides can be effectively mitigated by using the virtual channel approach.

### 4.2 System Models

#### 4.2.1 I/Q Imbalance Model

A frequency-dependent I/Q model at the receiver side is shown in Figure 4.1. As described in \[59\], the I/Q imbalances arise from two effects. One is the effect of the quadrature
demodulator, which is frequency-independent and determined by I/Q amplitude imbalance $g_{RX}$ and I/Q phase imbalance $\theta_{RX}$; another is the effect of branch components, which is frequency-dependent and modeled as two filters with frequency response $L_{I,RX}(f)$ and $L_{Q,RX}(f)$. If the I/Q branches are perfect, then $g_{RX} = 1$, $\theta_{RX} = 0$, and $L_{I,RX}(f) = L_{Q,RX}(f) \equiv 1$.

Assuming $r_{BB}(t)$ is the baseband equivalent signal of the received signal $r_{RX}(t)$, the downconverted signal $z_{RX}(t)$ can be written as

$$z_{RX}(t) = g_{1,RX}(t) \otimes r_{BB}(t) + g_{2,RX}(t) \otimes r_{BB}^*(t)$$  \hspace{1cm} (4.1)$$

where

$$g_{1,RX}(t) = \left[ l_{I,RX}(t) + l_{Q,RX}(t)g_{RX}e^{-j\theta_{RX}} \right] / 2$$  \hspace{1cm} (4.2)

$$g_{2,RX}(t) = \left[ l_{I,RX}(t) - l_{Q,RX}(t)g_{RX}e^{-j\theta_{RX}} \right] / 2$$

$l_{I,RX}(t)$ and $l_{Q,RX}(t)$ are the time-domain representations of $L_{I,RX}(f)$ and $L_{Q,RX}(f)$, respectively. From the point of view of the frequency domain, the expression in (4.1) can be written as

$$Z_{RX}(f) = G_{1,RX}(f)R_{BB}(f) + G_{2,RX}(f)R_{BB}^*(-f)$$  \hspace{1cm} (4.3)$$

where $R_{BB}(f)$ is the Fourier transform of $r_{BB}(t)$, and

$$G_{1,RX}(f) = \left[ L_{I,RX}(f) + L_{Q,RX}(f)g_{RX}e^{-j\theta_{RX}} \right] / 2$$  \hspace{1cm} (4.4a)

$$G_{2,RX}(f) = \left[ L_{I,RX}(f) - L_{Q,RX}(f)g_{RX}e^{j\theta_{RX}} \right] / 2$$

In (4.3), the term $R_{BB}^*(-f)$ represents the intercarrier interference (ICI) projected from the mirror frequency to the signal frequency. This is called image projection, a major problem caused by I/Q imbalances in signal demodulations.

Similarly, the relation between the signal $R_{TX}$ and the transmitted baseband signal $Z_{TX}$ with I/Q mismatch can be written as

$$Z_{TX}(f) = G_{1,TX}(f)R_{TX}(f) + G_{2,TX}(f)R_{TX}^*(-f)$$  \hspace{1cm} (4.5)$$
\[
G_{1,TX}(f) = \left[ L_{I,TX}(f) + L_{Q,TX}(f)g_{TX}e^{j\theta_{TX}} \right]/2
\]
\[
G_{2,TX}(f) = \left[ L_{I,TX}(f) - L_{Q,TX}(f)g_{TX}e^{-j\theta_{TX}} \right]/2
\]

where \( g_{TX} \) denotes the I/Q amplitude imbalance at TX, \( \theta_{TX} \) represents the I/Q phase imbalance at TX, and \( L_{I,TX}(f) \) and \( L_{Q,TX}(f) \) indicate the non-linear frequency characteristics of the I and Q branches at TX.

### 4.2.2 MIMO-OFDM Model with I/Q Imbalances

A block diagram of a MIMO-OFDM wireless communication system with Alamouti diversity scheme and frequency-dependent TX and RX I/Q imbalances is shown in Figure 4.2. In this system, there are two transmit antennas and \( N_r \geq 1 \) receive antennas. All signals are represented in the form of space-time coded (STC) blocks in the frequency domain. For example, \( S_{i,1}|S_{i,2} \) denotes an STC block data of \( N \times 2 \) matrix, where \( i = 1, 2, \cdots \) is the STC block index, and \( N \) is the number of the used OFDM subcarriers. Vector \( s_{i,j} = [S_{i,j}(-N/2) \cdots S_{i,j}(-1) \ S_{i,j}(1) \cdots S_{i,j}(N/2)]^T \) is an OFDM symbol to be transmitted over the system at the \( j \)th, \( j \in \{1, 2\} \) time slot of the \( i \)th STC block, where \( S_{i,j}(k) \) denotes the symbol at the \( k \)th, \( k \in \{-N/2, \cdots, -1, 1, \cdots, N/2\} \) subcarrier with average symbol energy \( E_s/2 \). Vector \( S_{i,1} \) is transmitted followed by vector \( S_{i,2} \). For simplicity, the block index \( i \) is omitted in Figure 4.2. \( H_{n,m} \) denotes the channel frequency response between the \( n \)th transmit antenna and the \( m \)th receive antenna, where \( n \in \{1, 2\} \) and \( m \in \{1, 2, \cdots, N_r\} \).

The TX I/Q imbalance parameters are denoted by \( G_{1,TX}^{(n)} \) and \( G_{2,TX}^{(n)} \), and the RX I/Q imbalance parameters are denoted by \( G_{1,RX}^{(m)} \) and \( G_{2,RX}^{(m)} \), where again, \( n \in \{1, 2\} \) and \( m \in \{1, 2, \cdots, N_r\} \).

Assume two consecutive data symbols, \( S_{i,1}(k) \) and \( S_{i,2}(k) \), to be transmitted over the \( k \)th subcarrier. Based on the Alamouti scheme, \( S_{i,1}(k) \) and \( -S_{i,2}^*(k) \) are distributed into the \( k \)th subcarrier data stream of the first OFDM modulator, while \( S_{i,2}(k) \) and \( S_{i,1}^*(k) \) are distributed into the \( k \)th subcarrier data stream of the second OFDM modulator. Data
Figure 4.2: Block diagram of a $2 \times N_r$ MIMO-OFDM wireless communication system with transmitter and receiver I/Q imbalances. The virtual channel is illustrated in the dashed block.
streams at all subcarriers are then processed through OFDM modulation, including operations of padding zeros, inverse fast Fourier transform (IFFT), and adding cyclic prefix (CP). Because the IFFT operation only transforms the signal from the frequency domain to the time domain, the signals (viewed in the frequency domain) are not changed after OFDM modulation. Therefore, after OFDM modulation, the two consecutive data symbols at the \( k \)th subcarrier of the first transmitter in the frequency domain are still \( S_{i,1}(k) \) and \( -S_{i,2}^{*}(k) \).

The OFDM-modulated signals are then distorted by TX I/Q imbalances. According to (4.5), the signals to be transmitted via the first transmit antenna are given by

\[
U_{i,1}^{(1)}(k) = G_{1,TX}^{(1)}(k)S_{i,1}(k) + G_{2,TX}^{(1)}(k)S_{i,2}^{*}(k)
\]

\[
U_{i,1}^{(1)}(k) = -G_{1,TX}^{(1)}(k)S_{i,2}^{*}(k) - G_{2,TX}^{(1)}(k)S_{i,1}(k)
\]

Similarly, the signals to be transmitted via the second transmit antenna are

\[
U_{i,1}^{(2)}(k) = G_{1,TX}^{(2)}(k)S_{i,2}(k) + G_{2,TX}^{(2)}(k)S_{i,1}^{*}(k)
\]

\[
U_{i,1}^{(2)}(k) = G_{1,TX}^{(2)}(k)S_{i,1}(k) + G_{2,TX}^{(2)}(k)S_{i,2}(k)
\]

The signals are then transmitted over a multipath fading channel. The received signals at the \( m \)th receive antenna are given as

\[
V_{i,1}^{(m)}(k) = H_{1,m}(k)U_{i,1}^{(1)}(k) + H_{2,m}(k)U_{i,1}^{(2)}(k)
\]

\[
V_{i,2}^{(m)}(k) = H_{1,m}(k)U_{i,2}^{(1)}(k) + H_{2,m}(k)U_{i,2}^{(2)}(k)
\]

The received signals at the \( m \)th receive antenna are further corrupted by I/Q imbalances in the \( m \)th receiver as follows:

\[
W_{i,1}^{(m)}(k) = G_{1,RX}^{(m)}(k)V_{i,1}^{(m)}(k) + G_{2,RX}^{(m)}(k)V_{i,1}^{*(m)}(k)
\]

\[
W_{i,2}^{(m)}(k) = G_{1,RX}^{(m)}(k)V_{i,2}^{(m)}(k) + G_{2,RX}^{(m)}(k)V_{i,2}^{*(m)}(k)
\]

Assuming the noise in the system is additive white Gaussian noise (AWGN), then

\[
X_{i,1}^{(m)}(k) = W_{i,1}^{(m)}(k) + N_{i,1}^{(m)}(k)
\]

\[
X_{i,2}^{(m)}(k) = W_{i,2}^{(m)}(k) + N_{i,2}^{(m)}(k)
\]

where \( N_{i,j}^{(m)}(k) \) is independently identically distributed (i.i.d.) complex zero-mean Gaussian noise with variance \( N_0 \).
Combining (4.7), (4.8), (4.9), (4.10), and (4.11), the received data symbols at the \( m \)th receive antenna before diversity combining can be written as

\[
X^{(m)}_{i,1}(k) = A^{(m)}(k)S_{i,1}(k) + B^{(m)}(k)S^*_{i,1}(-k) + C^{(m)}(k)S_{i,2}(k) + D^{(m)}(k)S^*_{i,2}(-k) + N^{(m)}_{i,1}(k)
\]

\[
X^{(m)}_{i,2}(k) = C^{(m)}(k)S_{i,1}(k) + D^{(m)}(k)S_{i,1}(-k) - A^{(m)}(k)S^*_{i,2}(-k) - N^{(m)}_{i,2}(k)
\]

(4.12)

where \( A^{(m)}(k), B^{(m)}(k), C^{(m)}(k), \) and \( D^{(m)}(k) \) are defined as

\[
A^{(m)}(k) \triangleq G^{(m)}_{1,RX}(k)G^{(1)}_{1,TX}(k)H_{1,m}(k) + G^{(m)}_{2,RX}(k)G^{(1)*}_{2,TX}(-k)H^*_{1,m}(-k)
\]

\[
B^{(m)}(k) \triangleq G^{(m)}_{1,RX}(k)G^{(1)}_{2,TX}(k)H_{1,m}(k) + G^{(m)}_{2,RX}(k)G^{(1)*}_{1,TX}(-k)H^*_{1,m}(-k)
\]

\[
C^{(m)}(k) \triangleq G^{(m)}_{1,RX}(k)G^{(2)}_{1,TX}(k)H_{2,m}(k) + G^{(m)}_{2,RX}(k)G^{(2)*}_{2,TX}(-k)H^*_{2,m}(-k)
\]

\[
D^{(m)}(k) \triangleq G^{(m)}_{1,RX}(k)G^{(2)}_{2,TX}(k)H_{2,m}(k) + G^{(m)}_{2,RX}(k)G^{(2)*}_{1,TX}(-k)H^*_{2,m}(-k)
\]

(4.13)

From (4.12) and (4.13), it is observed that the channel frequency response \( (H_{n,m}) \) and the I/Q effects \( (G^{(n)}_{1,TX}, G^{(n)}_{2,TX}, G^{(m)}_{1,RX}, G^{(m)}_{2,RX}) \) are mixed together and produce the coefficients \( A^{(m)}(k), B^{(m)}(k), C^{(m)}(k), \) and \( D^{(m)}(k) \). If we treat the I/Q effects as parts of the fading channels, we can model the dashed block in Figure 4.2 as a virtual channel with joint coefficients \( A^{(m)}(k), B^{(m)}(k), C^{(m)}(k), \) and \( D^{(m)}(k) \). Moreover, \( A^{(m)}(k) \) and \( C^{(m)}(k) \) are critical for data decoding, while the presence of \( B^{(m)}(k) \) and \( D^{(m)}(k) \) may introduce ICI. If the I/Q branches are perfect, then \( A^{(m)}(k) = H_{1,m}(k), B^{(m)}(k) = 0, C^{(m)}(k) = H_{2,m}(k), \) and \( D^{(m)}(k) = 0 \). Furthermore, the received data symbols at the \( k \)th subcarrier are distorted by the mixture effects of channel and I/Q imbalances, and interference is introduced by other data symbols within the STC block at the \( k \)th and the mirrored \( (-k) \)th subcarriers.

To compensate for the received signals, the joint coefficients should be estimated. The estimation methods are described in the next section. Now, assuming the accurate estimates of the joint coefficients are obtained, the received data can be combined to achieve the
transmit diversity as

\begin{equation}
Y_{i,1}^{(m)}(k) = A^*(m)(k)X_{i,1}^{(m)}(k) + C^{(m)}(k)X_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.14}
\end{equation}

\begin{equation}
Y_{i,2}^{(m)}(k) = C^*(m)(k)X_{i,1}^{(m)}(k) - A^{(m)}(k)X_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.15}
\end{equation}

It should be noted that the combining method is slightly different from the Alamouti scheme, where channel state information is employed. In our scheme, the joint coefficients \( A^{(m)}(k) \) and \( C^{(m)}(k) \) are used. If the I/Q branches are perfect, (4.14) is reduced to the standard Alamouti diversity combining scheme as

\begin{equation}
Y_{i,1}^{(m)}(k) = H_{1,m}^{*}(k)X_{i,1}^{(m)}(k) + H_{2,m}(k)X_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.16}
\end{equation}

\begin{equation}
Y_{i,2}^{(m)}(k) = H_{2,m}^{*}(k)X_{i,1}^{(m)}(k) - H_{1,m}(k)X_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.17}
\end{equation}

Substituting (4.12) and (4.13) into (4.14), we obtain

\begin{equation}
Y_{i,1}^{(m)}(k) = Q_{1}^{(m)}(k)S_{i,1}(k) + Q_{2}^{(m)}(k)S_{i,1}^{*\text{\tiny(-m)}}(k) + Q_{3}^{(m)}(k)S_{i,2}^{*\text{\tiny(-m)}}(k) + \tilde{N}_{i,1}^{(m)}(k) \tag{4.18}
\end{equation}

\begin{equation}
Y_{i,2}^{(m)}(k) = Q_{1}^{(m)}(k)S_{i,2}(k) + Q_{2}^{(m)}(k)S_{i,2}^{*\text{\tiny(-m)}}(k) - Q_{3}^{(m)}(k)S_{i,1}^{*\text{\tiny(-m)}}(k) + \tilde{N}_{i,2}^{(m)}(k) \tag{4.19}
\end{equation}

where

\begin{equation}
Q_{1}^{(m)}(k) = |A^{(m)}(k)|^{2} + |C^{(m)}(k)|^{2} \tag{4.20}
\end{equation}

\begin{equation}
Q_{2}^{(m)}(k) = A^{*(m)}(k)B^{(m)}(k) + C^{(m)}(k)D^{*(m)}(k) \tag{4.21}
\end{equation}

\begin{equation}
Q_{3}^{(m)}(k) = A^{*(m)}(k)D^{(m)}(k) - C^{(m)}(k)B^{*(m)}(k) \tag{4.22}
\end{equation}

and

\begin{equation}
\tilde{N}_{i,1}^{(m)}(k) = A^{*(m)}(k)r_{i,1}^{(m)}(k) + C^{(m)}(k)r_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.23}
\end{equation}

\begin{equation}
\tilde{N}_{i,2}^{(m)}(k) = C^{*(m)}(k)r_{i,1}^{(m)}(k) - A^{(m)}(k)r_{i,2}^{*\text{\tiny(m)}}(k) \tag{4.24}
\end{equation}

Finally, the received data symbols at multiple receive antennas are combined to obtain receiver diversity, and the raw data symbols are given by

\begin{equation}
Y_{i,1}(k) = \sum_{m=1}^{N_{r}} Y_{i,1}^{(m)}(k) \tag{4.25}
\end{equation}

\begin{equation}
Y_{i,2}(k) = \sum_{m=1}^{N_{r}} Y_{i,2}^{(m)}(k) \tag{4.26}
\end{equation}

\begin{equation}
Y_{i,1}(k) = \underbrace{Q_{1}(k)S_{i,1}(k)}_{\text{signal}} + \underbrace{Q_{2}(k)S_{i,1}^{*\text{\tiny(-m)}}(k)}_{\text{intercarrier interference}} + \underbrace{Q_{3}(k)S_{i,2}^{*\text{\tiny(-m)}}(k)}_{\text{noise}} + \tilde{N}_{i,1}(k) \tag{4.27}
\end{equation}

\begin{equation}
Y_{i,2}(k) = \underbrace{Q_{1}(k)S_{i,2}(k)}_{\text{signal}} + \underbrace{Q_{2}(k)S_{i,2}^{*\text{\tiny(-m)}}(k)}_{\text{intercarrier interference}} - \underbrace{Q_{3}(k)S_{i,1}^{*\text{\tiny(-m)}}(k)}_{\text{noise}} + \tilde{N}_{i,2}(k) \tag{4.28}
\end{equation}
where
\[
Q_1(k) = \sum_{m=1}^{N_r} [Q_1^{(m)}(k)] \\
Q_2(k) = \sum_{m=1}^{N_r} [Q_2^{(m)}(k)] \\
Q_3(k) = \sum_{m=1}^{N_r} [Q_3^{(m)}(k)]
\] (4.20)
are defined as the combined coefficients, and
\[
\tilde{N}_{i,1}(k) = \sum_{m=1}^{N_r} [\tilde{N}_{i,1}^{(m)}(k)] \\
\tilde{N}_{i,2}(k) = \sum_{m=1}^{N_r} [\tilde{N}_{i,2}^{(m)}(k)]
\] (4.21)
are the combined noise terms.

From (4.19), it can be seen that there is ICI in the signals after receiver combining, which is caused by the image projections from the mirrored frequency. To improve system performance, it is necessary to compensate for the received signals.

### 4.3 Estimators and signal compensation

In this section, two training sequence-based estimators are described to show how to estimate the joint coefficients of the virtual channel. The first is a minimal mean square error (MMSE) estimator. Although MMSE estimator is an optimal linear detector, it requires a priori knowledge of the estimated variables and is computationally intensive. An alternative is a least square (LS) estimator, which may significantly reduce the computational complexity at the expense of negligible BER degradation. The estimated joint coefficients can be used to perform diversity combining as in (4.14) and to compensate for the received signals as described at the end of this section.

#### 4.3.1 MMSE Estimator

Assume a total \(N_{tr}\) blocks of training sequences are used in this system \(^*\). Let \(P_{i,j}(k), j \in \{1, 2\}\) denote the \(j\)th training symbol in the \(i\)th block at the \(k\)th subcarrier. According

\(^*\)That is \(2N_{tr}\) OFDM symbols
to (4.12), the input-output relation for one block can be written as
\[ u_i^{(m)}(k) = P_i(k)v^{(m)}(k) + n_i^{(m)}(k), \] (4.22)

where
\[ u_i^{(m)}(k) = \begin{bmatrix} X_{i,1}^{(m)}(k) \\ X_{i,2}^{(m)}(k) \end{bmatrix}^T, \] (4.23)
\[ P_i(k) = \begin{bmatrix} S_{i,1}(k) & S_{i,2}^*(k) & S_{i,1}^*(k) \\ -S_{i,2}^*(k) & -S_{i,2}(k) & S_{i,1}(k) \end{bmatrix}, \] (4.24)
\[ v_i^{(m)}(k) = \begin{bmatrix} A^{(m)}(k) \\ B^{(m)}(k) \end{bmatrix}^T, \] and
\[ n_i^{(m)}(k) = \begin{bmatrix} N_{i,1}^{(m)}(k) \\ N_{i,2}^{(m)}(k) \end{bmatrix}^T. \] (4.25)

For the total \( T \) blocks, the input-output relation is written as
\[ u^{(m)}(k) = P(k)v^{(m)}(k) + n^{(m)}(k), \] (4.27)

where
\[ u^{(m)}(k) = \begin{bmatrix} u_1^{(m)}(k)^T \\ u_2^{(m)}(k)^T \\ \cdots \\ u_{N_{tr}}^{(m)}(k)^T \end{bmatrix}^T, \] (4.28)
\[ P(k) = \begin{bmatrix} P_1(k)^T \\ P_2(k)^T \\ \cdots \\ P_{N_{tr}}(k)^T \end{bmatrix}, \] and
\[ n^{(m)}(k) = \begin{bmatrix} n_1^{(m)}(k)^T \\ n_2^{(m)}(k)^T \\ \cdots \\ n_{N_{tr}}^{(m)}(k)^T \end{bmatrix}^T. \] (4.29)

The MMSE estimate of \( v \) is given as [72]
\[ \hat{v}^{(m)}(k) = R_{vu}R_u^{-1}u^{(m)}(k). \] (4.31)

where
\[ R_{vu} = E\{v^{(m)}(k)u^{(m)}(k)^H\} = R_vP^H(k), \] (4.32)
\[ R_u = E\{u^{(m)}(k)u^{(m)}(k)^H\} = P(k)R_vP^H(k) + R_n, \] (4.33)
\[ R_n = E\{n^{(m)}(k)n^{(m)}(k)^H\} = N_0I_{2T}, \] and
\[ R_v = E\{v^{(m)}(k)v^{(m)}(k)^H\}. \] (4.34)
4.3.2 LS Estimator

Although MMSE estimator is optimal, it suffers from high computational complexity and requires the knowledge of \( R_v \), which must be estimated using a large amount of transmission data. A simple but effective method is the least square estimator. To further reduce the computational complexity, a special training pattern is design to avoid a matrix inversion operation. In order to utilize this special pattern, training sequences must be transmitted in groups of two blocks. Let \( s, s, s, \) and \( s^* \) be the four consecutive training symbols within the \( i \)th and the \( (i+1) \)th STC blocks at the \( k \)th subcarrier, where \( s = p(1 + j) \) is a complex number with identical real and imaginary parts \( p \). The corresponding training symbols at the \( -(k-1) \)th subcarrier are also \( s, s, s, \) and \( s^* \). According to (4.12), the received data within the \( i \)th and the \( (i+1) \)th STC blocks at the \( k \)th subcarrier can be represented in matrix form as

\[
\begin{bmatrix}
X_{i,1}^{(m)}(k) \\
X_{i,2}^{(m)}(k) \\
X_{i+1,1}^{(m)}(k) \\
X_{i+1,2}^{(m)}(k)
\end{bmatrix} =
\begin{bmatrix}
s & s^* & s & s^* \\
-s^* & -s & s & s \\
s & s^* & s & s \\
-s & -s^* & s & s
\end{bmatrix}
\begin{bmatrix}
N_{i,1}^{(m)}(k) \\
N_{i,2}^{(m)}(k) \\
N_{i+1,1}^{(m)}(k) \\
N_{i+1,2}^{(m)}(k)
\end{bmatrix} +
\begin{bmatrix}
N_{i,1}^{(m)}(k) \\
N_{i,2}^{(m)}(k) \\
N_{i+1,1}^{(m)}(k) \\
N_{i+1,2}^{(m)}(k)
\end{bmatrix}
\]

(4.36)

Thus, the LS estimate of the joint coefficients is given as [73]

\[
\hat{\mathbf{v}}^{(m)}(k) = \begin{bmatrix}
s & s^* & s & s^* \\
-s^* & -s & s & s \\
s & s^* & s & s \\
-s & -s^* & s & s
\end{bmatrix}^{-1}
\begin{bmatrix}
X_{i,1}^{(m)}(k) \\
X_{i,2}^{(m)}(k) \\
X_{i+1,1}^{(m)}(k) \\
X_{i+1,2}^{(m)}(k)
\end{bmatrix}
\]

(4.37)

\[
= \frac{1}{4p}
\begin{bmatrix}
0 & -1-j & 1 & j \\
0 & -1+j & 1 & -j \\
1-j & 0 & j & 1 \\
1+j & 0 & -j & 1
\end{bmatrix}
\begin{bmatrix}
X_{i,1}^{(m)}(k) \\
X_{i,2}^{(m)}(k) \\
X_{i+1,1}^{(m)}(k) \\
X_{i+1,2}^{(m)}(k)
\end{bmatrix}
\]

The estimates of the virtual channel coefficients from different training sequence groups can be averaged to obtain a more accurate estimate.
4.3.3 Signal Compensation Approach

Based on the MMSE estimate given by (4.31) or LS estimate given by (4.37) of the joint coefficients, the estimate of the combined coefficients, $\hat{Q}_1(k), \hat{Q}_2(k), \hat{Q}_3(k)$, can be calculated according to (4.17) and (4.20), and then can be used to equalize the raw data symbols. According to (4.19), the raw data symbols at the $k$th and the $(-k)$th subcarriers within the $i$th STC block can be written in matrix form as

$$
\begin{bmatrix}
Y_{i,1}(k) \\
Y_{i,1}^*(-k) \\
Y_{i,2}(k) \\
Y_{i,2}^*(-k)
\end{bmatrix} =
\begin{bmatrix}
\hat{Q}_1(k) & \hat{Q}_2(k) & 0 & \hat{Q}_3(k) \\
\hat{Q}_2^*(-k) & \hat{Q}_1^*(-k) & \hat{Q}_3^*(-k) & 0 \\
0 & -\hat{Q}_3^*(-k) & \hat{Q}_1(k) & \hat{Q}_2^*(k) \\
-\hat{Q}_3(-k) & 0 & \hat{Q}_2(-k) & \hat{Q}_1^*(-k)
\end{bmatrix}
\begin{bmatrix}
S_1(k) \\
S_1^*(-k) \\
S_2(k) \\
S_2^*(-k)
\end{bmatrix} +
\begin{bmatrix}
\tilde{N}_{i,1}(k) \\
\tilde{N}_{i,1}^*(-k) \\
\tilde{N}_{i,2}(k) \\
\tilde{N}_{i,2}^*(-k)
\end{bmatrix}
$$

Thus, the zero-forcing estimates of the transmitted data symbols are given by

$$
\begin{bmatrix}
\hat{S}_1(k) \\
\hat{S}_1^*(-k) \\
\hat{S}_2(k) \\
\hat{S}_2^*(-k)
\end{bmatrix} =
\begin{bmatrix}
\hat{Q}_1(k) & \hat{Q}_2(k) & 0 & \hat{Q}_3(k) \\
\hat{Q}_2^*(-k) & \hat{Q}_1^*(-k) & \hat{Q}_3^*(-k) & 0 \\
0 & -\hat{Q}_3^*(-k) & \hat{Q}_1(k) & \hat{Q}_2^*(k) \\
-\hat{Q}_3(-k) & 0 & \hat{Q}_2(-k) & \hat{Q}_1^*(-k)
\end{bmatrix}^{-1}
\begin{bmatrix}
Y_{i,1}(k) \\
Y_{i,1}^*(-k) \\
Y_{i,2}(k) \\
Y_{i,2}^*(-k)
\end{bmatrix}
$$

(4.39)

4.4 Performance Analysis

According to (4.19), the received raw data symbols are contaminated by noise and interference from the signals at the mirrored subcarriers. If the ICI can be successfully canceled by the proposed algorithm, the post-processing SNR at the $k$th subcarrier, $\eta(k)$, can be calculated as

$$
\eta(k) = \frac{\mathbb{E} \left\{ |Q_1(k)S_{1,1}(k)|^2 \right\}}{\mathbb{E} \left\{ |\tilde{n}_{i,1}(k)|^2 \right\}} = \frac{\mathbb{E} \left\{ |Q_1(k)S_{i,2}(k)|^2 \right\}}{\mathbb{E} \left\{ |\tilde{n}_{i,2}(k)|^2 \right\}}
= \sum_{m=1}^{N_r} \left[ |A^{(m)}(k)|^2 + |C^{(m)}(k)|^2 \right] \frac{E_s/2}{N_0}
= \frac{1}{2} \sum_{m=1}^{N_r} \left[ |A^{(m)}(k)|^2 + |C^{(m)}(k)|^2 \right] \rho
$$

(4.40)
where $E_s/2$ is the average transmit energy per symbol period per antenna and $\rho = E_s/N_0$ can be interpreted as the average SNR for the single-input single-output scheme.

This post-processing SNR is determined by the joint effects of channels and I/Q imbalances. For classical i.i.d. channels [7] and perfect I/Q characteristics, the post-processing SNR becomes

$$\eta(k) = N_r \rho$$

This shows that the system with perfect I/Q over i.i.d. channel can achieve an array gain of $N_r$.

In OFDM systems, each subcarrier can be treated as a frequency-flat channel. Assuming optimum detection at the receiver, the corresponding symbol error rate for rectangular $M$-ary QAM is given by [74]

$$P_s(k) = 1 - \left( 1 - 2 \left( 1 - \frac{1}{\sqrt{M}} \right) Q \left( \sqrt{\frac{3\eta(k)}{M - 1}} \right) \right)^2$$

(4.42)

Assuming that only one single bit is changed for each erroneous symbol, the equivalent bit error rate for rectangular $M$-ary QAM is approximated as [75]

$$P_b(k) \approx \frac{1}{\log_2(M)} P_s(k)$$

(4.43)

### 4.5 Simulation Results

To evaluate the proposed virtual channel idea, the two estimators, and the signal compensation approach, a Monte Carlo simulation of an OFDM-based $2 \times N_r$ MIMO system with frequency-dependent TX and RX I/Q imbalances is performed. The size of fast Fourier transform (FFT) is 128, the number of used sub-carriers is 96, and the length of CP is 32. The multipath channel is modeled by six independent complex taps with a power delay profile of a 3 dB decay per tap. It should be noted that the actual channel length can be estimated [76]. The simulation bandwidth is set to 20 MHz, leading to a 156.25 KHz subcarrier spacing and a maximum 0.3 $\mu$s excess delay. Sixty-four quadrature amplitude modulation (64QAM) is used.
The non-linear frequency characteristics of the I and Q branches, \( L_I(f) \) and \( L_Q(f) \), are modeled as two first-order finite impulse response (FIR) filters. A form of parameters \( \{g, \theta, [a_I, b_I], [a_Q, b_Q] \} \) is used to describe the I/Q imbalance, where \([a_I, b_I]\) and \([a_Q, b_Q] \) are the coefficients of the FIR filters for the I and Q branches, respectively. I/Q parameters of \{1.03, 3, [0.01, 0.9], [0.8, 0.02]\}, \{1.04, 4, [0.8, 0.02], [0.01, 0.9]\} are used for the two transmitters, respectively. For simplification of simulation, all receivers use I/Q parameters of \{1.05, 3, [0.8, 0.02], [0.9, 0.01]\}. Because the estimation of the joint coefficients is performed separately in each receiver, the same I/Q parameters for different I/Q models still lead to generalization of the simulation results. It should be noted that the I/Q imbalance parameters are chosen to be worst case in order to evaluate the robustness of the proposed approach.

A frame-by-frame transmission scheme is employed in the simulation. The multipath channel is independently generated for each frame. One frame consists of \( N_{tr} \) STC blocks of training symbols followed by 50 STC blocks of data symbols. A total of 5,000 frames (288 Mbits) are simulated for each scenario at a given SNR.

Figure 4.3 shows the frequency response of two of the FIR filters used for simulating the frequency-dependent characteristics of I/Q imbalances. For both filters, the variations of the amplitude are within 0.5 dB, but the average gains are differentiated by 1 dB. It should be noted that the signals after TX I/Q distortions must be normalized in the simulations to compensate for the energy lost due to attenuations of the filters. While the variation of the phase response for the first filter is small, the variation is very large for the second filter. The amplitude and phase differences of the filters are suitable to simulate the frequency-dependent characteristics of I/Q imbalances.

Figure 4.4 shows the typical constellations of one frame of symbols generated in an ideal channel environment (without multipath fading and noise). Figure 4.4 (a) and (b) show the constellations of the raw data symbols under frequency-independent and frequency-dependent I/Q imbalances, respectively. It is observed that the constellation in Figure 4.4
Figure 4.3: Frequency response of two of the FIR filters used for simulating the frequency-dependent characteristics of I/Q imbalances.

(b) becomes nearly random compared with Figure 4.4 (a) due to the effect of frequency-dependent I/Q imbalances. Figure 4.4 (c) shows the constellation of signals recovered by the proposed LS algorithm, which shows that the proposed algorithm can perfectly compensate for frequency-independent and frequency-dependent I/Q imbalances.

The BER performances of the proposed estimators and compensation approach are shown in Figures 4.5-4.10. To make better comparisons, a series of simulations under different scenarios was conducted, including a scenario of perfect I/Q and CSI known at receivers termed as “ideal case”, a scenario with frequency-independent I/Q imbalances termed as “indep-IQ”, and a scenario with frequency-dependent I/Q imbalances termed as “dep-IQ”. The legend term of “NoComp” means that I/Q imbalances are present but no compensation scheme is applied (the CSI is estimated under I/Q imbalances), “MMSE(\(N\))” means that the MMSE estimator with \(N\) STC blocks of training sequences (the total \(2 \times N\)
OFDM symbols) is used, and “LS(\(N\))” means that the LS estimator with \(N\) STC blocks of training sequence is used to estimate the joint coefficients. For both MMSE and LS estimators, the proposed compensation approach is applied to compensate for the received raw data symbols. Furthermore, the BER is theoretically calculated according to (6.28) and is shown in the following figures with legend term “analysis”.

Figure 4.5 and Figure 4.6 show the performance of a 2 × 1 and a 2 × 2 systems with frequency-independent I/Q imbalances, respectively. It is observed from the “NoComp” curves that the I/Q imbalances significantly degrade the system performance, resulting in high error floor. These results agree with the constellation analysis mentioned above. With the proposed estimators and signal compensation approach, the I/Q distortion can be effectively mitigated and the system performance is significantly improved. By using two STC blocks of training sequences, the system performance resulting from both MMSE and LS estimators is close to the ideal case. The performance degradation is less than 1 dB. Although LS estimator performs a little worse than MMSE estimator, the low computational
Figure 4.5: Performance of a $2 \times 1$ MIMO-OFDM system with TX and RX frequency-independent I/Q imbalances over multipath fading channel.

Figure 4.6: Performance of a $2 \times 2$ MIMO-OFDM system with TX and RX frequency-independent I/Q imbalances over multipath fading channel.
complexity makes the LS estimator more competitive. By assuming perfect estimation of the joint coefficients and compensation of the received signal, it is reasonable that the analysis results are slightly better than the ideal case.

The performance of the systems with frequency-dependent I/Q imbalances is shown in Figure 4.7 and Figure 4.8 for the $2 \times 1$ and $2 \times 2$ scenarios, respectively. The frequency dependent characteristic of the I/Q imbalances causes fatal influence on the MIMO-OFDM systems. Without compensation, the BER remains one-half regardless of the SNR. Our proposed approach can also successfully combat the deadly effect caused by frequency-dependent I/Q imbalances, resulting in good performance that is close to the ideal case. This significant performance improvement is not reported by other literature.

An intuitive sense is that a longer training sequence could result in better performance. To demonstrate this, the system performances are compared with different lengths of training symbols in Figure 4.9 and Figure 4.10 for MMSE and LS estimators, respectively. It is
observed that BER decreases with the increase of the training symbol numbers. When four blocks of training sequences are utilized, the performance loss compared to the ideal case is negligible.

4.6 Summary

In this chapter, a new virtual channel concept is introduced to analyze the I/Q imbalances in a MIMO-OFDM wireless communication system over multipath fading channels [65,70,71]. The input-output relation is derived in frequency domain, which incorporates the effect of I/Q imbalances with multipath fading channels. The integrated effect can be represented by the joint coefficients of the virtual channel. By using this approach, inaccurate estimation of the channel state information can be avoided at the diversity combining stage. The joint coefficients are estimated by using the proposed MMSE and LS estimators, and are used to compensate for the received signals. Simulation results show that the proposed approach can
Figure 4.9: Comparison of the performances of the MMSE estimator with different lengths of training symbols for the $2 \times 1$ MIMO-OFDM system with TX and RX frequency-independent I/Q imbalances over multipath fading channel.

effectively mitigate the TX and RX I/Q imbalances in MIMO-OFDM systems. Although only a two transmit antenna scheme is illustrated in this chapter, our proposed approach can be easily extended to any number of transmit antenna configurations by using orthogonal space-time block coding.
Figure 4.10: Comparison of the performances of the LS estimator with different lengths of training symbols for the 2×1 MIMO-OFDM system with TX and RX frequency-independent I/Q imbalances over multipath fading channel.
Chapter 5

Distributed MIMO Using Cooperative Diversity

5.1 Introduction

In wireless communications, channel fading, an inherent property of wireless communication links, severely limits the increase of the data rate. The most popular and effective way to combat channel fading is to exploit the diversity from the received signals. By transmitting a signal via multiple independent channels, e.g., at different time slots, different frequency bands, and different spatial directions, the receiver can receive different copies of the signal and thus achieve the time, frequency, and space diversity gains by employing optimal combining schemes.

Spatial diversity techniques are particularly attractive since they provide diversity gain without incurring an extra cost of transmission time and bandwidth. Traditionally, spatial diversity is achieved by using multiple antennas at the transmitter and/or receiver, where the antennas are packed together with spacing of the order of wavelength, referred as co-located multiple-input multiple-output (MIMO). Because of the diversity gain, co-located MIMO architectures are effective in increasing system throughput and are capable of combating channel fading.

However, the benefits of the co-located MIMO technique are limited in practical systems. The reasons for this limitation are two-fold. First, spatial correlation causes performance degradation. In a co-located MIMO system, antennas at each node have to be placed close to each other. Thus, radio signals at the co-located antennas experience a similar scattering environment, and the channels may be correlated, especially when a line-of-sight (LOS) channel between the transmitter and receiver dominates. The channel matrices could be ill-conditioned, resulting in significant capacity decrease. Second, due to the terminal size
limitation, the node cannot be equipped with many antennas. Since the diversity gain is proportional to the number of antennas, the co-located MIMO system with few antennas cannot produce the expected performance.

To mitigate the aforementioned drawbacks in the co-located MIMO systems, a new technique named “distributed MIMO” was proposed and has attracted much attention [28]. The major difference between the distributed MIMO and the co-located MIMO is that multiple antennas at the front-end of wireless networks are distributed among widely-separated radio nodes. In a distributed MIMO system, each node may be only equipped with one antenna. Many nodes at different locations transmit the same information to the receiver. In this manner, multiple nodes form a virtual antenna array that achieves higher spatial diversity gain. This kind of spatial diversity is referred to as user cooperation diversity [28] or, simply, cooperative diversity [29].

This chapter provides a detailed study of the recent advances in distributed MIMO technologies in cooperative wireless networks. The basic concepts of a cooperation system are first introduced, followed by the detailed discussion of relay protocols and cooperative strategies. Simulation results are then presented to demonstrate the effectiveness of the cooperative network with full user cooperation diversity and improved bandwidth efficiency.

5.2 Cooperation Systems

A cooperative wireless network consists of a source, a number of relays, and a destination, which is illustrated in Figure 5.1. Because we deal with physical layer techniques instead of higher layer protocols in this article, it is reasonably assumed in the network that all nodes use the same multiple-access resources. For example, they may use the same sub-channel in a frequency division multiple access (FDMA) system. Therefore, the network in Figure 5.1 is a subset of a practical network. It could be a cell in a cellular system, or a same-frequency cluster in a mesh network.

In Figure 5.1, the source node $S$ is intending to transmit information to the destination
node $D$. Other nodes in the networks could be selected as the helpers or relays for the transmission between the source and the destination. Assuming that the nodes $R_1$, $R_2$, \ldots, and $R_n$ are selected to be the helpers, these helpers are treated as relay nodes, which forward the signals from the source to the destination. The relays together with the source form a virtual transmit array to achieve the spatial diversity. Relays in a cooperation network are different from that in a relay network where the relays only forward signals from other nodes. In cooperation networks, any nodes could function as a source or a relay. When a node collects and transmits information, it works as a source. Otherwise, it can help other nodes as a relay.

When a communication link is established for transmitting information, relay nodes are selected based on a set of rules or relay selection strategies. Usually the matrices such as the locations, the loads, and the end-to-end performance of the relays are considered in a network. To complete this task, a cross-layer design is employed, which is beyond the scope
of this article. Interested readers can refer to an excellent article [77] for details.

The communication between the source and the destination proceeds in two phases: information sharing and cooperative transmission. In the information sharing phase, the source broadcasts its information to the relays and the destination. This step is inevitable because the spatial diversity can only be achieved from the independent transmission of the same information. Through information sharing, all relays get the information from the source and enable an independent data transmission. In the second phase, the information is forwarded by the relays to the destination. In the meantime, the source could either transmit or remain inactive. Because the relays are randomly selected and they are usually separated far away from others, it is highly likely that the channels between each relay and the destination are uncorrelated. In the cooperative transmission, multiple relays and a source node (that are equipped with a single antenna) form a virtual antenna array for a distributed MIMO system. This distributed MIMO provides the benefits of the cooperative system by overcoming the size limitation and ill-conditioned channel in co-located MIMO systems.

Co-channel interference is one of the serious problems in the cooperative wireless network. When the information is relayed to the destination, there exists a co-channel interference in that the signals from different relays may interfere with each other at the destination. Although the interference cancellation at the destination is a possible solution, the required algorithm is complex and the performance may not be very satisfying. The common cooperative strategy is to avoid the interference by transmitting the relayed signals in orthogonal subchannels. The orthogonality could be acquired by using repetition-based strategy or by using distributed space-time coding (DSTC). For the repetition-based strategy, the relays forward the signal in different time slots, i.e., in each time slot, only one relay transmits information, while the other relays stay inactive. This strategy is easy to implement, but it results in poor bandwidth efficiency. By using DSTC, the relays can forward information in the same time slot. The orthogonality is constructed in both time and space domains.
Although DSTC-based strategy leads to a more complex network, the bandwidth is utilized more efficiently. Both repetition-based and DSTC-based cooperative strategies can achieve full spatial diversity, i.e., the order of the spatial diversity. However, the achieved diversity is not only decided by the cooperative strategies, but also determined by the methods or relay protocols. The relay protocols are discussed in the next section.

5.3 Relay Protocols

Relay protocols significantly affect the system performance in cooperative wireless networks. In this section, an overview of commonly used relay protocols is presented.

5.3.1 Amplify-and-Forward

The simplest relay protocol is amplify-and-forward (AF) [78]. In AF, each relay amplifies the received noisy signals and forwards them to the destination. This simple processing benefits cooperative wireless networks with full spatial diversity at high signal-to-noise ratios (SNRs). Because the noise component is also amplified in AF, the bit-error-rate (BER) performance could be degraded. To optimize the performance in AF systems, a scalar used for amplification is chosen adaptively based on the channel coefficient.

5.3.2 Decode-and-Forward

For decode-and-forward (DF) relay protocol, the relays will first decode the received signals, and then forward the re-encoded signals to the destination node [79]. The decoding can be done fully in bit level or partially in symbol level. When the channel between the source and the relay good quality, DF provides error correlation capability and then is superior to AF. However, when the channel link suffers from deep fading, the decoding could produce errors because no effective method can be applied to combat the fading. These errors will propagate to the destination, leading to worse performance overall. Although DF protocol cannot provide full diversity by itself, it can achieve full diversity when more complex coding
schemes are applied at relays.

5.3.3 Selection Relaying

To mitigate the effect of the noise amplification in AF and error propagation caused by DF, another relay protocol, named “selection relaying,” was proposed by Laneman et al. in [80]. In selection relaying, AF or DF is adopted only when the fading channel has high instantaneous signal-to-noise ratio. Otherwise, the relay suspends forwarding. Selection relaying can offer full spatial diversity. A similar relay protocol, adaptive relaying, was proposed by Li [81]. According to this protocol, either AF or DF is selected based on the decoding result.

5.4 Cooperative Strategies

In a cooperative wireless network, when a relay protocol is selected and the received signals are processed, the relay is ready to forward the signals to the destination. As mentioned before, both repetition-based and DSTC-based orthogonal relaying can be adopted as the cooperative strategy. In this section, these two cooperative strategies are discussed in detail.

5.4.1 Repetition-Based Cooperative Strategy

In a repetition-based cooperative strategy, the relays forward signals sequentially, i.e., only one relay is allowed to forward signals at each time slot [80]. Figure 5.2 (a) illustrates the time slot utilization in repetition-based strategy. In phase one, the source broadcasts the information to the destination and the relays at the same time slot. In phase two, each relay forwards the received signal to the destination sequentially. Hence, a total $n$ time slots are required to finish phase two. This repetition scheme takes a long time to complete the forwarding process, leading to inefficient bandwidth utilization. It is easy to verify that the data rate of the repetition-based cooperative strategy is $1/n.$
To improve the bandwidth efficiency, a novel relay protocol named “incremental relaying” was proposed to reduce the relay repetitions [80]. In incremental relaying, the destination will estimate the signal at the end of phase one and feedback a single bit to the source and the relays to indicate the success or failure of the direct transmission. If the direct transmission succeeds, the relays will not forward the signals and the source will continue to the next time slot of new information transmission. Otherwise, relays will forward the signals to the destination. This protocol improves the bandwidth utilization only at high SNRs.

5.4.2 DSTC-Based Cooperative Strategy

Repetition-based cooperative diversity algorithms can achieve full spatial diversity at the expense of decreasing bandwidth efficiency. The utilization of incremental relaying cannot overcome this drawback when the source-destination link is in poor condition. To further improve bandwidth efficiency, distributed space-time coding (DSTC) can be used to enable relays to transmit in the same time slot in cooperative systems [82]. In the DSTC-based
cooperative strategy, the source broadcasts information in phase one. Contrary to the above repetition-based cooperative strategy, the source and all relays simultaneously transmit coded signals in phase two. Thus, the full cooperative diversity gain $n + 1$ is achieved.

DSTC-based cooperative strategy is usually applied together with the AF or DF relay protocol [83]. After the signals are amplified or decoded, the relays will re-encode the signal before forwarding. In contrast to the decode-and-forward protocol, the signals are re-encoded by using distributed space-time codes in the DSTC-based strategy. The distributed space-time codes can be directly obtained from the conventional space-time codes such that each code is applied to the antenna at each node. The commonly used distributed space-time codes are distributed space-time block codes [9,10] and distributed space-time trellis codes [84]. These codes guarantee that the signals from different relays are orthogonal, and hence they can be separated at the destination without interference. In this manner, all relays forward the signals at the same time slot, as shown in Figure 5.2 (b). Comparing Figure 5.2 (a) and (b), it is evident that the channel utilization of the DSTC-based strategy is better than that of repetition-based strategy.

Improvement of the bandwidth efficiency provided by the DSTC-based strategy comes at the cost of complex signaling and signal processing. To implement distributed space-time-coding, the relays should have a priori knowledge of the space-time codes assigned to them. This requires extra signaling over the dedicated channels. However, the bandwidth for the extra signaling is negligible compared to the improved bandwidth utilization. While the space-time coding adds some computation complexity to the relays, the one-antenna design simplifies the relays significantly. Consequently, the nodes in a cooperative wireless network are relatively simple compared to the nodes in a traditional MIMO system, which are mounted with multiple antennas and have to process signals from multiple physical channels.
5.5 Performance Comparisons

In this section, simulation results are presented that compare the performance of cooperative wireless networks with different relay protocols and cooperative strategies. In [80] and [85], Laneman et al. analyzed the bandwidth efficiency by studying the outage probability \( \Pr [I < R] \), i.e., given the channel realization, the probability of the mutual information \( I \) is less than a given data rate \( R \). The outage probabilities for different relay protocols are compared in Figure 5.3, where x-axis is the signal-to-noise ratio and y-axis is the outage probability \( P_{\text{outage}} \). The data rate is set to \( R = 1 \text{ bit/s/Hz} \) and the number of relay \( n = 1 \) in this scenario. Compared with the direct transmission, the AF, selection DF, and incremental AF protocols can achieve full diversity gain (2 in this scenario) because their curves are nearly twice as steep compared to that of the direct transmission. The incremental AF protocol performs even better since the one-bit feedback can effectively reduce the relay repetitions. For example, the incremental AF protocol achieves about 17 dB gain over the direct transmission at the outage probability of \( 10^{-3} \). The DF protocol, however, performs similarly to the direct transmission because it cannot achieve full spatial diversity. In this single relay scenario, the DF protocol cannot achieve any spatial diversity.

The outage capacities of repetition-based cooperative strategy is shown and compared in Figure 5.4, where x-axis is the data rate in bit/s/Hz and y-axis is the outage probability \( P_{\text{outage}} \). It is observed that the outage probabilities for the direct transmission and repetition-based cooperative strategy increase with the data rate. This is reasonable based on the definition of outage probability. However, the relationship between the outage probability and the number of relays becomes complicated. At low data rates, the outage probability performance becomes better with more relays, while at high data rates, the outage probability becomes worse when more relays are used. For example, at 1 bit/s/Hz data rate, the outage probability is \( 3 \times 10^{-4} \) for one-relay scheme, and it improves to \( 2 \times 10^{-5} \).
for a three-relay scheme. When the data rate is above 1.4 bit/s/Hz, however, the outage probability of a three-relay scheme is higher than that of a one-relay scheme. This phenomenon results from the poor bandwidth efficiency of the repetition-based cooperative strategy. From the above analysis, it is realized that the repetition-based cooperative strategy can guarantee a specific low data rate, but it cannot increase the data rate by adding more relays in the cooperative wireless network.

In contrast to repetition-based cooperative strategy, distributed space-time coding based cooperative strategy offers better bandwidth efficiency, as shown in Figure 5.5, where x-axis is the data rate in bit/s/Hz and y-axis is the outage probability $P_{\text{outage}}$. When three relays are used, the outage probability is about $10^{-7}$ at 1 bit/s/Hz data rate, which is much lower than the outage probability $2 \times 10^{-5}$ of the repetition-based cooperative strategy. This bandwidth utilization improvement results from the simultaneous transmission of a group of relays. Due to the same reason, adding more relays will not decrease the data rate.
Figure 5.4: Outage probabilities for repetition-based cooperative diversity. Results of 1, 2, and 3 relays are shown. The signal-to-noise ratio is set to 20 dB.

On the contrary, more relays will increase the data rate due to the higher order of spatial diversity. For example, in Figure 5.5, comparing the three-relay scheme to the one-relay scheme, the outage probability becomes lower by about order of two. It should be noted that the achievable data rate cannot exceed the channel capacity. Therefore, the curves in Figure 5.5 will converge at $P_{\text{outage}} = 1$ for sure when the data rate is greater than the channel capacity.

Finally, the BER performance of repetition-based and distributed space-time block coding based cooperative strategies is shown in Figure 5.6, where x-axis is the signal-to-noise ratio in dB and y-axis is the average bit-error rate. The code used in the simulation is single-symbol maximum likelihood decodable distributed STBC proposed in [86]. Three relays and amplify-and-forward relay protocol are used in the simulation. Given the same data rate, DSTC-based strategy outperforms the repetition-based strategy in terms of average BER. For example, at 2 bit/s/Hz data rate in Figure 5.6, the DSTC-based cooperative
strategy acquires about 7 dB gain over the repetition-based cooperative strategy at $10^{-4}$ average BER. When the data rate increases, the BER performance of both strategies degrades. In particular, it is observed that the degradation for repletion-based strategy is more severe. For instance, at average BER $10^{-4}$, the BER degradation from 2 bit/s/Hz to 1 bit/s/Hz is about 5 dB for the DSTC-based cooperative strategy but about 10 dB for the repetition-based cooperative strategy. This simulation result shows that repetition-based strategy is bandwidth inefficient.

### 5.6 Summary

This chapter presented a detailed discussion of the latest distributed MIMO technologies in cooperative wireless networks. This included the principle of cooperative wireless communications and the popular relay protocols and cooperative strategies. The analysis incorporated a performance comparison of outage probability and bit-error rates. The simulation
Figure 5.6: Bit error rate performance comparison of repetition-based and DSTC-based cooperative strategies. Amplify-and-forward relay protocol and relays are used in simulation.

Results indicate that distributed MIMO can provide full user cooperation diversity, and the data rate in the cooperative networks can be significantly increased by using distributed space-time coding.
Chapter 6

Enhancing Self-Encoded Spread Spectrum with Multi-Antenna Transmission

6.1 Introduction

Conventional direct sequence spread spectrum system employs pseudo-noise (PN) code generators. In contrast, by deriving its spreading sequences from the user data stream, self-encoded spread spectrum (SESS) provides a feasible implementation of random-coded spread spectrum and has a number of unique features, including enhanced transmission security, anti-jamming capability, multi-rate applications, modulation gain and inherent time diversity [87–93]. It has been shown that the modulation memory associated with self-encoding can be exploited with iterative detection to achieve a 3 dB gain and an N-fold time diversity (where N is the spreading length) [92]. These advantages improve the system performance over fading channels.

In this chapter, MIMO techniques are incorporated into SESS systems to improve the performance [94–96]. MIMO-SESS provides a novel means to combating fading in wireless channels by exploiting diversities in both space and time domains [97]. The BER performance of the system under Rayleigh fading is analyzed. The closed-from BER expression of the N-fold, time-diversity SESS detector is derived. By approximating the probability density function (pdf) associated with the time-diversity detector by a Dirac delta function, a lower-bound expression is obtained for the BER of the iterative detector.

6.2 System Model

In this section, the transceiver of the MIMO-SESS system with iterative detection is described.
6.2.1 Transmitter

The block diagram of the proposed transmitter is shown in Figure 6.1, where the rounded corner blocks represent $N$ delay registers and $T_b$ is the bit interval. Alamouti scheme-based space-time block coding (STBC) is utilized to achieve transmit diversity.

The source information $b$ is assumed to be bi-polar values of $\pm \sqrt{E_b/2}$, where $E_b$ is the average transmit energy per bit. It should be mentioned that the energy per transmit antenna is one-half of the total transmit energy in order to make the multi-antenna system comparable to a single antenna system. The bits are first spread by the self-encoded spreading sequence of length $N$ at a chip rate of $N/T_b$. This sequence is constructed from the user’s information stored in the delay registers that are updated every $T_b$. Thus, with a random input data stream, the sequence is also random and time-varying from one bit to another. For example, the spreading sequence for the $k$th bit, $b(k)$, is given as

$$s(k) = [b(k-1) \ b(k-2) \ \cdots \ b(k-N)]^T,$$

and the spreading chips are given as

$$c(k) = b(k)s(k).$$
To facilitate the description in the sequel, let $c(k, n)$ denote the $n$th chip of the $k$th bit, which can be expressed as

$$c(k, n) = b(k)b(k - n).$$  \hspace{1cm} (6.3)

The spreading chips are then divided into two streams by applying the Alamouti scheme, where a block of two consecutive chips, $c(k, 2i)$ and $c(k, 2i + 1)$, is transmitted by sending $c(k, 2i), -c^*(k, 2i + 1)$ to the first antenna, and $c(k, 2i + 1), c^*(k, 2i)$ to the second antenna. Here $i \in \{0, 1, \cdots, N/2 - 1\}$ is the block index for the chips of the $k$th bit. The signals are then transmitted over a MIMO fading channel.

The channel between each transmit and receive antenna pair is assumed to undergo Rayleigh fading, which remains constant over $T_b$ but is independent from bit to bit [92,98]. The channels for different transmit/receive antenna pair are independent.

### 6.2.2 Correlation Detection

Figure 6.2 shows the block diagram of the receiver. For the $m$th antenna, the received signals within the $i$th block are given as

$$x_m(k, 2i) = h_{1,m}(k)c(k, 2i) + h_{2,m}(k)c(k, 2i + 1) + e_m(k, 2i),$$  \hspace{1cm} (6.4)
\[ x_m(k, 2i + 1) = -h_{1,m}(k)c^*(k, 2i + 1) + h_{2,m}(k)c^*(k, 2i) + e_m(k, 2i + 1), \quad (6.5) \]

where \( h_{1,m}(k) \) and \( h_{2,m}(k) \) respectively denote the normalized complex channel impulse response coefficients for the \( k \)th bit between the 1st and 2nd transmit antennas and the \( m \)th receive antenna; \( e_m \) is a Gaussian noise with zero mean and variance \( NN_0/2 \). It should be noted that the noise here is broadband because it is sampled at chip level. Its variance is thus the narrow-band noise variance \( N_0/2 \) multiplied by the spreading factor \( N \).

It is assumed that the delay registers in the receiver have been synchronized with the transmitter [93], and that perfect channel knowledge is available at the receiver. Under these assumptions, diversity combining from the \( M \) receiver antennas is carried out over two consecutive chip intervals according to [7,23] as

\[
y(k, 2i) = \sum_{m=1}^{M} (h_{1,m}^*(k)x_m(k, 2i) + h_{2,m}(k)x_m^*(k, 2i + 1)) + w(k, 2i)
= \alpha(k)c(k, 2i) + w(k, 2i), \quad (6.6)
\]

\[
y(k, 2i + 1) = \sum_{m=1}^{M} (h_{2,m}^*(k)x_m(k, 2i) - h_{1,m}(k)x_m^*(k, 2i + 1)) + w(k, 2i + 1)
= \alpha(k)c(k, 2i + 1) + w(k, 2i + 1), \quad (6.7)
\]

where

\[
\alpha(k) = \sum_{m=1}^{M} \left( |h_{1,m}(k)|^2 + |h_{2,m}(k)|^2 \right) \quad (6.8)
\]

and

\[
w(k, n) = \begin{cases} 
\sum_{m=1}^{M} (h_{1,m}^*(k)e_m(k, n) + h_{2,m}(k)e_m^*(k, n + 1)) , & \text{if } n \text{ is even} \\
\sum_{m=1}^{M} (h_{2,m}^*(k)e_m(k, n - 1) - h_{1,m}(k)e_m^*(k, n)) , & \text{if } n \text{ is odd} 
\end{cases} \quad (6.9)
\]

Because the channel coefficients and the white noise are independent, the noise term \( w \) is a random variable with zero means and variance \( MN_0 \).

The combined signals given in (6.6) and (6.7) can be written in one equation as

\[
y(k, n) = \alpha(k)c(k, n) + w(k, n), \quad (6.10)
\]
and further in vector form as

\[ y(k) = \alpha(k)c(k) + w(k), \]  

(6.11)

where

\[ y(k) = [y(k, 1) y(k, 2) \cdots y(k, N)]^T, \]  

(6.12)

and

\[ w(k) = [w(k, 1) w(k, 2) \cdots w(k, N)]^T. \]  

(6.13)

After diversity combining, the chips are despread and detected. The correlation estimate of the \( k \)th bit is given as

\[ \hat{b}(k) = \frac{1}{N} y^T(k)s(k) = \alpha(k)b(k) + v_1(k) \]  

(6.14)

where

\[ v_1(k) = \frac{1}{N} \sum_{n=1}^{N} w(k, n)b(k - n) \]  

(6.15)

is a random variable with zero mean and variance \( MN_0 \). The conditional SNR of the correlation detection given the channel coefficients is

\[ \gamma_1 = \frac{|\alpha(k)b(k)|^2}{\mathbb{E}\{|v_1(k)|^2\}}. \]  

(6.16)

Because the channel fading coefficients, the information bits, and the thermal noise are independent of each other, it is easy to see that Equation (6.16) is reduced to

\[ \gamma_1 = \frac{E_b}{N_0} \alpha(k). \]  

(6.17)

A hard decision is then performed on the correlation output, which in turn is fed back to the receiver delay registers in order to update the despreading sequence for the next bit.

\[ \tilde{b}(k) = \text{sgn}[\hat{b}(k)] = \begin{cases} 1 & , \quad \hat{b}(k) > 0 \\ -1 & , \quad \hat{b}(k) < 0 \end{cases} \]  

(6.18)

This also provides an estimate of the corresponding bit if no iterative detection is employed.
6.2.3 Time-Diversity Detection

SESS provides a unique encoding scheme that can be utilized to achieve temporal diversity. To better illustrate this mechanism, let us write the following $N^2$ chips in a square matrix as

$$
P(k) = \begin{bmatrix}
\alpha(k + 1)b(k + 1)b(k) & \alpha(k + 1)b(k + 1)b(k - 1) & \cdots & \alpha(k + 1)b(k + 1)b(k - N + 1) \\
\alpha(k + 2)b(k + 2)b(k + 1) & \alpha(k + 2)b(k + 2)b(k) & \cdots & \alpha(k + 2)b(k + 2)b(k - N) \\
\vdots & \vdots & \ddots & \vdots \\
\alpha(k + N)b(k + N)b(k + N - 1) & \alpha(k + N)b(k + N)b(k + N - 2) & \cdots & \alpha(k + N)b(k + N)b(k)
\end{bmatrix}
$$

(6.19)

where each element represents a chip as given in (6.10) and each row includes the chips of one bit. For simplicity, the noise term is omitted.

It is observed that the $k$th bit, $b(k)$, is present in the diagonal elements of the matrix $P(k)$. This means that the information of the $k$th bit is effectively transmitted in the next $N$ bits, which is a unique characteristic of the SESS modulation scheme. By defining $d(k) = \text{diag}(P(k))$, the diversity estimate of $b(k)$ can be obtained from the hard decisions of the next $N$ bits, $[\tilde{b}(k + 1) \tilde{b}(k + 2) \cdots \tilde{b}(k + N)]$, as

$$
\hat{b}(k) = \frac{1}{N} d(k)[\tilde{b}(k + 1) \tilde{b}(k + 2) \cdots \tilde{b}(k + N)]^T + v_2(k)
$$

$$
= \frac{1}{N} \sum_{n=1}^{N} \alpha(k + n)b(k) + v_2(k),
$$

(6.20)

where

$$
v_2(k) = \frac{1}{N} \sum_{n=1}^{N} w(k + n, n)\tilde{b}(k + n)
$$

(6.21)

is a random variable with zero mean and variance $MN_0$. Notice that the effect of the possible bit errors from the correlation detection has been ignored - this is justified with sufficient SNR as shown in Section 6.4.

The conditional SNR given the channel coefficients for the diversity detection is

$$
\gamma_2 = \frac{\left| \frac{1}{N} \sum_{n=1}^{N} \alpha(k + n)b(k) \right|^2}{\mathcal{E}\{|v_2(k)|^2\}}.
$$

(6.22)
Because $\alpha(k+n)$, $n \in \{1, 2, \cdots, N\}$, $b(k)$, and $v_2(k)$ are independent of each other, Equation (6.22) reduces to

$$\gamma_2 = \frac{E_b}{N N_0} \sum_{n=1}^{N} \alpha(k+n).$$ \hspace{1cm} (6.23)

It should be noted that the diversity detection introduces a time delay of $NT_b$ and that the structure is similar to a Rake receiver employing $N$ fingers to exploit the temporal diversity of SESS signals.

### 6.2.4 Iterative Detection

The estimate of $b(k)$ can be improved iteratively with the summation of the correlation estimate, $\hat{b}(k)$, and the diversity estimate, $\hat{\hat{b}}(k)$. Thus, let’s define

$$b(k) = \hat{b}(k) + \hat{\hat{b}}(k)$$

$$= \left( \alpha(k) + \frac{1}{N} \sum_{n=1}^{N} \alpha(k+n) \right) b(k) + v(k),$$ \hspace{1cm} (6.24)

where $v(k) = v_1(k) + v_2(k)$.

It is easy to see that the conditional SNR of the iterative detection, conditioned on the channel coefficients, is simply the summation of the SNR of the two independent signals, as follows:

$$\gamma = \frac{\left| \left( \alpha(k) + \frac{1}{N} \sum_{n=1}^{N} \alpha(k+n) \right) b(k) \right|^2}{\mathcal{E}\{ |v(k)|^2 \}}$$

$$= \frac{E_b}{N N_0} \left[ \alpha(k) + \frac{1}{N} \sum_{n=1}^{N} \alpha(k+n) \right]$$

$$= \gamma_1 + \gamma_2.$$

The final hard decision is then obtained by

$$\tilde{b}(k) = \text{sgn}[\hat{b}(k)] = \begin{cases} 1 & , \hat{b}(k) > 0 \\ -1 & , \hat{b}(k) < 0 \end{cases}$$ \hspace{1cm} (6.26)
6.3 Performance Analysis

In this section, we derive the distributions of the SNRs given in (6.17), (6.23) and (6.25), and the corresponding BER expressions. We proceed with the distribution of the normalized channel gain, \(|h(k)|^2\). It is well known that the coefficients of the Rayleigh fading channel are generated as \(h(k) = (h_r + jh_i)/\sqrt{2}\), where \(h_r\) and \(h_i\) are real values and normally-distributed as \(N(0,1)\). The denominator \(\sqrt{2}\) is for power normalization and the channel gain \(|h(k)|^2 = (|h_r|^2 + |h_i|^2)/2\), is then gamma-distributed as \(\Gamma(1,1)\) \[99\].

Because the summation of independent and identically-distributed (i.i.d.) gamma random variables still follows a gamma distribution \[99\], the spatial diversity gain \(\alpha(k)\) given in (6.8) has a \(\Gamma(2M,1)\) distribution. Furthermore, the conditional SNR of the correlation detector given in (6.17) follows \(\Gamma(2M,E_b/N_0)\) distribution, i.e.,

\[
p_{\gamma_1}(\gamma) = \frac{\gamma^{2M-1}e^{-\frac{\gamma}{E_b/N_0}}}{(2M-1)!(E_b/N_0)^{2M}}, \gamma \geq 0.
\]  

(6.27)

Now the bit-error probability for binary phase shift keying (BPSK) in AWGN with an SNR of \(E_b/N_0\) is given in \[98\] as

\[
P_b = Q\left(\sqrt{\frac{2E_b}{N_0}}\right). \tag{6.28}
\]

Given the conditional SNR of \(p_{\gamma_1}(\gamma)\), the BER expression for the correlation detection is given by \[98, Eq. 14.4-15\]:

\[
P_{e,corr} = \int_0^\infty Q\left(\sqrt{2\gamma}\right)p_{\gamma_1}(\gamma)d\gamma
= \left[\frac{1}{2}(1 - \mu_1)\right]^{2M-1} \sum_{i=0}^{2M-1} \binom{2M-1 + i}{i} \left[\frac{1}{2}(1 + \mu_1)\right]^i \tag{6.29}
\]

where

\[
\mu_1 \triangleq \sqrt{\frac{E_b/N_0}{1 + E_b/N_0}}. \tag{6.30}
\]

A similar analysis would show that the conditional SNR of the time-diversity detector given in (6.23) follows a \(\Gamma(2NM,E_b/N_0/N)\) distribution, i.e.,

\[
p_{\gamma_2}(\gamma) = \frac{\gamma^{2NM-1}e^{-\frac{\gamma}{E_b/N_0/N}}}{(2NM-1)!(E_b/N_0/N)^{2NM}}, \gamma \geq 0. \tag{6.31}
\]
and the BER expression for the diversity detection can then be obtained as

\[
P_{e,\text{div}} = \int_{0}^{\infty} Q\left(\sqrt{2\gamma}\right) p_{\gamma_2}(\gamma) d\gamma
\]

\[
= \left[\frac{1}{2}(1 - \mu_2)^{2NM-2}\right] \sum_{i=0}^{2NM-1} \left(\frac{2NM - 1 + i}{i}\right) \left[\frac{1}{2}(1 + \mu_2)^{i}\right]^{\gamma_2}
\]

(6.32)

where

\[
\mu_2 \triangleq \sqrt{\frac{E_b/N_0/N}{1 + E_b/N_0/N}}.
\]

(6.33)

Notice that the correlative detector has an \(M\)-fold (spatial) diversity whereas the time-diversity detector has an \(MN\)-fold (spatial and temporal) diversity.

For the iterative detection, since the conditional SNR \(\gamma\) is the summation of the independent conditional SNRs \(\gamma_1\) and \(\gamma_2\), the pdf of \(\gamma\) is the convolution of the gamma pdfs of \(\gamma_1\) and \(\gamma_2\). This is written as follows:

\[
p_\gamma(\gamma) = p_{\gamma_1}(\gamma) \otimes p_{\gamma_2}(\gamma)
\]

\[
= \frac{\gamma^{M-1} e^{-\frac{\gamma}{E_b/N_0/N}} \otimes \gamma^{NM-1} e^{-\frac{\gamma}{E_b/N_0/N}}}{(M-1)!(NM-1)! (E_b/N_0/N)^M (E_b/N_0/N)^{NM}}, \quad \gamma \geq 0.
\]

(6.34)

The BER expression can then be obtained by averaging \(Q\left(\sqrt{2\gamma}\right)\) over the conditional pdf of \(\gamma\).

The complexity of such a calculation can be obviated with the observation that the pdf \(p_{\gamma_2}(\gamma)\) approaches a Dirac delta function as \(N\) becomes large. This stems from the fact that the gamma distribution approaches a Gaussian distribution if the degree of freedom, here \(2NM\), is large [99]. Furthermore, the Gaussian distribution tends toward a Dirac delta function as its variance, here \(2NM(E_b/N_0/N)^2 = 2M(E_b/N_0)^2/N\), becomes very small [99]. It follows that if the spreading factor \(N\) is sufficiently large, the distribution of \(p_{\gamma_2}(\gamma)\) can be approximated by an impulse located at the mean value of \(\gamma_2\), which is given as \(2NM(E_b/N_0/N) = 2M(E_b/N_0)\). In other words, \(p_{\gamma_2}(\gamma)\) is approximatively equal to \(\delta(\gamma - 2ME_b/N_0)\).
So as $N$ becomes large, the pdf of $\gamma_2$ approaches an impulse and the pdf of $\gamma$ can be obtained as the shifted pdf of $\gamma_1$:

$$p_\gamma(\gamma) \approx p_{\gamma_1}(\gamma) \otimes \delta(\gamma - 2ME_b/N_0)$$

$$= \begin{cases} 
  \frac{(\gamma - 2ME_b/N_0)^{2M-1} e^{-\frac{\gamma - 2ME_b/N_0}{E_b/N_0}}}{(2M-1)! (E_b/N_0)^{2M}}, & \gamma \geq 2M \frac{E_b}{N_0} \\
  0, & \text{else} 
\end{cases}$$

(6.35)

The BER of the iterative detector can be calculated as

$$P_e = \int_0^\infty Q\left(\sqrt{2\gamma}\right) p_\gamma(\gamma) d\gamma$$

$$\approx \int_{2ME_b/N_0}^\infty Q\left(\sqrt{2\gamma}\right) \frac{(\gamma - 2ME_b/N_0)^{2M-1} e^{-\frac{\gamma - 2ME_b/N_0}{E_b/N_0}}}{(2M-1)! (E_b/N_0)^{2M}} d\gamma$$

$$= Q\left(\sqrt{4M \frac{E_b}{N_0}}\right) - \sqrt{\frac{\mu_1}{2\pi}} e^{2M} \sum_{k=0}^{2M-1} \frac{N_0^k}{E_b^k k!} \sum_{l=0}^{k} \binom{k}{l} (\mu_1)^{k-l} (-2M \frac{E_b}{N_0})^l \Gamma\left(k - l + \frac{1}{2}, 2M \left(1 + \frac{E_b}{N_0}\right)\right).$$

(6.36)

The complicated expression in 6.36 can be derived as follows:

Define $a = 2ME_b/N_0$, $b = E_b/N_0$, and $L = 2M$; then the BER of the iterative detector can be written as

$$P_e \approx \int_a^\infty Q\left(\sqrt{2\gamma}\right) \frac{(\gamma - a)^{L-1} e^{-\frac{\gamma - a}{b}}}{(L-1)! b^L} d\gamma$$

$$= \int_0^\infty Q\left(\sqrt{2(x+a)}\right) \frac{x^{L-1} e^{-\frac{x}{b}}}{(L-1)! b^L} dx$$

$$= \int_0^\infty \int_{\sqrt{2(x+a)}}^\infty e^{-\frac{u^2}{2}} x^{L-1} e^{-\frac{x}{b}} du \frac{x^{L-1} e^{-\frac{x}{b}}}{(L-1)! b^L} dx$$

(6.37)

By changing the order of the integrals, (6.37) becomes

$$P_e \approx \frac{1}{\sqrt{2\pi}} \frac{1}{(L-1)! b^L} \int_0^\infty e^{-\frac{u^2}{2}} P_1 du$$

(6.38)

where

$$P_1 = \int_0^{\frac{a^2}{2} - \frac{a}{2}} x^{L-1} e^{-\frac{x}{b}} dx$$

(6.39)
Let \( z = \frac{x}{b} \), then
\[
P_1 = b^L \int_0^{\frac{u^2}{2b} - \frac{a}{b}} z^{L-1} e^{-z} dx
\] (6.40)

Using the indefinite integral equation given in [100, Eq. 7.4.322], \( P_1 \) can evaluated as
\[
P_1 = -b^L e^{-\frac{u^2}{2b} + \frac{a}{b}} \sum_{k=1}^{L-1} \frac{(L-1)!}{k!} \left( \frac{u^2}{2b} - \frac{a}{b} \right)^k - b^L (L-1)! \left( 1 - e^{-\frac{u^2}{2b} + \frac{a}{b}} \right)
\] (6.41)

Substituting (6.41) into (6.38) to determine \( P_2 \):
\[
P_e \approx \sqrt{\frac{b}{2a}} - e^{\frac{a}{b}} \sum_{k=0}^{k=0} \frac{1}{k!} \left( \frac{u^2}{2b} - \frac{a}{b} \right)^k - b^L (L-1)! \left( 1 - e^{-\frac{u^2}{2b} + \frac{a}{b}} \right)
\] (6.42)

This can be further transformed with the substitution \( t = \frac{u^2}{2b} + \frac{a}{b} \):
\[
P_2 = 2^{k-1} \sqrt{\frac{2b}{1+b}} \int_0^\infty e^{-t} t^{-\frac{1}{2}} \left( \frac{b}{1+b} t - a \right)^k dt
\] (6.43)

where
\[
P_2 = \sqrt{\frac{b}{2a}} - e^{\frac{a}{b}} \sum_{k=0}^{k=0} \frac{1}{k!} \left( \frac{u^2}{2b} - \frac{a}{b} \right)^k - b^L (L-1)! \left( 1 - e^{-\frac{u^2}{2b} + \frac{a}{b}} \right)
\] (6.44)

where \( \Gamma(a, x) \) denotes the incomplete gamma function with shape \( a \) and scale \( x \) [101, Eq. 6.5.3]. Substituting (6.44) into (6.42), we have:
\[
P_e \approx Q \left( \sqrt{\frac{2a}{b}} - \sqrt{\frac{b}{1+b}} \right)
\] (6.45)
The final expression for $P_e$ in (6.36) can be obtained with the defined values for $a$, $b$, and $L$:

$$P_e \approx Q\left(\sqrt{4ME_bN_0}\right) - \sqrt{\frac{\mu_1}{2\pi}} e^{2M} \sum_{k=0}^{2M-1} \frac{N_k}{E_b^k k!} \sum_{l=0}^{k} \binom{k}{l} (\mu_1)^{k-l} (-2M E_b N_0)^l \Gamma\left(k-l+1, 2M \left(1 + \frac{E_b}{N_0}\right)\right)$$

(6.46)

where $\mu_1$ is given by (6.30).

It should be noted that the impulse approximation of the pdf yields a lower bound for the BER, because it can only be approached when the spreading factor $N$ tends to infinity.

### 6.4 Numerical Results

The distributions of the conditional SNRs are first presented and the delta approximation related to the iterative detection is discussed. Figure 6.3 shows the distributions of the conditional SNRs of the correlation detection $\gamma_1$, diversity detection $\gamma_2$, and iterative detection $\gamma$, for different scenarios. Each sub-figure also includes a curve that shows the distribution of $\gamma_1$ that has been right-shifted by $2M E_b N_0$. The coordinates for different sub-figures have been adjusted in order to illustrate the distributions in detail. As analyzed in Section 6.3, the mean and variance of the conditional SNR of the diversity detection $\gamma_2$ are $2M E_b N_0$ and $\frac{2M}{N} (E_b N_0)^2$, respectively. This means that while the number of receive antennas and the SNR affect both position and shape of the “pulse,” the spreading length only influences its shape. Figure 6.3 (a) and (b) show that the position and the shape of the pulse vary with the number of antennas. In both cases, the pulse is not very narrow due to the small value of $N = 8$, resulting in a discernable difference between the shifted version of the distribution of $\gamma_1$ (dotted curve) and the distribution of $\gamma$ (dashed curve). The “pulse” looks sharper in Figure 6.3 (c) since $N = 64$ is much larger. This sharper pulse approximates a delta function such that there is negligible difference between the shifted distribution of $\gamma_1$ and the distribution of $\gamma$. Also, Figure 6.3 (c) and (d) shows that the delta approximation is not very sensitive to SNR, although it is more accurate with lower SNR.
Next, the BER performance of MIMO-SESS is presented and is compared with a conventional MIMO, PN-coded spread spectrum (MIMO-PNSS) system. The channel between each transmit and receive antenna pair is assumed to be Rayleigh fading that remains constant over $T_b$ but is independent from bit to bit \([92, 98]\). In addition, the channels for different transmit/receive antenna pair are independent. The length of the spreading sequence is set to $N = 64$ unless noted otherwise. For each scenario and bit signal-to-noise ratio (SNR), 100 runs of 100,000 bits are simulated to obtain the average bit error rate.
Figure 6.4: Comparison between MIMO-PNSS and MIMO-SESS with correlation detection, N=64.

(BER).

Figure 6.4 compares the BER of MIMO-SESS with correlation detection to a MIMO-PNSS system. It is observed that there is no time diversity gain without iterative detection and the performance with or without self-encoding is the same as expected under high SNR. The performance degradation of MIMO-SESS at low SNR is due to error propagation [87]. In particular, Figure 6.4 shows that the effect of error propagation is quite severe for a BER greater than 10%. The effect of error propagation can be efficiently alleviated with more antennas, as shown by the example $2 \times 2$ scenario, since larger spatial diversity reduces BER to below 10% even at low SNR. The plots in Figure 6.4 show excellent agreement between the analytical and simulation results at high SNR, where error propagation becomes insignificant.

The performance of MIMO-SESS with time-diversity detection is shown in Figure 6.5.
Figure 6.5: Comparison between MIMO-PNSS and MIMO-SESS with diversity detection, N=64.

The plots clearly show that the proposed system significantly outperforms conventional MIMO-PNSS systems. As an example, there is about 4.5 dB gain for the $2 \times 2$ configuration at $10^{-4}$ BER. This performance improvement can be attributed to the $N$-fold time diversity introduced by self encoding. Due to the significantly improved BER, error propagation is effectively mitigated as shown by the $2 \times 2$ scenario. Moreover, the agreement with the simulation results verifies that the analysis has been justified in ignoring error propagation.

Figure 6.6 compares the BER with the iterative detector. Again, there is excellent agreement between the analytical and simulation results at sufficiently high SNR. The performance gain over conventional MIMO-PNSS systems is almost 7 dB at $10^{-4}$ BER for the $2 \times 2$ configuration. The excess gain beyond the expected 3 dB SNR improvement can be attributed to the diversity gain from the time-diversity detection. In fact, the plot shows that a $2 \times 2$ MIMO-SESS would require an SNR of only 3 dB to achieve a $10^{-4}$
BER. The results verify the veracity of the performance analysis and demonstrate that MIMO-SESS can completely mitigate the effect of Rayleigh fading. The difference between the numerical and simulation results at low SNR is due to error propagation. This can be easily demonstrated in simulation by feeding the true (transmitted) bits into the delay registers at the receiver. The results of this simulation are compared with the numerical calculations in Figure 6.7. The excellent agreement between the simulation and numerical results demonstrates the validity of the statistical models and approximations.

Figure 6.8 shows the numerical results of MIMO-SESS with the iterative detection for different spreading lengths. For both $2 \times 1$ and $2 \times 2$ cases, the performance approaches the lower bound when the spreading length increases. Notice that the lower bound is very tight for $N \geq 64$. Also, the lower bound is tighter for the $2 \times 1$ case and at lower SNR. These results are consistent with the discussion in Section 6.3. It can be seen by comparing the
lower bound and the performance of BPSK in AWGN that $2 \times 2$ MIMO-SESS can provide about 5.2 dB gain over BPSK at $10^{-4}$ BER. This significant performance improvement is clearly due to the combined temporal and spatial diversities associated with MIMO-SESS design.

6.5 Summary

In this chapter, MIMO techniques are explored to enhance the self-encoded spread spectrum systems [94–97]. The closed-form BER expressions for the correlation detector and time diversity detector are derived, and a lower bound for the iterative detector is obtained. The veracity of the analysis has been confirmed with the numerical calculations based on the analytical expressions, which have demonstrated excellent agreement with the simulation results. The performance analysis has shown that MIMO-SESS offers almost 7 dB of gain at
a $10^{-4}$ BER compared to a $2 \times 2$ MIMO PN-coded spread spectrum system. Furthermore, the system requires only about 3 dB SNR to achieve a BER of $10^{-4}$. This demonstrates that MIMO-SESS can provide a very effective means to exploit both spatial and temporal diversities in order to achieve robust performance in wireless environments.
Chapter 7

Securing Wireless Communications by Exploring Physical Layer Characteristics

7.1 Introduction

Wireless networks are susceptible to eavesdropping due to their broadcast nature. During the past few decades, security in wireless networks has been mainly considered at higher layers using cryptography [102]. Recently, researchers are seeking security methods at the physical layer. The key idea of physical layer security is to exploit the wireless physical characteristics, e.g., modulation, coding, channel fading, and diversities, to secure wireless communications. The fundamental ability of the physical layer to provide security is characterized by secrecy capacity, which is defined as the maximum achievable rate of information that can be sent in secret from a transmitter to its desired receiver in the presence of an eavesdropper.

A feasible solution to this question is to employ cooperative relaying and cooperative jamming. In a cooperative relaying scheme, one or more relays work together with the transmitter to increase the secrecy capacity. For example, relays which utilize decode-and-forward (DF) [103] and amplify-and-forward (AF) cooperative strategies [104] have been studied. By optimizing the transmitting power weights among the transmitter and relays, the secrecy capacity was increased subject to a fixed transmit power constraint. In cooperative jamming, a relay transmits jamming signals in order to hide the information-bearing signal or deny the eavesdropper’s reception. For instance, a noise-forwarding (NF) strategy was proposed to increase the secrecy capacity of a four-node relay-eavesdropper channel [105]. Based on this NF method, the relay node cooperates with the transmitter by forwarding independent noise to the eavesdropper. However, the problem in the afore-
mentioned methods remains that the channel state information (CSI) was assumed globally known, but not at the eavesdropper.

Another promising solution to achieving secrecy capacity bound is to utilize multiple antennas. It has been shown that information security and information-hiding capabilities can be enhanced by employing the space-time diversity schemes at the transmitter [106]. A transmission scheme exploiting the redundancy of the transmit antenna array was proposed for multiple-input single-output (MISO) systems [107]. By randomizing the eavesdropper’s signals, the secrecy capacity can be increased. By adding artificially generated noise to the information-bearing signal [13, 108], it can successfully degrade the eavesdropper’s signal quality without affecting the main channel. The artificial noise is generated based on the null space of the main channel, which provides \( M - N \) degrees of freedom for the noise, where \( M \) and \( N \) denote the numbers of the antennas at the transmitter and the receiver, respectively. This method, therefore, requires more antennas are deployed at the transmitter than that at the receiver [13]. Otherwise, this method becomes invalid because no null spaces exist for such antenna configurations.

This chapter proposes to increase secrecy capacity by jamming the eavesdropper’s reception with artificially generated noise signal, which is intentionally transmitted together with the information-bearing signal [109–111]. This jamming signal significantly degrades the signal quality at the eavesdropper but not at the intended receiver. Two methods are proposed to generate the jamming noise signal: one is based on the null space of an equivalent channel of the system, and another generates the jamming signal from the eigenvectors of the Hermitian matrix \( H^H H \), where \( H \) is the channel matrix. The first method is referred to as null space (NS)-based jamming, while the second is called eigenvector (EV)-based jamming.

Compared to the artificial noise method presented in [13], our proposed methods demonstrate several significant advantages. First, our approaches overcome the limitation of the number of receive antenna elements. Regardless of the number of the transmit antennas,
our methods can be applied in a system with any number of receive antennas. Second, the degree of freedom for the jamming noise signal is \( M - 1 \) and is independent of the number of receive antennas. This facilitates our schemes with the unique ability of randomizing the generated jamming noise signal, significantly increasing the level of information security. Third, our scheme is capable of maintaining the secrecy capacity even if the eavesdropper employs a large size of antenna array or even moves its position closer to the transmitter.

### 7.2 System Model and Problem Statement

The wireless system under our consideration is depicted in Figure 7.1, where a transmitter with \( M \) antennas communicates with an intended receiver with \( N \) antennas in the presence of an eavesdropper with \( K \) antennas. The following describes the functions and assumptions of the transmitter, receiver, and eavesdropper.
7.2.1 Transmitter

At the transmitter, the complex data symbol $s \in \mathbb{C}^{M \times 1}$ is modulated by a normalized beamforming weighting vector $t \in \mathbb{C}^{M \times 1}$ into $M$ branches, where $t^H t = 1$. An intentionally generated jamming signal vector $w \in \mathbb{C}^{M \times 1}$ is precoded into the information-bearing signal. The transmitted signal $x \in \mathbb{C}^{M \times 1}$ can be expressed as

$$x = ts + w. \quad (7.1)$$

Both the intended receiver and the eavesdropper are within communication range of the transmitter. The intended receiver receives the signal over a MIMO channel denoted by the channel matrix $H \in \mathbb{C}^{N \times M}$, while the eavesdropper receives the signal via a MIMO channel represented by the channel matrix $H_e \in \mathbb{C}^{K \times M}$. Both $H$ and $H_e$ are assumed to be quasi-static flat fading channels. In addition, the channel matrix $H$ is assumed to be known to both the transmitter and the desired user, but the channel matrix $H_e$ is only known to the passive eavesdropper. In other words, the eavesdropper is incapable of obtaining the channel matrix between the transmitter and the desired receiver, and the transmitter doesn’t need information about the eavesdropper’s channel. To satisfy this assumption, both the transmitter and the desired receiver can transmit a training sequence to each other. The CSI is estimated at both ends without feedback. Note that during the channel estimation process, the weighting vector at the transmitter is initially set to be a unit vector.

7.2.2 Desired Receiver

In a flat-fading scenario, the received signal vector $y \in \mathbb{C}^{N \times 1}$ at the desired receiver can be written as

$$y = Hx + n, \quad (7.2)$$

where $n \in \mathbb{C}^{N \times 1}$ is the complex white Gaussian noise vector with zero-mean and covariance matrix $\sigma_n^2 I_N$. The received signal is then combined using the receive weighting vector
\( \mathbf{r} \in \mathbb{C}^{N \times 1} \) as
\[
z = \mathbf{r}^H \mathbf{y}. \tag{7.3}
\]

Combining (7.1), (7.2), and (7.3), the received symbol \( z \) at the desired receiver can be written as
\[
z = \mathbf{r}^H \mathbf{H}_t \mathbf{s} + \mathbf{r}^H \mathbf{H}_w + \mathbf{r}^H \mathbf{n}, \tag{7.4}
\]
where the second term on the right-hand side, \( \mathbf{r}^H \mathbf{H}_w \), is the interference caused by the intentionally added jamming signal \( \mathbf{w} \).

The receive weighting vector is assumed to be normalized, i.e., \( \| \mathbf{r} \|^2 = 1 \), and the transmit powers for the information signal and the jamming signal are set to be \( P_s \) and \( P_w \), respectively (i.e., \( E\{|s|^2\} = P_s \) and \( \| \mathbf{w} \|^2 = P_w \)). The total transmit power is constrained to \( P \), i.e., \( E\{\mathbf{x}^H \mathbf{x}\} = P_s + P_w \leq P \). Thus, the achievable rate between the transmitter and the desired receiver is formulated as follows:
\[
C_{\text{main}} = \log \left( 1 + \frac{\| \mathbf{r}^H \mathbf{H}_t \|^2 P_s}{\| \mathbf{r}^H \mathbf{H}_w \|^2 P_w + \sigma_n^2} \right) \tag{7.5}
\]
subject to \( E\{\mathbf{x}^H \mathbf{x}\} = P_s + P_w \leq P \)

To maximize the achievable rate at the intended receiver, we maximize the signal-to-interference plus noise ratio (SINR) in (7.5). Thus, the transmit weighting vector \( \mathbf{t} \) is chosen as the eigenvector \( \mathbf{v} \) corresponding to the largest eigenvalue \( \lambda_{\text{max}} \) of \( \mathbf{H}^H \mathbf{H} \) (as in MRT), and the receive weighting vector \( \mathbf{r} \) is chosen to be \( \mathbf{r} = \mathbf{H} \mathbf{v} / \| \mathbf{H} \mathbf{v} \| \) (as in MRC) [112] so that we can eliminate the interference component at the desired receiver.

### 7.2.3 Eavesdropper

Similar to the analysis for the intended receiver, the received signal at the eavesdropper is weighted by \( \mathbf{r}_e^H \) and given as
\[
z_e = \mathbf{r}_e^H (\mathbf{H}_e \mathbf{v} \mathbf{s} + \mathbf{H}_e \mathbf{w} + \mathbf{n}_e), \tag{7.6}
\]
where \( \mathbf{r}_e \in \mathbb{C}^{K \times 1} \) and \( \mathbf{n}_e \in \mathbb{C}^{K \times 1} \) are the eavesdropper’s receive weighting vector and white Gaussian noise vector with zero-mean and covariance matrix \( \sigma^2_{\mathbf{n}_e} \mathbf{I}_K \). Therefore the achievable rate at the eavesdropper is formulated as

\[
C_{\text{eave}} = \log \left( 1 + \frac{\| \mathbf{r}_e^H \mathbf{H}_e \mathbf{v} \|^2 P_s}{\| \mathbf{r}_e^H \mathbf{H}_e \mathbf{w} \|^2 P_w + \sigma^2_{\mathbf{n}_e}} \right) \tag{7.7}
\]

subject to equal gain combining of \( \mathbf{r}_e \) and worst case \( \sigma^2_{\mathbf{n}_e} \to 0 \)

Because the eavesdropper has no information about the beamforming vector \( \mathbf{w} \), the MRC method is not applicable. However, to maximize its achievable rate, the eavesdropper may select the suboptimal method of equal gain combining, i.e., \( \mathbf{r}_e = \frac{1}{\sqrt{K}} [1 \ 1 \ \cdots \ 1]^T \), and choose the noiseless receiver such that \( \sigma^2_{\mathbf{n}_e} \approx 0 \), which may be the worst case for secure wireless communications.

### 7.3 Proposed Approach

It is observed from (7.4) and (7.6) that the combined signal at both the desired receiver and the eavesdropper includes interference caused by the jamming signal \( \mathbf{w} \). The secrecy capacity is usually defined as the difference between (7.5) and (7.7), or \( C_s = (C_{\text{main}} - C_{\text{eave}})^+ \). The key idea to increasing the secrecy capacity is to design the transmit weighting factor \( \mathbf{w} \) such that the interference is removable at the intended receiver but not at the eavesdropper. The method using noise generation in the null space of the main channel provides insight into this concept [13]. This method, however, can only be used in systems where the number of transmit antennas is greater than the number of receive antennas, which is impractical as it imposes configuration constraints for transmitters, receivers, and eavesdroppers. In this section, two methods are presented that can overcome this limitation.

#### 7.3.1 Null Space-Based Jamming

The interference component at the desired receiver resulting from the jamming noise signal in Eq. (7.4) can be written as \( \mathbf{a}^H \mathbf{w}/\| \mathbf{H} \mathbf{v} \| \), where \( \mathbf{a} \in \mathbb{C}^{M \times 1} \) is defined as \( \mathbf{a} = \mathbf{H}^H \mathbf{H} \mathbf{v} \).
We can generate a jamming signal vector in the null space of the row vector $\mathbf{a}^H$, which offers $M - 1$ degrees of freedom regardless of the number of receive antenna elements. Our selection of $\mathbf{w}$ will maximize (7.5) while minimizing (7.7).

The procedure to generate the jamming noise signal is described as follows:

1. Find the null space matrix $\mathbf{\Gamma} \in \mathbb{C}^{M \times (M-1)}$ of $\mathbf{a}^H$, so that $\mathbf{a}^H \mathbf{\Gamma} = (\mathbf{0}_{M-1})^T$ and $\mathbf{\Gamma}^H \mathbf{\Gamma} = \mathbf{I}_{M-1}$;
2. Construct a vector $\mathbf{f} \in \mathbb{C}^{(M-1) \times 1}$ with components to be i.i.d. Gaussian with zero-mean and variance $\sigma^2_f = P_w/(M - 1)$;
3. Choose $\mathbf{w} = \mathbf{\Gamma} \mathbf{f}$, such that the interference term $\mathbf{a}^H \mathbf{w}/\|\mathbf{Hv}\| = 0$ results in a complete removal of the jamming noise signal interference at the desired receiver.

### 7.3.2 Eigenvector-Based Jamming

The interference component due to the jamming signal at the desired receiver can also be written as $(\mathbf{Hv})^H \mathbf{Hw}/\|\mathbf{Hv}\|$. Instead of generating the jamming signal based on the null space concept, another method is to design the jamming noise signal such that it ensures $\mathbf{Hv} \perp \mathbf{Hw}$. This design can be realized by taking advantage of the orthogonality between any two different eigenvectors of a normal matrix. Assume the $M$ eigenvalues of matrix $\mathbf{H}^H \mathbf{H}$ are $\lambda_i, \; i \in \{1, 2, \cdots, M\}$, and their corresponding eigenvectors are $\mathbf{v}_i, \; i \in \{1, 2, \cdots, M\}$.

Because the matrix $\mathbf{H}^H \mathbf{H}$ is normal, its eigenvectors are mutually orthogonal [113]. That is, $\mathbf{v}_i^H \mathbf{v}_j = \delta(i - j)$.

Without loss of generality, it is assumed that $\lambda_M$ and $\mathbf{v}_M$ are the largest eigenvalue and its corresponding eigenvector, respectively. We may choose $\mathbf{w}$ as a linear combination of eigenvectors $\mathbf{v}_i, \; i \in \{1, 2, \cdots, M - 1\}$. The procedure to generate the jamming signal is summarized as follows:

---

*Matrix $\mathbf{A}$ is normal if $\mathbf{AA}^H = \mathbf{A}^H \mathbf{A}$. 
1. Construct an orthogonal set $V \in \mathbb{C}^{M \times (M-1)}$ with each column as one eigenvector corresponding to one of the least $M-1$ eigenvalues of $HH^H$, e.g., $V = [v_1 \ v_2 \ \cdots \ v_{M-1}]$;

2. Randomly select a vector $f \in \mathbb{C}^{(M-1)\times 1}$ with components to be i.i.d. Gaussian with zero-mean and variance $\sigma_f^2 = P_w/(M - 1)$;

3. Generate $w = Vf$.

It should be noted that a similar method was applied in a singular value decomposition (SVD)-based MIMO system to find a fixed SINR solution [114].

In this way, the interference component in Eq.(7.4) becomes

$$r^Hw = \frac{v_M^H H^H HVf}{\|Hv_M\|}$$

$$= [\lambda_1 v_M^H v_1 \ \lambda_2 v_M^H v_2 \ \cdots \ \lambda_{M-1} v_M^H v_{M-1}]f$$

$$= 0 \quad (\text{for } \forall f),$$

resulting in non-influence to the desired receiver.

In the aforementioned nullspace (NS) and eigenvector (EV)-based methods, the jamming signal doesn’t interfere with the intended receiver. The output SINR at the desired receiver can be written as

$$\gamma_r = \frac{\sqrt{\lambda_{\text{max}}}|s|^2}{E\{|r^Hn|^2\}} = \frac{\lambda_{\text{max}} P_s}{\sigma_n^2},$$

and the expected main channel capacity is given by

$$C_{\text{main}} = \log \left(1 + \frac{\lambda_{\text{max}} P_s}{\sigma_n^2}\right).$$

However, the jamming signal causes significant interference at the eavesdropper, and the output signal-to-interference-plus-noise ratio (SINR) is given by

$$\gamma_e = \frac{E|w^HHev|^2 P_s}{E|e^HHe|w^2 P_w + \sigma_{ne}^2}.$$
The eavesdropper’s channel capacity is given by

\[ C_{\text{eave}} = \log \left( 1 + \frac{E|r_e^H H_{\text{e}} w|^2 P_s}{E|r_e^H H_{\text{e}} w|^2 P_w + \sigma^2_n} \right). \]  \tag{7.12}

Next, we will evaluate the secrecy capacity based on the aforementioned methods.

7.4 Simulation Results

This section investigates the secrecy capacity of the transmit-beamforming diversity system with proposed jamming noise signal under the i.i.d. channel \cite{115} and the 3GPP spatial channel model (SCM) \cite{15}. The performance is first studied by using the i.i.d. channel model.

The main channel \( H \) and the eavesdropper’s channel \( H_{\text{e}} \) are generated statistically independently. It is assumed the thermal noise at the desired receiver and the eavesdropper have the same variance, i.e., \( \sigma^2_n = \sigma^2_{n_e} \). The total transmit power \( P \) is normalized with respect to the variance. Without the position (and thus the path loss) information of the passive eavesdropper, it is impossible to adaptively optimize the power allocation between the information-bearing signal and the jamming signal. Therefore, we examine two fixed power allocation schemes: one is equal power allocation, i.e., \( P_s = P_w = P/2 \), and another is without the jamming signal, namely \( P_s = P \) and \( P_w = 0 \). The antenna configuration is represented by the triple \([M, N, K]\), where \( M, N, \) and \( K \) denote the number of the transmit antennas, receive antennas, and eavesdropper antennas, respectively.

Figure 7.2 shows the main channel capacities associated with the normalized transmit power of the transmit-beamforming system with jamming noise signal. Results under different antenna configurations are compared. As shown in (7.10), the capacity is determined by two factors: the expectation of the largest eigenvalue and the normalized transmit power (the ratio between the transmit power and the noise variance). According to the analysis results in \cite{116}, the largest eigenvalue is related to the antenna numbers at the transmitter and the desired receiver. Given a specific antenna configuration, the main channel capacity
increases with the normalized transmit power. For fixed normalized transmit power, the channel capacity increases with the transmit and receive antenna numbers.

The eavesdropper’s channel capacities for transmit-beamforming systems with jamming noise signal under different antenna configurations are shown in Figure 7.3. From this figure, it is observed that the eavesdropper’s channel capacity is only determined by the transmit antenna number but is independent of the antenna number at the eavesdropper or the desired receiver. This means that the eavesdropper cannot increase its channel capacity by deploying more antenna elements. This advantage of our proposed scheme is helpful when designing a secure wireless system.

When comparing the main channel capacities and the eavesdropper’s channel capacities shown in Figure 7.2 and Figure 7.3, it is observed that the secrecy capacity increases significantly, which is shown in Figure 7.4 by the curve set labeled “with jamming.” These curves also show that secrecy capacity can be increased with the normalized signal power.

Figure 7.2: Comparison of the main channel capacities for different antenna configurations, with jamming noise signal, i.i.d. channel model.
Figure 7.3: Comparison of the eavesdropper’s channel capacities for different antenna configurations, with jamming noise signal, i.i.d. channel model.

Figure 7.4: Comparison of simulation results with and without jamming noise signal, i.i.d. channel model.
Figure 7.4 also compares the simulation results with and without jamming noise signal. Our results and analysis indicate that the proposed approach significantly increases secrecy capacity. For example, the increase in secrecy capacity is about 7 bits/s/Hz when the normalized transmit power is 30 dB and the antennas are configured as [4,4,4].

Next, the performance of the proposed methods is evaluated over the 3GPP spatial channel model. In this scenario, the transmitter is assumed to be a fixed base station, while the desired receiver and the eavesdropper could be at any location within the cell’s coverage area. The “urban macro” environment is deliberated, where the transmitter antenna height is 32 m, the receiver and eavesdropper antenna height is 1.5 m, and the carrier frequency is 1900 MHz. The path loss is calculated by $PL = 34.5 + 35 \log_{10}(d)$ (dB), where $d$ is the distance between the transmitter and the receiver. Two scenarios are studied:

**Scenario 1** The transmitter is fixed in position; the intended receiver and the eavesdropper move around the transmitter, and they are $d$ meters far away from the transmitter.

**Scenario 2** The transmitter and intended receiver are fixed in position, and the distance between them is 100 meters; the eavesdropper moves between the transmitter and the intended receiver, and it is 35 to 80 meters away from the transmitter.

It is worth noting that the path loss model limits the minimum distance between the transmitter and the receiver to 35 meters. It is assumed that the eavesdropper cannot be very close to the desired receiver, leading to uncorrelated channel matrix $H$ and $H_e$.

The thermal noise at the desired receiver and the eavesdropper is assumed to be -95 dBm, i.e., $\sigma_n^2 = \sigma_{n_e}^2 = -95$ dBm. The total transmit power $P$ is set as 1 W. As for the i.i.d. model, two power allocation schemes, with (equal power) and without jamming noise signal, are studied.

Figure 7.5 shows the results of the ergodic secrecy capacities for scenario 1. The antenna configuration is [4,4,4]. For both cases with and without jamming noise signal, the main channel capacity decreases with increasing distance between the transmitter and the
receiver. This result is intuitive because the received signal power becomes weaker when the receivers are further away from the transmitter. Since the transmit signal power is reduced to one-half of the total transmit power for the case with jamming noise signal, the main channel capacity is about 1 bit/s/Hz less than that of the case without jamming noise signal.

However, the eavesdropper’s channel capacities show different trends for the two cases, resulting in different secrecy capacity tendencies: with jamming noise signal, the eavesdropper’s channel capacity is low (about 2 bits/s/Hz) and maintains nearly the same level whatever the distance is due to the irremovable jamming noise signal; without jamming noise signal, the eavesdropper’s channel presents a relatively high capacity, even though the capacity decreases with increasing distance. Without maximum-ratio combining, the eavesdropper’s channel capacity is lower than the main channel capacity.

The secrecy capacity is calculated from the main channel and the eavesdropper’s channel
capacity. Without the jamming noise signal, the secrecy capacity is shown as 5 bits/s/Hz regardless of the distance $d$, while the secrecy capacity is much higher with jamming noise signal. The increase of the secrecy capacity by adding the jamming noise signal is about 8 bits/s/Hz when the distance $d$ is 40 m and 3 bits/s/Hz at 120 m.

The cumulative distribution function (CDF) of the secrecy capacities is shown in Figure 7.6 in order to better evaluate the secrecy capacity distribution. The secrecy capacity shows a wide range of about 18 bits/s/Hz. This is due to the randomly generated jamming noise signal and the random realization of the channels. Nonetheless, outage secrecy capacity remains high. For example, when the distance is 40 m, the 10% outage secrecy capacity is about 10 bits/s/Hz. This guarantees that secret wireless communications are feasible in such a system. In addition, the distributions of the eavesdropper’s channel capacities for different eavesdropper locations are very similar. This result further corroborates that the eavesdropper cannot change system secrecy capacity by moving its position.
Figure 7.7 shows the simulation results of the second scenario. Without the jamming noise signal, secrecy capacity decreases when the eavesdropper moves closer to the transmitter. If the eavesdropper moves close enough to the transmitter, its channel capacity may increase significantly so that secrecy capacity goes to zero. However, if the jamming noise signal is employed, the eavesdropper hardly acquires more information by moving closer to the transmitter. Moreover, comparing the results of the configurations $[2, 2, 2]$ and $[2, 2, 8]$, it can be seen that the eavesdropper cannot change secrecy capacity by employing more antenna elements.

7.5 Summary

In this chapter, jamming noise signals are used to secure wireless communications in transmit-beamforming diversity systems [109–111]. Two jamming noise signal generation methods are proposed based on the null space of an equivalent channel of the system and the eigenvectors of the channel matrix. The proposed approach can be applied in systems with any
antenna configurations. Compared with other classical security methods, our approach can provide more degrees of freedom for jamming noise signals, significantly increasing the level of security. Given the dynamic nature of the wireless channel and the short amount of time available during which to successfully determine the employed jamming noise signal generation parameters, physical layer security can be ensured using our presented approach.
Chapter 8

Conclusion and Future Work

In this dissertation, the new features of multi-antenna wireless systems are studied. Solutions to long-range channel prediction and destructive I/Q imbalance in MIMO-OFDM systems are proposed. The MIMO technique is incorporated into SESS system to mitigate error propagation and enhance system performance. As a novel idea, multi-antenna technology is also employed to provide physical layer security for wireless communications. In this chapter, we conclude this dissertation by reviewing the novel contributions and discuss possible future work.

8.1 Contributions

In this dissertation research, the following contributions have been made:

1. A novel multi-block linear channel predictor is proposed to compensate for performance degradation caused by feedback delay in limited feedback precoded spatial multiplexing MIMO-OFDM systems. A publication related to this topic is found in [50].

2. A novel virtual channel concept is proposed to compensate for the I/Q imbalances in a MIMO-OFDM wireless communication system over multipath fading channels. The studies have been published in [65, 70, 71].

3. MIMO technology is incorporated into the SESS system to mitigate the error propagation and enhance system performance. This new scheme and its performance analysis have been published in [94–97].
4. A method based on artificial jamming noise is proposed to secure wireless communications in the physical layer. The related publications are [109–111].

8.2 Suggested Future Work

Some of the topics presented in this dissertation can be further studied. First, performance of the physical layer security method proposed in Section 7 highly depends on the CSI at the transmitter. The channel estimation error and the feedback delay may cause the CSI at the transmitter to be inaccurate. The study of the influence of the inaccurate CSI at the transmitter on the system is an interesting topic. Second, the analysis of the MIMO-SESS system is based on BPSK modulation. However, higher order modulation is necessary in a practical system. How to implement higher order modulation, such as M-QAM, in a MIMO-SESS system is a challenging task. Third, the concept of distributed MIMO can be employed in a smart grid to enhance wireless sensor networks. By grouping one-antenna sensors into clusters and making the sensors in each cluster cooperate with each other to form a virtual antenna array, the overall transmission range and the link quality could be dramatically enhanced.
Bibliography


