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A STUDY ON COMPRESSED SENSING BASED CHANNEL ESTIMATION FOR MIMO-OFDM SYSTEMS

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Abstract

A multiple-input multiple-output (MIMO) wireless communication system combined with the orthogonal frequency division multiplexing (OFDM) modulation technique can mitigate the effects of multipath fading and achieve reliable high data rate transmission over broadband wireless channels. Pilots-assisted channel estimation is essential in many MIMO-OFDM systems as it enables the receiver to acquire the channel knowledge which is necessary by signal detection. Among many channel estimation algorithms. Compressed Sensing (CS) can achieve higher accuracy using a small number of pilots than that of conventional interpolation based methods. However, due to its large-sized measurement matrix, CS suffers from highly computational complexity, making it difficult to apply in many practical scenarios.

This research achieves good performance with low complexity in Compressed Sensing based Channel Estimation Algorithm for MIMO-OFDM Systems. We reduced the computational complexity by optimized the matrix vector of measurement matrix. In conventional compressed sensing, CS algorithms are processed one by one on each channel. Consequently, we proposed CS method by using the same measurement matrix for CS algorithm process, subsequently we selected a small number of pilots randomly in the receiver side to obtain low computational complexity. A small number of pilots obtain small size measurement matrix, and it has low complexity.

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In addition, for multiple antenna systems, a misdetection of the CIR index position caused performance degradation. Therefore, assuming that the position of CIR in the time domain are almost same, we used an average process to reduce the AWGN noise component to find the correct positions of CIR in order to achieve better BER performance. The simulation results showed that our proposed method provides a good BER performance for the channel estimation in comparison the conventional method. Furthermore, our proposed CS method reduced computational complexity to 75%. The performance of the existing OMP algorithm is comparable with other algorithms such as CoSaMP and SAMP algorithm.

Keywords:

Channel Estimation, Compressed Sensing, MIMO-OFDM, Measurement Matrix, OMP, CoSaMP, SAMP

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1 Introduction

1.1 Background

In the last decades, telecommunication technologies are developing rapidly due to the increasing demand of telecommunication consumers towards a more sophisticated and faster telecommunication activity. Second Generation (2G) technology is invented 30 years ago with a feature to send voice and text message. Afterwards, the Third Generation (3G) technology is developed to extend its usage for multimedia. The latest innovation is the Fourth Generation (4G) technology which is able to facilitate high-speed data connection with extensive capacity and lower latency. However, the research on wireless communication enables the advance of the Fifth Generation (5G) in developing progress to face the next challenges [1].

Orthogonal Frequency Division Multiplexing (OFDM) has become a basis of many telecommunications standards including wireless local area network (LANs), digital radio and television broadcasting, 4G and 5G wireless communications. OFDM is a type of multicarrier modulation scheme whose subcarriers overlap with each other. OFDM is capable of reducing the effect of multipath fading by making efficient use of complex equalizers [2].

MIMO can increase the transmission process of data (signal) to the receiver. During the detection of data processing on the receiver, it is needed the role of channel estimation process. The usage of an element of MIMO will significantly improve the performance. However, it becomes less efficient because each distribution channel condition in the time domain is not always concurrent. There are elements of MIMO which is not enabled simultaneously for all channel conditions [3]. MIMO communication system combined with OFDM modulation technique (MIMO-OFDM) can mitigate the effects of multipath fading and achieve reliable high data rate transmission over the broadband wireless channel. Figure 1.1. shows the block diagram of a MIMO-OFDM system with N_t transmit antennas, N_r receive antennas and N subcarriers. [4]

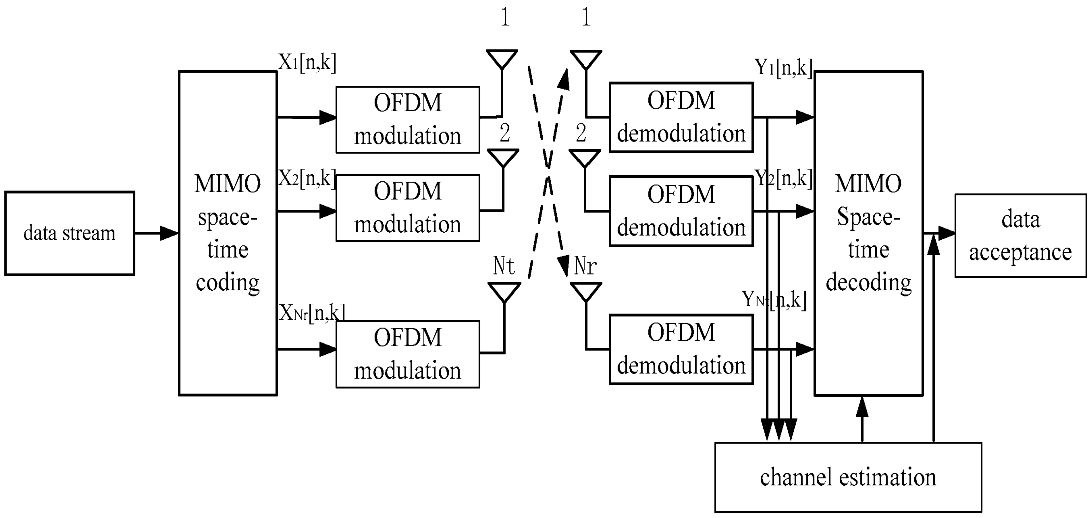

Figure 1.1: Block Diagram of Trnsmitter and Receiver MIMO-OFDM

The communication system is composed of the transmitter, receiver, and a medium called channel. As shown in Figure 1.2, transmitted signal gets distorted or various noise is added to the signal while the signal goes through the channel. n wireless communication system, the channel has an important role in determining the quality of the signal transmission. The several factors that determine the quality of wireless communication are noise, attenuation (damping), and multipath fading which can degrade the signal [5] [6]. A multiple-input multiple-output communication system combined with the orthogonal frequency division multiplexing modulation technique (MIMO-OFDM) can mitigate the effects of multipath fading and achieve reliable high data rate transmission over the broadband wireless channel. We should figure out the characteristic of the channel to demodulate the transmitted signal properly.

The general used channel estimation method's mechanism is to use pilot symbols. Pilot symbols are utilized to collect information and to estimate the channel conditions. Pilot symbols will be transmitted at the beginning of the frame as a

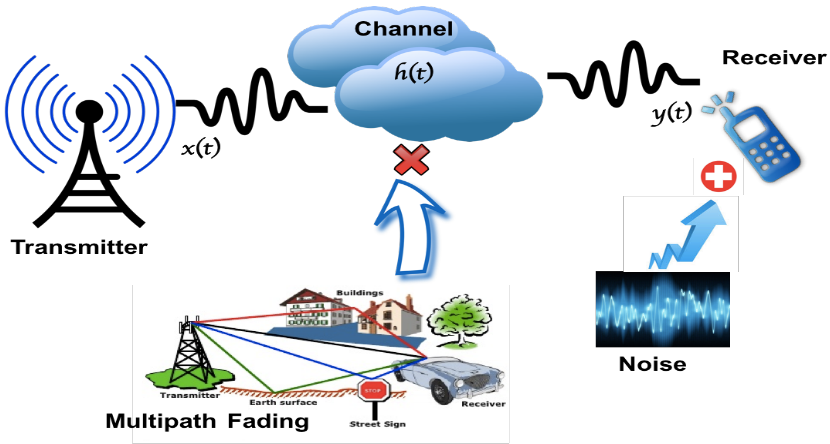

Figure 1.2: Mobile Communication Channel Model

preamble. Previous research which discusses Channel State Information (CSI) acquisition shows that base station (BS) broadcast pilots relied on the terminals estimate of their corresponding channel responses. These terminal estimates are then quantized and return to the BS. In this aspirant solution, BS sends pilots to terminals via FDD. Consequently, terminals send pilots to BS again via TDD [7]. Yet, this scenario still has a side effect in limited channel coherence time, channel reciprocity calibration, and pilot contamination problem. Parameter estimation and detection in Massive MIMO systems using Zero-Forcing (ZF), Minimum Mean Square Error (MMSE), Matched Filtering (MF), Block-iterative Generalized Decision Feedback Equalization (BI-GDFE), Likelihood Ascent Search (LAS), etc. are presently under development to deliver its optimal solution [8]. Usually, channel state information (CSI) performed by inserting pilot symbols into subcarriers, and calculate using Interpolation method. But using Interpolation method needs plenty of a number of pilots to achieve better performance. Therefore, we did with Compressed Sensing to increase the performance by using a small number of pilots [9].

Recently compressed sensing (CS) shown that it can be applied to sparse channel estimation. CS algorithms can achieve higher correctness of channel status using a small number of pilots [9]. But it has high complexity. In CS, the measurement matrix should have a small correlation to achieve low complexity. So, we proposed a method to reduce the computational complexity. This research was directed to achieve good performance with low complexity in Compressed Sensing based Channel Estimation Algorithm for MIMO-OFDM Systems. One of the advantages of compressed sensing in MIMO-OFDM is that we can achieve good performance by using a lower number of pilots than Interpolation. However, the main problem of conventional CS in MIMO-OFDM is its high complexity. Especially if we apply the high order MIMO, the complexity will be even higher. Due to in conventional compressed sensing, CS algorithms are processed one by one on each channel. Consequently, we proposed CS method by using the same measurement matrix for CS algorithm process, subsequently we selected a small number of pilots randomly in the receiver side to obtain low computational complexity.

1.2 Motivation and Purpose

Our motivations for this works are: 1) It is an interesting research problem in wireless communication systems, especially for mobile telecommunication systems. 2) It is also projected to serve ultra-high speed transmission, highly reliable communication network, wider bandwidth, ultra-dense, and other demands. And MIMO-OFDM is one of several innovations and ideas which has been established to answer these demands.

Our purposes of this thesis are: 1) To improve and develop current compressed sensing based channel estimation algorithms in MIMO-OFDM systems. 2) To reduce the computational complexity of measurement matrix in the compressed sensing algorithm. 3) To achieve a good performance by implied a small number of pilots and low computational complexity.

1.3 Contributions of this thesis

The conventional compressed sensing in MIMO has two major problems. The first problem is the performance degradation due to incorrect impulse position detection for each channel. In our simulation, sometimes there is a mistake in detecting the CIR index position. The second problem is high complexity due to its large-sized measurement matrix. The objectives of this research are solutions of the major problems in our system:

1. For multiple antenna systems, assuming that the position of CIR in the time domain are almost same. We used an average process to reduce the AWGN noise component to find the correct positions of CIR and lead us to improve the performance of the channel estimation.

2. We used the same measurement matrices for all channel estimations of MIMO systems because the pilot arrangements of STBC MIMO system are the same resulting to a computational complexity.

3. In addition, we also proposed compressed sensing method by the selected small number of pilots randomly to reduce the complexity. By selected a small number of pilot, the measurement matrix size will be smaller and the computation complexity of the measurement matrix size will be reduced.

1.4 Organization

This thesis is organized as follows. Chapter 2 provides the details of literature for related work of compressed sensing based channel estimation for MIMO-OFDM systems. Chapter 3 gives brief information about our system model that we use in this work. We will also give a brief explanation of our proposed method. Chapter 4 describes the simulation result. We also will describe our next step, which is the evaluation of our work. Finally, Chapter 5 summarizes this work, with the conclusion, limitation, and suggestion to future work.

2 Compressed Sensing Based Channel Estimation in MIMO-OFDM System

2.1 MIMO-OFDM

2.1.1 OFDM

OFDM is basically a multicarrier transmission scheme that incorporates a multiplexed modulation technique. The basic concept of OFDM is data transmission through a number of subcarriers and each modulated at low rates. Thus, an OFDM signal can be said to consist of a set of narrowband carriers transmitted from the same source at different frequencies [3] [10].

One of the phenomena that occur in radio transmission systems is multipath fading, which is the occurrence of fluctuations in receiver power as the transmission signal travels through different fading paths. The received signal is the sum of the transmitted signals on multiple paths with varying damping and delays time. In the wideband system, if the transmission bandwidth is wider than the coherent bandwidth, then the signal will experience frequency selective fading, ie the signal will experience different treatment (response) by the channel for each frequency spectrum, either the phase or amplitude response.

Figure 2.1 shows an OFDM transmitter and receiver. In the transmitter side, it is composed of the modulation block, IFFT, add a cyclic prefix, and P/S. The information or data to be sent in the form of serial, and then converted into parallel. The modulator block maps the binary data onto complex symbol based on the complex modulation technique, such as QPSK and QAM. For example,

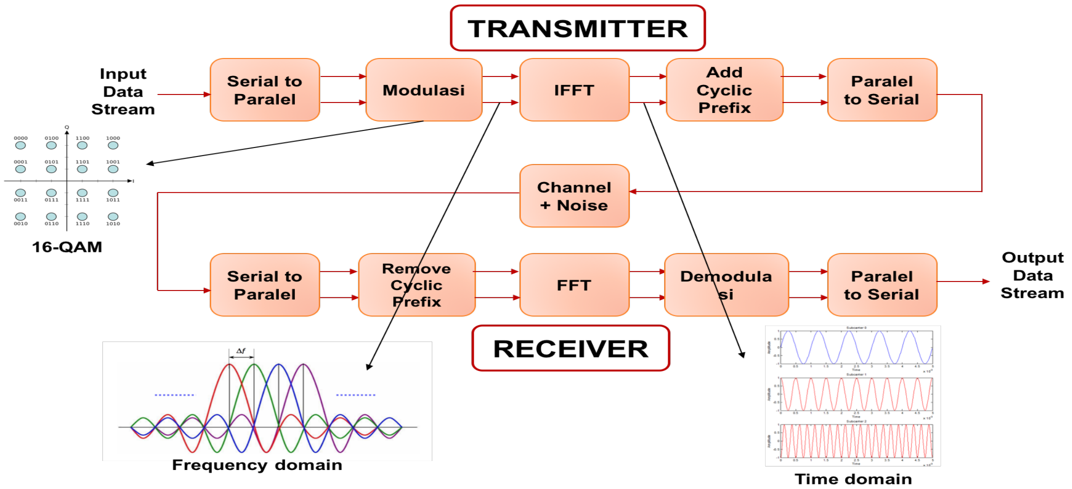

Figure 2.1: OFDM transmitter with spectrum

16-QAM modulation maps 4 bits to a complex symbol. These complex symbols are treated as frequency domain signals. The frequency domain signal is applied to IFFT to convert to the time domain signal. After that, the cyclic prefix is added as the carrier frequency separator overlaps each other. The cyclic prefix is a copy of the end of the OFDM symbol added at the beginning of the symbol. Using cyclic prefix will reduce ISI (inter-symbol interference) and ICI (inter-carrier interference). After the cyclic prefix is added, it is converted into serial form. Afterwards, the signal is transmitted. The transmitted signal in time domain can be expressed as, [3] [5]

$$y(t) = h(t) \otimes x(t) + n(t) \tag{2.1}$$

where

$$x(t) = \sum_{k=-\frac{T}{2}}^{\frac{T}{2}-1} X_k e^{\frac{j2\pi kt}{T}} \tag{2.2}$$

In OFDM transmission, multiple subcarriers are transmitted each carrying different data symbols to increase the data rate and throughput. Data coded in frequency domain view in Figure 2.1, visible OFDM signal arrangement, which generally consists of a set of subcarriers orthogonal to each other. The orthogonality allows overlapping spectral between the subcarriers, where the spectrum of each subcarrier has a zero value at the center frequency of the other adjacent subcarrier so there will be no interference between subcarriers. Therefore, OFDM is more efficient in bandwidth usage [10] [11].

Afterward, we consider a multipath environment where the impulse response between transmitter and receiver modeled as [12]

$$h(n) = \sum_{p=0}^{N_p-1} \eta_p(n)\delta(n - \tau_p(n)), \tag{2.3}$$

where N_p is the number of path, $\eta_p(n)$ is the amplitude gain, and $\tau_p(n)$ is the delay path.

The signal which comes out of the transmitter is a signal that overlaps each other so as the bandwidth usage more efficient. In OFDM, this overlapping condition does not cause interference between channels. At the receiver, the received signal is obtained by multiplying the data sequence by channel frequency response and adding additive white Gaussian noise. Then, the received signal corrupted by both AWGN and multipath fading is given by, [3] [5]

$$\mathbf{Y} = \mathbf{H}\ \mathbf{X} + \mathbf{Z} \tag{2.4}$$

where $\boldsymbol{Z}$ are zero mean complex Gaussian independent random variables representing AWGN. Afterward, the signal is converted from serial to parallel, then removes the cyclic prefix to get the original symbol. Then the signal is described in FFT block (Fast Fourier Transform) to separate carrier frequency with OFDM symbol. Afterward, the signal is demodulated and before it is received in the form of information, the signal is converted from parallel to serial.

2.1.2 MIMO

One of the phenomena that occur in radio transmission systems is multipath fading, which is the occurrence of fluctuations in receiver power as the transmission signal transmit through different fading paths. Multiple Input Multiple Output (MIMO) technology was first introduced by Jack Winters of Bell Laboratories in 1984, which is useful for overcoming multipath fading. MIMO is a system consisting of a number of transmitting and receiving terminals (antennas). Each antenna circuit for communication is combined to minimize errors and increase data rates. MIMO is one of several types of smart antenna technology. Unlike conventional antenna systems that are particularly vulnerable to multipath, MIMO system work best on multipath components. The multipath component is exploited to improve bandwidth diversity and efficiency [3] [13].

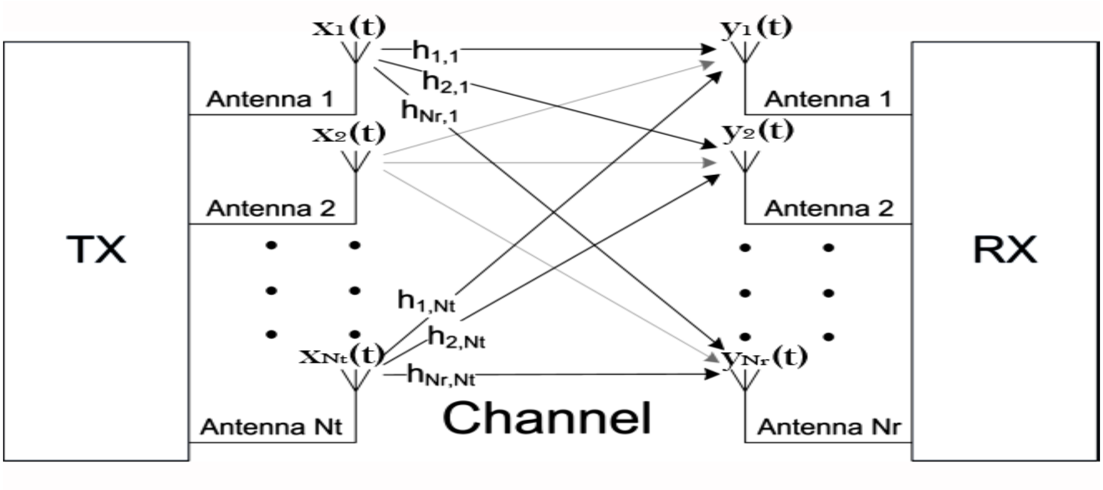

Figure 2.2: Block Diagram of MIMO

Figure 2.2 shows a MIMO system with multiple transmitter and receiver antennas. Let us assume that the signal from the k-th transmitter antenna. The received signal at the l-th receiver antenna is given by

$$y_l(t) = \sum_{k=1}^{N_t} h_{lk}(t)x_k(t) + n_l(t); l \in [1, \ldots, N_r] \tag{2.5}$$

where $n_l(t)$ is the additive white Gaussian noise at the l-th receiver antenna, N_t and N_r are the number of transmitter and receiver antennas, respectively $h_{lk}(t)$ is the complex attenuation factor between the k-th transmitter and l-th receiver antennas.

$$y(t) = H(t)x(t) + n \tag{2.6}$$

for all N_t signals, matrix notation is used:

$$\mathbf{y(t)}= \begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_{N_r}(t) \end{bmatrix}$$

,

$$\mathbf{H(t)}= \begin{bmatrix} h_{11}(t) & h_{12}(t) & \dots & h_{1N_t}(t) \\ h_{21}(t) & h_{22}(t) & \dots & h_{2N_t}(t) \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_r1}(t) & h_{N_r2}(t) & \dots & h_{N_rN_t}(t) \end{bmatrix} \tag{2.7}$$

,

$$\mathbf{x(t)}= \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_{N_t}(t) \end{bmatrix}$$

Matrix $\boldsymbol{H}$ is the MIMO channel matrix formed from the estimated h_{lk} value of the transmission channel. This matrix will be useful in retrieving the information signal at the receiver. The information signal is obtained by multiplying the pseudo inverse matrix of $\boldsymbol{H}$ with the received signal

$$H(t)y(t) = H(t)(H(t)x(t) + n(t)) = \tilde{x}(t) \tag{2.8}$$

The influence of multidimensional statistical characters from the MIMO Fading channel ($\boldsymbol{H}$ matrix) has a very significant role in system performance. Therefore, designing the MIMO channel model becomes an important thing.

In the MIMO system, the orthogonal space-time block code transmission method is one example of linear method codes. The orthogonal transmission scheme of space-time block code is a transmission scheme introduced by Alamouti [3] [5].

2.1.3 System Model

In wireless communication, MIMO-OFDM provides high data rates and are robust to multipath delay. We consider a MIMO-OFDM system with N_t transmitted antenna, N_r received antenna, N-subcarriers, P-subcarriers are used as pilots, and cyclic prefix length N_{CP}. The signal transmitted binary data stream drawn from quadrature phase-shift keying (QPSK) signal modulation.

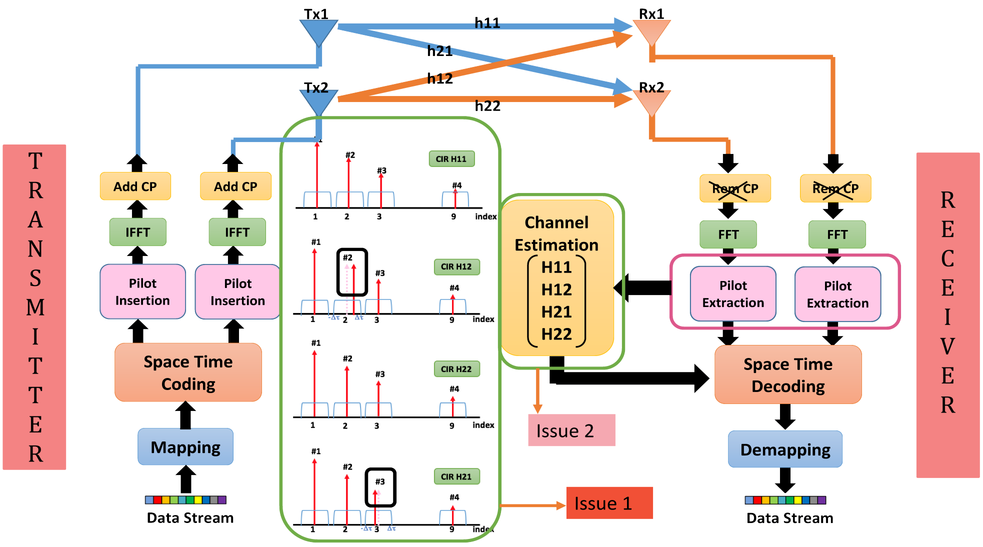

Figure 2.3: System Model of STBC 2 × 2 MIMO-OFDM

Figure 2.3 describes the general block diagram of our MIMO-OFDM system. In the 1st stage, we applied 2 × 2 Alamouti STBC MIMO with considered pilot placement to estimate the channel. The Alamouti method can be applied to obtain a higher order of diversity. In this case, it is possible to make a $2M$ order diversity with two transmitted antennas and M received antenna. In STBC, we transmitted 2 symbols signal. First, two symbols x_1 and x_2 transmitted on two different antennas at the same time on antenna 1 and antenna 2. Over the next symbol period, symbol -x_2^* is transmitted from antenna 1 and symbol x_1^* is transmitted from antenna 2. The received signal denotes as

$$y_1 = y_t = h_1 x_1 + h_2 x_2 + n_1 \tag{2.9}$$

$$y_2 = y_{t+T} = -h_1 x_2^* + h_2 x_1^* + n_2 \tag{2.10}$$

The received vector matrix after the first time slot is given by

$$\begin{bmatrix} y_1^1 \\ y_2^1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} n_1^1 \\ n_2^1 \end{bmatrix} \tag{2.11}$$

and received vector matrix over the next symbol time slot is given by

$$\begin{bmatrix} y_1^2 \\ y_2^2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} -x_2^* \\ x_1^* \end{bmatrix} + \begin{bmatrix} n_1^2 \\ n_2^2 \end{bmatrix} \tag{2.12}$$

By combining the (2.14), (2.11), and (2.12), we get

$$\begin{bmatrix} y_1^1 \\ y_2^1 \\ y_1^{2*} \\ y_2^{2*} \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \\ h_{12}^* & -h_{11}^* \\ h_{22}^* & -h_{21}^* \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} n_1^1 \\ n_2^1 \\ n_1^{2*} \\ n_2^{2*} \end{bmatrix} \tag{2.13}$$

We simulate the 2×2 STBC MIMO-OFDM system over multipath fading channel with 2048 subcarriers, leading subcarriers spacing of $\Delta f = 9.765$ kHz. The cyclic prefix (CP) duration equals 6.25 μs, and the number pilots are 128. The channel model which applied in this system are Extended Pedestrian A (EPA), Extended Vehicle A (EVA), and Extended Typically Urban (ETU). Table 2.1 shows the parameters of our simulation and the delay profile of our channel model described by Table 2.2 as EPA channel model, Table 2.3 as EVA channel moel, and Table 2.4 as ETU channel model [14].

Table 2.1: Parameters of 2×2 MIMO-OFDM

Parameters	Specification
Number of transmitted antenna	2
Number of received antenna	2
FFT size	2048
Modulation	QPSK
Pilots	128
Cyclic Prefix	1/16
Bandwidth	20 MHz
Channel model	EPA, EVA, ETU

Table 2.2: Extended Pedestrian A (EPA) delay profile

Tap number	Power [dB]	Delay [ns]
1	0	0
2	-1	30
3	-2	70
4	-3	90
5	-8	110
6	-17.2	190
7	-20.8	410

2.2 Compressed Sensing

2.2.1 Basic of Compressed Sensing

Before discussing the mathematical model of Compressed Sensing (CS), it is necessary to discuss the terminology associated with CS. These terminologies include signal sparsity, measurement matrix, and restricted properties of isometric property. This terminology is described in CS literature such as Hayashi et al [15].

Sparse Signal. Sparse signal states the number of nonzero elements in the signal. This sparsity level is expressed by sparsity k. For example, $k = 3$ states

Table 2.3: Extended Vehicular A (EVA) delay profile

Tap number	Power [dB]	Delay [ns]
1	0	0
2	-1.5	30
3	-1.4	150
4	-3.6	310
5	-0.6	370
6	-9.1	710
7	-7.0	1090
8	-12.0	1730
9	-16.9	2510

Table 2.4: Extended Typically Urban (ETU) delay profile

Tap number	Power [dB]	Delay [ns]
1	-1.0	0
2	-1.0	50
3	-1.0	120
4	0	200
5	0	230
6	0	500
7	-3.0	1600
8	-5.0	2300
9	-7.9	5000

that the signal contains 3 nonzero values. Figure 2.4 shows an example of a sparse signal in the time domain with sparsity $k = 3$.

Measurement Matrix. Measurement matrix is also known as sensing matrix. This matrix serves to reduce the number of samples to be the original signal. If the original matrix $\boldsymbol{x}$ consists of $\boldsymbol{n}$ elements, then to reduce the number of samples matrix $\boldsymbol{y}$ into element $m(m < n)$, then measurement matrix $\boldsymbol{A}$ dimension $m \times n$

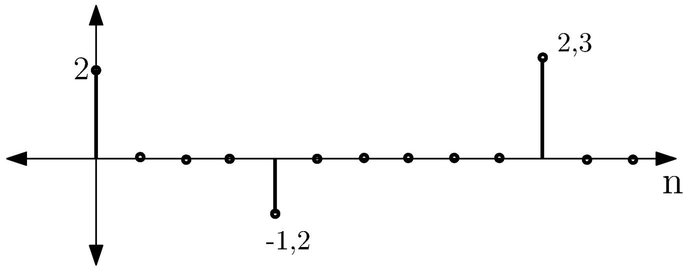

Figure 2.4: Sparse Signal in Time Domain

is required. The resulting signal $\boldsymbol{y}$is obtained by multiplying the $\boldsymbol{x}$ signal by measurement matrix $\boldsymbol{A}$.

$$\mathbf{y} = \mathbf{A} \ . \ \mathbf{x} \tag{2.14}$$

In equation (2.14), signal y dimension $m \times 1$, matrix $\boldsymbol{A}$ dimension $m \times n$, and matrix $\boldsymbol{x}$ dimension $n \times 1$. The signal $\boldsymbol{x}$ is called the sparse signal and the signal $\boldsymbol{y}$ is called the measurement signal.

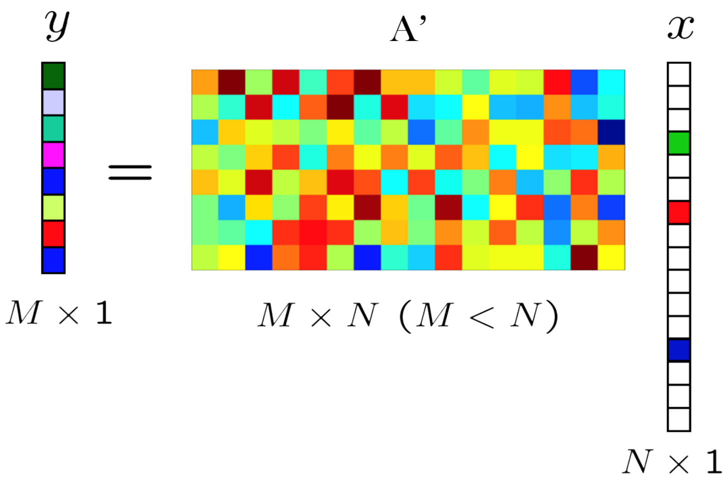

Figure 2.5: Illustration of Compressed Sensing

Restricted Isometric Property (RIP). Another important issue in CS is to select a measurement matrix $\boldsymbol{A}$ such that the original $\boldsymbol{x}$ signal can be returned from the $\boldsymbol{y}$ measurement. Emmanuel Candes [24] briefed the requirements of a measurement matrix $\boldsymbol{A}$ called RIP. A measurement matrix $\boldsymbol{A}$ is said to be RIP if it meets the following conditions:

$$(1 - \delta_s).|x|_2 \leq |A.x|_2 \leq (1 + \delta_s).|x|_2 \tag{2.15}$$

With δ_s is a small number.

2.2.2 Reconstruction Algorithm in the Literature

The purpose of CS is to do a sampling of sparse signal $x(n)$ to obtain the sampled signal $y(n)$ which has fewer samples than $x(n)$. Reduction of this sample is done so that it is possible to recover the original signal $x(n)$ through the reconstruction process. The sampling process is expressed by equation (2.14) for a compressive measurement matrix $\boldsymbol{A}$. Figure 2.5 shows the illustration of CS. The problem of reconstruction to be solved if $y(n)$ is the result of CS and the measurement matrix $\boldsymbol{A}$ is given, how to recover this $x(n)$ signal. There are 2 main schemes to solve the reconstruction problem, namely: base pursuit (BP) and greedy [16] [15]. And in this thesis, we will discuss the greedy algorithm.

The greedy algorithm scheme was theoretically pioneered by Friedman and Stuetzle [17] in his study of regression projection pursuit as the solution of a linear equation. The compressive sensing problem as represented in equation (2.14), in the greedy scheme, is seen as the linear combination problem of each column (basis) of the measurement matrix $\boldsymbol{A}$, with the combination using coefficients at $\boldsymbol{x}$. The greedy scheme performs the inverse step of the linear combination. The inversion process begins by finding the nearest base of $\boldsymbol{A}$, which is closest to the $\boldsymbol{y}$ measurement vector. The nearest base is taken as the base that gives the largest $\boldsymbol{y}$ projection result. The projected value is multiplied by $\boldsymbol{y}$ and subtracted by the selected base, and yields a residue. The next closest base is searched for this residual projection to the remaining base. Thus the process is repeated so that the residual value is less than a threshold value.

The term matching pursuit is used by Mallat and Zhang to describe the process of finding the basis of the signal. If each base is orthogonal, the Matching Pursuit scheme proposed by Mallat and Zhang becomes an Orthogonal Matching Pursuit

(OMP) scheme. OMP is one of the popular algorithms in CS that was introduced by Tropp [18]. Tropp formulates the OMP scheme as follows:

1. Initialization of the process with basis $A_1, A_2, ...A_n$, and the initial residue $r_1 = y$
2. Select base A_i that maximizing inner product: max $(< A_j, r_i >)$ for all j
3. Calculate the residue r_i for the next iteration: $r_i = r_i - 1- < A_i, r_i > .r_i$
4. Repeat steps 2 and 3 above until the residual value is smaller than a threshold

2.3 Relative researches

Compressed sensing is a recently introduced principle and methodology for the efficient reconstruction of sparse signals from few samples. Compressed sensing provides a new mind on how to acquire and process signal, as long as the signal is sparse in a certain transform domain [16] [15].

Recently, many approaches focus on reducing the computational complexity of compressed sensing algorithm. Such study [19] have proposed measurement matrix optimization by selected small number of pilots that achieved a good performance with low complexity in SISO-OFDM system. On the other hand, reference [20] and [12] proposed pilot arrangements in several compressed sensing algorithms to meet the best performance and low computational complexity.

3 Computational Complexity Reduction and Accuracy Improvement Method

3.1 Proposed Method

The conventional system has two major problems. The first problem is the performance degradation due to incorrect impulse position detection for each channel. In our simulation, sometimes there is a mistake to detect the CIR index position. For example, the right position of CIR index should be at 2. But in the simulation, we found the different position and it makes this performance worse. The second problem is how to reduce the complexity in CS algorithm. In CS part, because we have 4 different channel in 2×2 MIMO, there are 4 different processing in sensing matrix algorithm. For example, we applied OMP method, we processed 4 times OMP (for each channel) method that caused high complexity. Figure 3.1 and Figure 3.2 shows the illustration of the 1st issue and 2nd issue.

To solve the problem, we proposed a solution which illustrated in figure 3.3. Assuming that the position of CIR in the time domain are almost same. Therefore, we can use the average process to reduce the AWGN noise component to find the correct positions of CIR which its vital for CS based channel estimation. The average process increases the robustness to noise due to the enhanced accuracy of the reference coefficients and leads us to improve the performance of the channel estimation. In the other hand, for STBC MIMO, the pilot matrix of multiple antennas are same. Therefore, we can use the same measurement matrix for CS algorithm process to reduce its computational complexity.

Figure 3.4 and Figure 3.5 shows why we can use the same measurement ma-

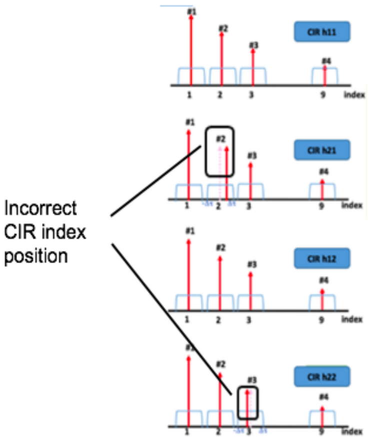

Figure 3.1: 1st Issue of STBC 2×2 MIMO-OFDM

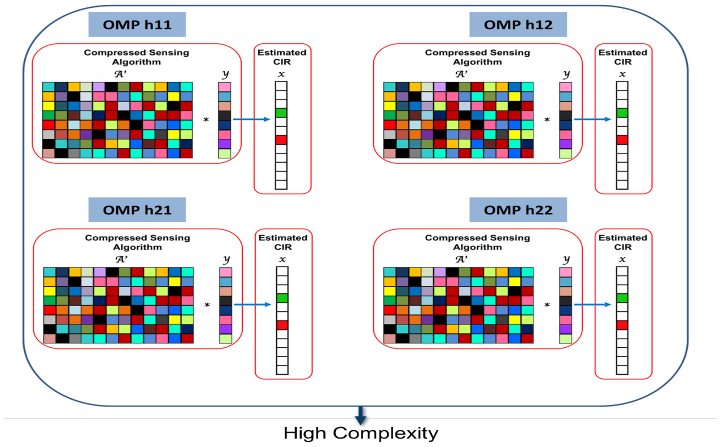

Figure 3.2: 2nd Issue of STBC 2×2 MIMO-OFDM

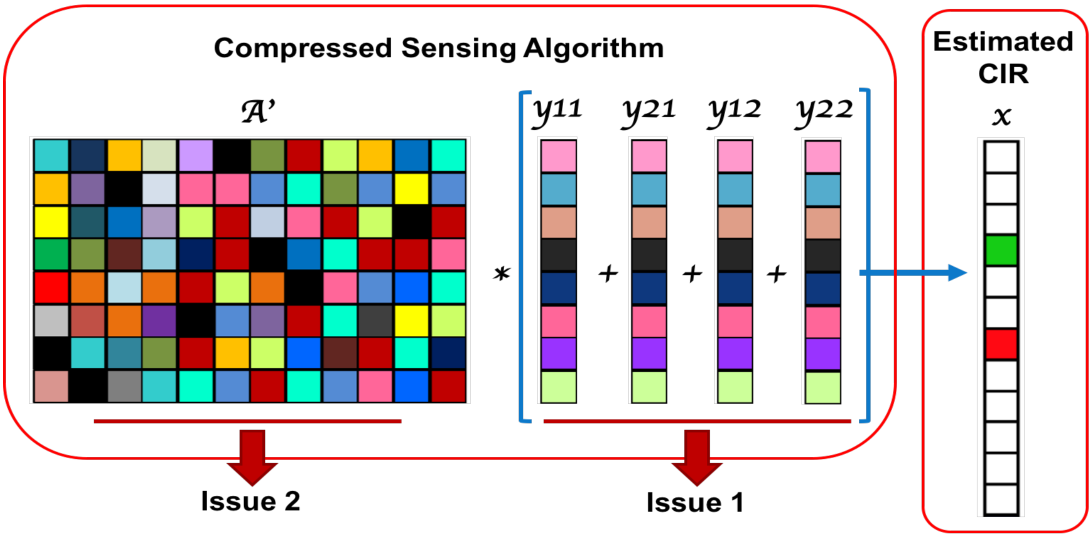

Figure 3.3: Illustration of Proposed Method for the Issues

trix based on the pilot arrangement. For example, the red ones shows the pilot arrangement for symbol x_1 in antenna 1 and the green one shows the pilot arrangement for symbol x_2 in antenna 2. Over the next symbol period, symbol $-x_2^*$ is transmitted from antenna 1 and symbol x_1^* is transmitted from antenna 2.

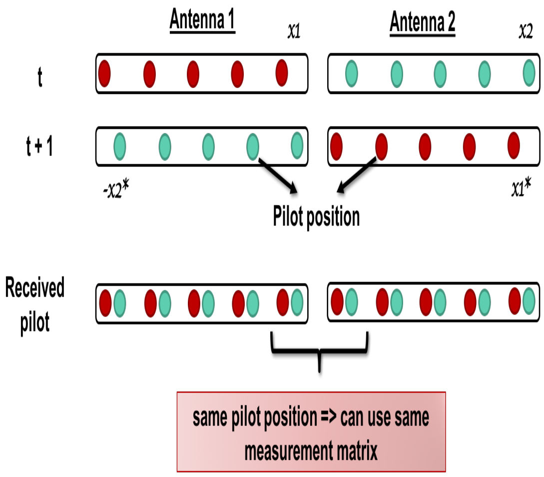

Figure 3.4: 1st Pilots Arrangement

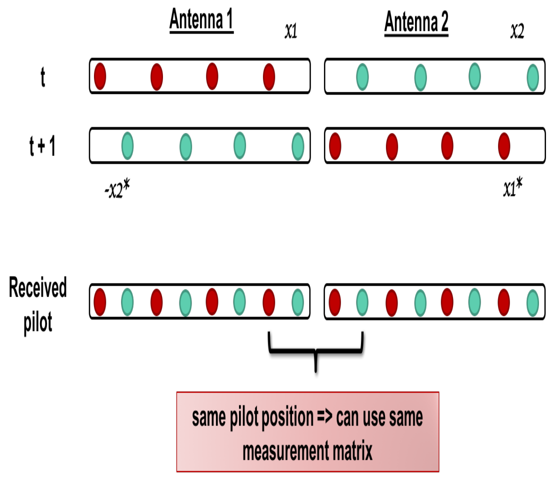

Figure 3.5: 2nd Pilots Arrangement

And then we received same information of pilot position both from antenna 1 and antenna 2. Therefore, we used the same measurement matrix for CS and reduced the computational complexity. We considered two pilot placement scheme. In the Figure 3.5, the pilots generated by linear form $f_1(n) = 16n - 1$ for antenna 1 and $f_2(n) = 16n$ for antenna 2. Thereupon, linear for for pilot placement in Figure 3.6 generated from $f_1(n) = 16n - 8$ for antenna 1 and $f_2(n) = 16n$ for antenna 2. Noted that n is an integer value.

In addition, we also proposed low complexity CS based channel estimation by randomly selected small number of pilots to optimize the matrix vector of measurement matrix. Figure 3.6 the illustration of proposed method by randomly selected a small number of pilots. In this illustration, we have the measurement matrix A dimension $M \times N$, and observed vector dimension $M \times 1$. And then, we selected some pilots randomly and obtained the new measurement matrix A dimension to be $L \times N$, and observed vector dimension to be $L \times 1$. Where L value less than M value. If we selected a small number of pilot, the measurement matrix size will And the computation complexity is linear to the measurement matrix size. And also, a small number of pilots means lower complexity. Previously, this idea had been applied in the SISO-OFDM systems [19], and then we applied in MIMO systems.

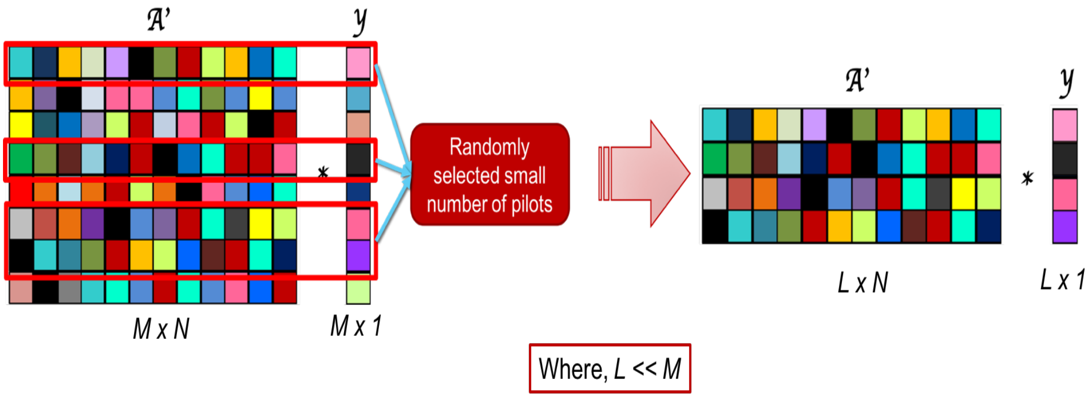

Figure 3.6: Illustration of Proposed Method by Randomly Selected a Small Number of Pilots

3.2 Compressed Sensing Algorithms

In this system, we apply OMP, CoSaMP, and SAMP algorithms for channel estimation.

3.2.1 Orthogonal Matching Pursuit (OMP)

Orthogonal Matching Pursuit (OMP) algorithm is one of a classical and popular algorithm. The process of OMP algorithm is to selects an index of the highest coherence between the residual vector r_t and column of measurement matrix $\boldsymbol{A}$. The advantage of OMP algorithm is its simplicity and fast implementation. The algorithm of OMP stated as [15]

OMP never select the same index twice since the residual is orthogonal to the already chosen column vectors. The loop of OMP algorithm stops after K_max iteration.

3.2.2 Compressive Sampling Matching Pursuit (CoSaMP)

Compressive Sampling Matching Pursuit (CoSaMP) is an improvement of OMP algorithm. The process of a CoSaMP algorithm is to find the index of the $2K_{max}$ highest coherence between the residual vector r_t and column of measurement

Table 3.1: Orthogonal Matching Pursuit (OMP) Algorithm

Imput: Measurement matrix $\boldsymbol{A}$, observation vector $\boldsymbol{y}$
Action:
Initialize the residual $r_0 = y$, subset index $\Gamma_0 = \emptyset$
Presents the iteration counter $t = 1$
Find the maximum index and update the subset index $\Gamma_{t+1} = \Gamma_t \cup (argmax_i \vert c_t(i))$
Obtaining suboptimal $x_{t+1} = argmin_\mu \vert\vert y - A_{\Gamma_{t+1}} \mu \vert\vert_2$
Update residu $r_{t+1} = y - A_{\Gamma_{t+1}} x_{t+1}$
Calculated a new estimated value $t = t + 1$
Output: k-sparse signal x by OMP

matrix $\boldsymbol{A}$. CoSaMP requires the level of sparsity K as a priori information to determine the number of iteration. Therefore, we assume that the sparsity K in known [15]. In this simulation, we set sparsity level $K = 10$. The algorithm of CoSaMP stated as

Table 3.2: Compressive Sampling Matching Pursuit (CoSaMP) Algorithm

Input: Measurement matrix $\boldsymbol{A}$, observation vector $\boldsymbol{y}$, maximum sparsity K_{max}
Action:
Initialize the residual $r_0 = y$
Approximated sparse vector x_t at iteration $t(x_0 = 0)$
Presents the iteration counter $t = 1$
Find the index of $2K_{max}$ and update the subset index $\Lambda = supp([c_t]_{2K_{max}})$; $\Gamma_{t+1} = \Lambda \cup supp(x_t)$
Obtaining suboptimal $v\vert_{\Gamma_{t+1}} = argmin_\mu \vert\vert y - A_{\Gamma_{t+1}} \mu \vert\vert_2$
Obtain the approximated sparse vector at the current iteration $x_{t+1} = [v]_{K_{max}}$
Update residu $r_{t+1} = y - Ax_{t+1}$
Calculated a new estimated value $t = t + 1$
Output: k-sparse signal x by CoSAMP

3.2.3 Sparsity Adaptive Matching Pursuit (SAMP)

Sparsity Adaptive Matching Pursuit (SAMP) also improvement of OMP algorithm. Different from CoSaMP which required the level of sparsity K, SAMP generalize when the level of sparsity K is unknown and does not require K as a priori information. SAMP algorithm obtain requires to define the step size s which obtain a faster recovery speed than OMP, where $s \leq K$. In this simulation we set $s = 1$. The algorithm of SAMP stated as [12]

Table 3.3: Sparsity Adaptive Pursuit Matching Pursuit (SAMP) Algorithm

Imput: Measurement matrix $\boldsymbol{A}$, observation vector $\boldsymbol{y}$, step size s
Action:
Initialize the residual $r_0 = y$, subset index $\Gamma_0 = \emptyset$,
size in the first stage $I = s$, stage index $j = 1$
Presents the iteration counter $t = 1$, stage index $s = 1$
Find the maximum index and update the subset index $S_{t+1} = \Gamma_t \cup (argmax(\lvert\Phi r_t\rvert, I)$
Obtaining suboptimal $x_{t+1} = argmax(\lvert\Phi_{S_{t+1}} y\rvert, I)$
Compute the residu $r_{t+1} = y - \Phi_{\Gamma_{t+1}} y$
Stage switching $\lvert\lvert r\rvert\rvert_2 \geq \lvert\lvert r_t\rvert\rvert_2$
Update the stage index $j = j + 1$
Update the residu $r_{t+1} = r$
Calculated a new estimated value $t = t + 1$
Output: k-sparse signal x by SAMP

4 Simulation Result

4.1 Bit Error Rate (BER) Performance for Proposed CS Process

First, we compare the BER performance of our OMP proposed method with Interpolation and OMP conventional methods for a MIMO-OFDM system in EPA channel model, shown in Figure 4.1. Conventional CS here means we still used 4 times OMP CS process and Proposed CS means only 1-time OMP CS processed by used the same measurement matrix. From the Figure 4.1, we observed that by using the same measurement matrix, we get better performance and we also have lower complexity in matrix sensing.

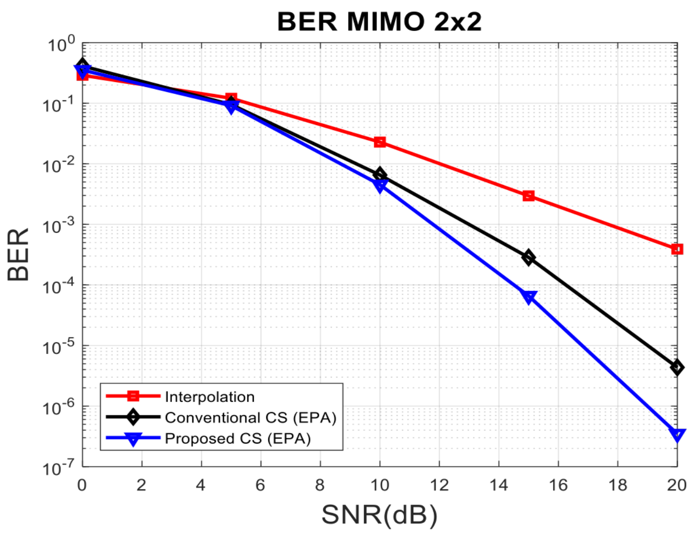

Figure 4.1: BER Performance of Interpolation, Conventional, and Proposed CS

Besides comparing BER performance with Interpolation method, Figure 4.2 and Figure 4.3 describes the comparison of a classic greedy matching pursuit of OMP algorithm with two others algorithms, namely CoSaMP and SAMP in EPA channel model. In general simulation result, Figure 4.2 showed that SAMP algorithm is a compressed sensing signal reconstruction algorithm with better BER performance than OMP and CoSaMP algorithm. Both CoSaMP and SAMP algorithm are an improvement from OMP algorithm. However, the SAMP is always more accurate than OMP and CoSaMP although it may require fewer iteration in its process. SAMP algorithm also found the CIR index faster than OMP because we set the step size s in the initial stage. In addition, when $s = K$, SAMP only needs one stage to find the sparse index. Despite the BER performance of CoSaMP slightly better than OMP, but the complexity of CoSaMP algorithm higher than OMP. As we discussed in Chapter 3, CoSaMP required sparsity level as a priori information for exact recovery.

Meanwhile, in Figure 4.3 there is a conventional CS process which also compared with interpolation and proposed CS process. In general, the simulation results show a similar performance analysis with Figure 4.2 for each algorithm. In addition, proposed CS process achieved better BER performance than conventional CS.

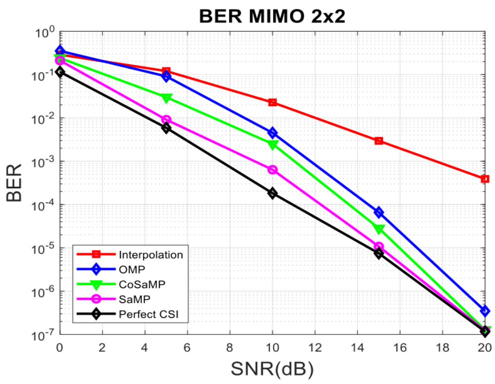

Figure 4.2: BER Performance of Interpolation and Proposed CS for OMP, CoSaMP, and SAMP Algorithm

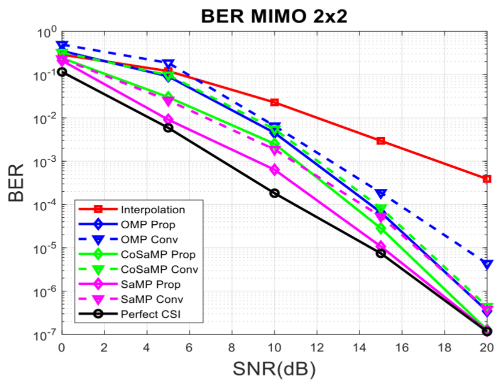

Figure 4.3: BER Performance of Interpolation, Conventional, and Proposed CS for OMP, CoSaMP, and SAMP Algorithm

4.2 Bit Error Rate (BER) Performance for Proposed Randomly Selected Small Number of Pilots

The simulation result of our proposed method by a randomly selected small number of pilots is shown in Figure 4.4, 4.5, and 4.6. Figure 4.4 performs that our proposed OMP algorithm for channel estimation with a randomly selected small number of pilots at the receiver side can achieve n identically BER performance than the conventional OMP algorithm with a large number of pilots. Similarly in CoSaMP and SAMP algorithm that showed in Figure 4.5 and 4.6, by selected a small number of pilots achieved an identically BER performance than the conventional CS algorithms.

A small number of pilots obtained a small size of measurement matrix, which has low complexity. By optimizing of measurement matrix, our proposed method reduced the complexity to 50%. Figure 4.7 compares the size of observation vector matrix using conventional CS and proposed CS. From this figure, it can be seen that proposed CS decreased the observation vector matrix to 75% compared with conventional.

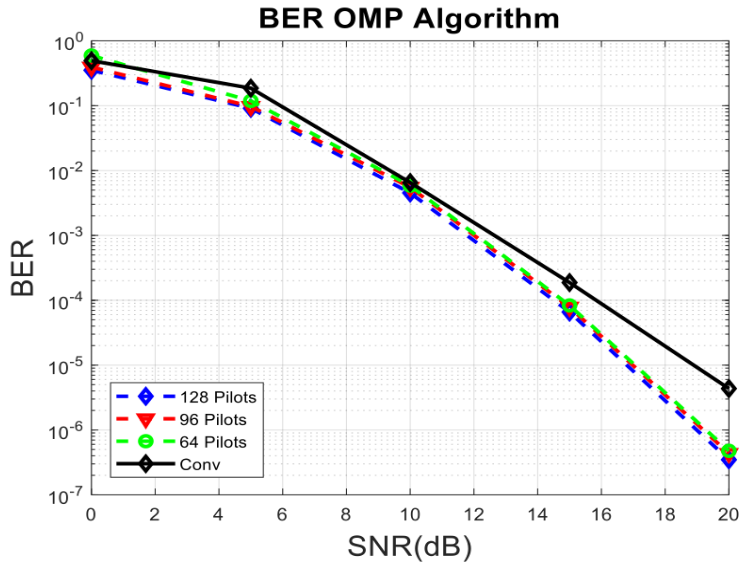

Figure 4.4: BER Proposed OMP Algorithm with Randomly Selected 128 Pilots, 96 Pilots, and 64 Pilots

4.3 Bit Error Rate (BER) Performance for MIMO-OFDM System over Different Channel Model and Different Pilots Arrangement

Figure 4.8 and Figure 4.9 show the comparison of BER performance of OMP algorithm with 96 Pilots and 64 Pilots in 3 different channel models, namely EPA, EVA, and ETU channel model. At the environment, ETU channel had been changed rapidly that caused the performance not as good as the EVA and EPA channel models. The characteristic of each channel is showed based on the delay profile. Figure 4.10 and Figure 4.11 describes the BER performance with different pilots arrangement. The 2nd pilots' arrangement more scattered than the 1st arrangement which showed in the previous section. According to the simulation result, between the 1st and the 2nd pilot's arrangement achieved identically BER performance. However, the 2nd arrangement is a bit achieve

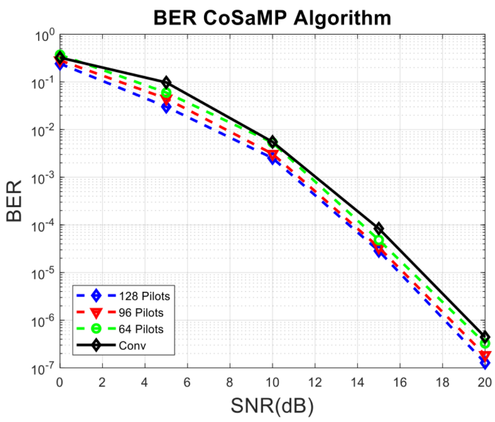

Figure 4.5: BER Proposed CoSaMP Algorithm with Randomly Selected 128 Pilots, 96 Pilots, and 64 Pilots

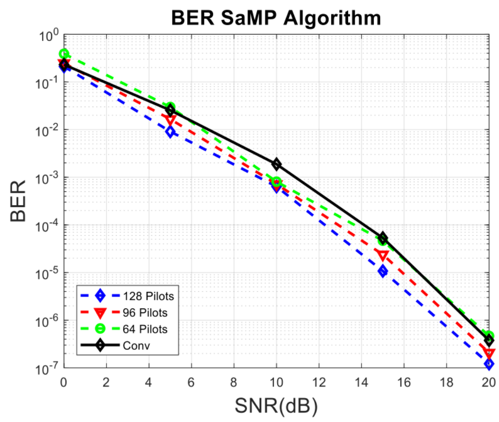

Figure 4.6: BER Proposed SAMP Algorithm with Randomly Selected 128 Pilots, 96 Pilots, and 64 Pilots

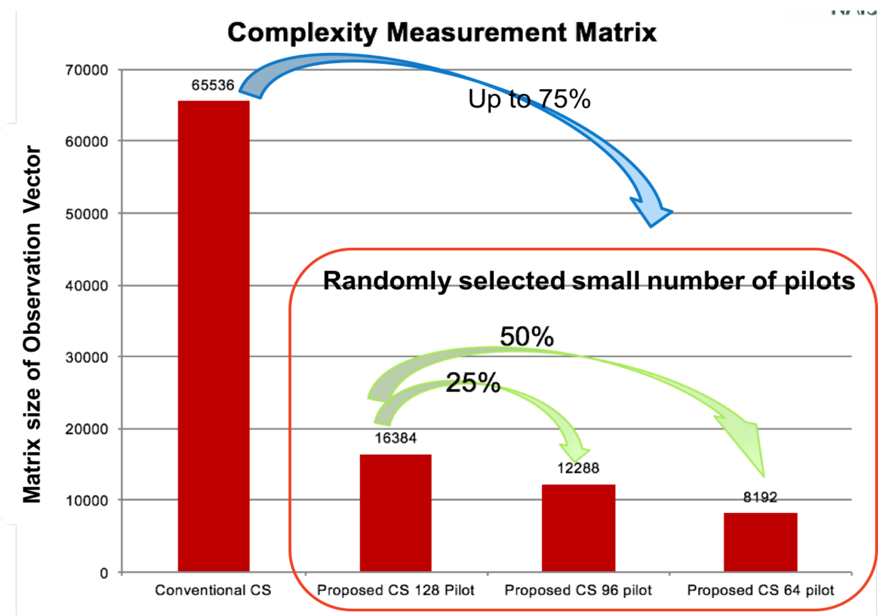

Figure 4.7: Complexity of Measurement Matrix

better than the 1st even though the difference not much significant.

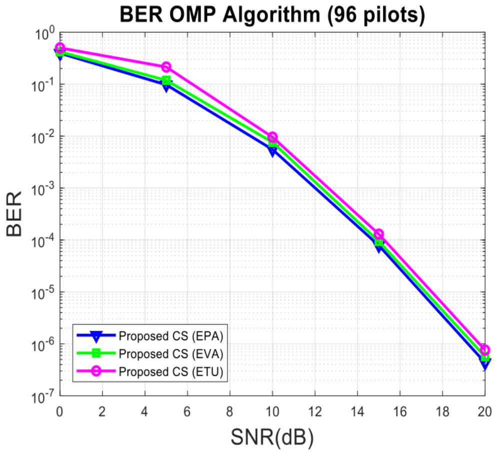

Figure 4.8: BER OMP Algorithm with 96 Pilots in EPA, EVA, and ETU Channel Model

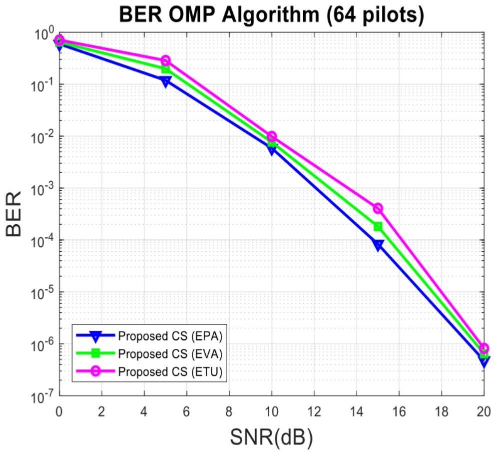

Figure 4.9: BER OMP Algorithm with 64 Pilots in EPA, EVA, and ETU Channel Model

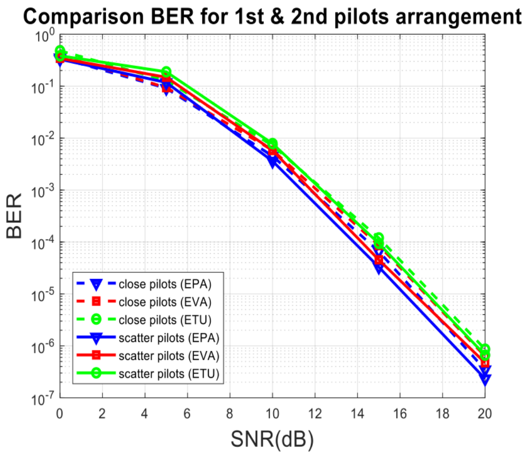

Figure 4.10: Comparison of BER OMP Algorithm between Close and Scatter Pilots Arrangement

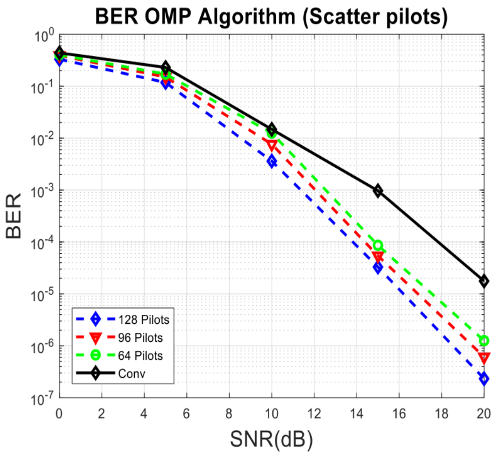

Figure 4.11: BER Scatter Pilots Arrangement with Randomly Selected 128 Pilots, 96 Pilots, and 64 Pilots

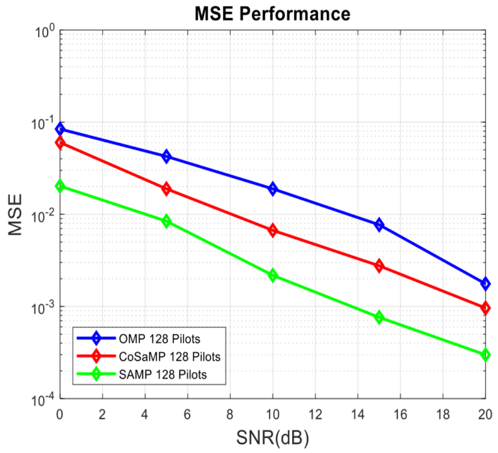

Figure 4.12: MSE Performance of OMP, CoSaMP, SAMP Algorithm with 128 Pilots

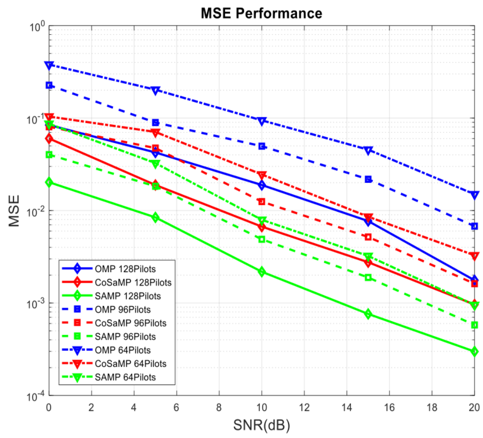

Figure 4.13: MSE Performance of OMP, CoSaMP, SAMP Algorithm with 64, 96, and 128 Pilots

4.4 Mean Square Error (MSE) Performance for MIMO-OFDM System

Figure 4.12 and 4.13 plots the MSE of OMP, CoSaMP, and SAMP algorithms versus SNR. Figure 4.12 shows that CoSaMP has a better performance than OMP algorithm. Similarly, SAMP algorithm achieved better performance than OMP and CoSaMP. According to Figure 4.13, as the number of the pilot are decreases, the MSE performance increases for all algorithms. Moreover, SAMP algorithm with 96 pilots achieved a better MSE performance than CoSaMP and OMP algorithm with 128 pilots. In addition, the SAMP algorithm with 64 pilots achieved identically MSE performance with a CoSaMP algorithm with 128 pilots. In the other words, for the same level of MSE performance, the SAMP algorithm uses a fewer number of pilots than OMP and CoSaMP algorithm.

5 Conclusions and Future Research

5.1 Conclusions

On wireless communication system, the channel has an important role in determining the quality of the signal transmission from the transmitter to receiver. In this works, we should figure out the characteristic of the channel to meet the good performance of transmitting signal. The generally used channel estimation algorithm is Interpolation method that needs plenty of a number of pilots to achieve better performance. Therefore, we did by applied compressed sensing to increase the performance by using small number of pilots. However, CS methods have high complexity. The objective of this thesis was to achieve good performance with low complexity in compressed sensing algorithm by selected small number of pilots for a MIMO-OFDM system.

We have proposed a 2×2 STBC MIMO-OFDM system. We reduced the computational complexity by optimized the measurement matrix. We selected randomly small number of pilots in the CS algorithm in order to lower the complexity in comparison to conventional CS. A small number of pilots obtained small size measurement matrix, which has low complexity. The simulation results showed that our proposed method provides a good BER performance for the channel estimation. Furthermore, our proposed CS method reduced computational complexity down to 75%. The OMP applied the existing OMP algorithm but also we keep performance is comparable with other algorithms such as CoSAMP and SAMP algorithm. The simulation result confirmed that SAMP algorithm achieved better BER performance for compressed sensing signal reconstruction than OMP and CoSAMP algorithm.

5.2 Future Research

This research was not deep and comprehensive. We applied a simple 2×2 MIMO-OFDM system over multipath fading channel without considering the Doppler shift. We can increase the challenge by apply the high order MIMO-OFDM to get better analysis. For the CIR detection, we assumed that all the CIR index position for all channel are the same. Whereas in the real environment, the CIR index position is not exactly same for each channel. It would have better if we also consider the system applied in the real environment. On the other hand, there are some methods that focus on the pilot's arrangement to improve the performance.

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References

[1] NTT DOCOMO, INC. 5G Radio Access : Requirements, Concept, and Technologies. July, 2014.

[2] Datang Telecom Technology and Industry Group. Evolution, Convergence, and Innovation 5G white paper. Datang Wireless Mobile Innovation Center, December, 2013.

[3] Cho, Yong Soo, Won Young Yang, Chung-Gu Kang. MIMO-OFDM Wireless Communicatios with MATLAB. Singapore. 2010.

[4] Youssefi, M. A., and El Abbadi, J., "Optimal pilot-symbol patterns for MIMO OFDM systems under time varying channels," *Journal of Theoretical and Applied Information Technology*, 65(1), 183–191. 2014

[5] Andrea Goldsmith. Wireless Communications. Stanford University. 2005

[6] http://www.sharetechnote.com/html/CommunicationChannelEstimation.html/ referred January, 7 2018.

[7] Arman Farhang, Nicola Marchetti, Fabricio Figueiredo, and Joao Paulo Miranda, "Massive MIMO and Waveform Design for 5th Generation Wireless Communication Systems," *IEEE Communication Magazine and Journal*, 2014.

[8] Kan Zheng, Long Zhao, Jie Mei, Bin Shao, Wei Xiang, and Lajos Hanjo, "Survey of Large-Scale MIMO Systems," *IEEE Communication Surveys and Tutorials*, Vol 17, No. 3. Third Quarter. 2015.

[9] Chun-hui Ma, Chun-yun Xu, Lei Shen, and Shi-lian Zheng. A Fast Sparsity Adaptive Matching Pursuit Algorithm for Compressed Sensing. China Electronic Technology Corporation, Jiaxing 314001, China lancer711@163.com

[10] Stüber, G. L., Barry, J. R., Mclaughlin, S. W., Li, Y. E., Ingram, M. A., and Pratt, T. G., "Broadband MIMO-OFDM wireless communications," *Proceedings of the IEEE*, (Vol. 92, pp. 271–293), 2004.

[11] Van Zelst, A., and Schenk, T. C., "Implementation of a MIMO OFDM-based wireless LAN system," *IEEE Transactions on Signal Processing*, 52(2), 483–494, 2004.

[12] Zhang, Y., Venkatesan, R., Dobre, O. A., and Li, C., "Novel Compressed Sensing-Based Channel Estimation Algorithm and Near-Optimal Pilot Placement Scheme," *IEEE Transactions on Wireless Communications*, Vol. 15, no. 4, pp. 2590–2603, April, 2016.

[13] Abbas, Waseem and Abbas, Nasim and Majeed, Uzma and Khan, Sadaf and Rawalpindi, "EFFICIENT STBC FOR THE DATA RATE OF MIMO-OFDMA," *Science International Journal*, 1013-5316, 2016.

[14] Mathworks."Documentation". http://www.mathworks.com/help/referred January, 7 2018.

[15] Hayashi, K., Nagahara, M., and Tanaka, T., "A user's guide to compressed sensing for communications systems," *IEICE Transactions on Communications*, vol. E96-B, no. 3, pp. 685-712, Mar. 2013.

[16] Hui Xie. Sparse Channel Estimation in OFDM System. Electronics. UNIVERSITE DE NANTES, SOUTH CHINA UNIVERSITY OF TECHNOLOGY, Guangzhou, China, 2014.

[17] J. H. Friedman and W. Stuetzle, "Projection pursuit regression," *Journal of the American Statistical Association*, Vol. 76, No. 376, pp. 817-823, Dec, 1981.

[18] J. A. Tropp, "Greed is good : Algorithmic results for sparse approximation," *IEEE Transactions on Information Theory*, Vol.50, No.10, 2004.

[19] Rian Ferdian, Ratih H. Puspita, Yafei Hou, Minoru Okada, "Low Complexity Compressed Sensing Based Channel Estimation with Measurement Matrix Optimization for OFDM System," *IEICE Technical Report*, 2016.

[20] He, X., Song, R., and Zhu, W.-P., "Pilot Allocation for Distributed Compressed Sensing Based Sparse Channel Estimation in MIMO-OFDM Systems," *IEEE Transactions on Vehicular Technology*, 65(5), 2990–3004, 2016.

[21] Reinoso Chisaguano, Di. J., Hou, Y., Higashino, T., and Okada, M., "Low-Complexity Channel Estimation and Detection for MIMO-OFDM Receiver with ESPAR Antenna," *IEEE Transactions on Vehicular Technology*, 65(10), 8297–8308, 2016.

[22] Yanbo Wei 1 , Zhizhong Lu 1,*, Gannan Yuan 1 , Zhao Fang 1 and Yu Huang 2. Sparsity Adaptive Matching Pursuit Detection Algorithm Based on Compressed Sensing for Radar Signals. Sensors 2017, 17, 1120; doi:10.3390/s17051120

[23] Gabor Fodor, Piergiuseppe Di Marco, and Miklos Telek, "Performance Analysis of Block and Comb Type Channel Estimation for Massive MIMO Systems," *IEEE Communication Magazine and Journal*, 2014.

[24] E. Candes, "Compressive sampling," *Proceedings of the International Congress of Mathematicians*, Madrid, Spain, 2006.