

MIMO-OFDM BASED COGNITIVE RADIO NETWORKS

Sarun Babu

P.G Student, Mount Zion College Of Engineering, Kadammanitta

Abstract: MIMO-OFDM is considered to be one of the most promising technologies for further generation mobile communication systems like 3GPP LTE. At the same time Cognitive Radio (CR) was also proposed to enhance the utilization of the spectrum usage. Thus, the combination of MIMO-OFDM and Cognitive Radio, MIMO-OFDM based Cognitive Radio technology is treated as a prospect scheme for future dynamic spectrum access network or spectrum sharing system. Since only a finite number of subcarriers are occupied by the primary users (PUs) in CR networks, the secondary users (SUs) can detect the spectrum holes (the unoccupied subcarriers) and opportunistically access those unoccupied spectrum subcarriers. In traditional MIMO-OFDM system, the signals received in each antenna are sampled by an individual analog-to-digital converter (ADC). Which will increase of front-end cost. Thus, the problem is how to design efficient receiving scheme for reducing the power consume and hardware cost in MIMO system. Considering the sparsity property of the received signals, we proposed a novel spectrum sensing scheme for the MIMO-OFDM based CR network by exploiting compressive sensing technology in this paper. Different to traditional MIMO-OFDM system, by exploiting the sparsity model, the signals received in our receivers are mixed together from multiple antennas and then sampled by a single ADC. Thus, the hardware cost and energy consumption can be significantly reduced in our scheme. Besides, our proposed scheme can detect the spectrum usage without the prior information of sparsity, which is also suitable for the real wireless application environment.
Index Terms: Compressive sensing; MIMO-OFDM; Cognitive Radio, Spectrum Sensing, ADC;

I. INTRODUCTION

BOTH MIMO and OFDM techniques have received widely attention in past few years. For OFDM, it can effectively avoid frequency selective fading. Besides, inter channel interference (ICI) and inter symbol interference (ISI). For MIMO, it can increase the transmission capacity by exploiting space diversity technology. The combination of MIMO and OFDM techniques can significantly improve the transmission performance of wireless system. Thus, MIMO-OFDM have also been adopted as the standards of many wireless systems, such as WiMax, 3GPP LTE. Cognitive Radio considered as a promising technology to promote the efficiency of spectrum usage in recently. In CR system, the SUs detect the spectrum holes which are the spectrum bands that are not occupied by the PUs currently and then access those unoccupied spectrum bands for their own communication. By combining MIMO-OFDM technology with CR module, the MIMO-OFDM based CR technology can

have great potential in the application of future dynamic spectrum access network and spectrum sharing system. Compared to traditional MIMO-OFDM system, there are only one ADC in receiver to sample the mixed signals from all channels in our scheme. Since only a part of subcarriers are used by the PUs, the whole subcarriers are sparse in frequency domain. Thus, the transmission signals can be recovered by exploiting the compressive sensing (CS) technology. By estimating the transmission signals, the usage of subcarriers can also be detected at same time.

II. SYSTEM MODEL

We consider a MIMO-OFDM based CR network by exploiting sparse signal modeling. First we consider an OFDM primary user in a MIMO system with N_p transmitting antennas. We also assume there are N_f subcarriers used for transmission in each MIMO antenna. We set the number of active subcarriers as $N_{f'}$. In order to make use of the spectrum holes to transmit its signals, the SU need to sense the spectrum usage of the PU as the first task. By reconstructing or estimating the signals transmitted from the PU in receiver, the SU can figure out the frequencies of active subcarriers, which also stands for the information of spectrum usage. In traditional MIMO-OFDM receiver, the signal received in each antenna of our receiving scheme is modulated by a set of random sequence at first. Then all received and modulated signals are mixed together and sampled by a single ADC. The sampled (converted) signals are sent to a DSP (digital signal process) block, in where the sampled signals can be reconstructed by running recovery algorithm.

A Transmission and Channel Model

Let $b_i(k)$ stands for the k th transmitted OFDM symbol from the i th antenna. We set \mathbf{b}_i as the modulated OFDM symbol which are allocated to all subcarriers. The n th coefficient of the IFFT on the i th antenna is given by

$$x_i(n) = \frac{1}{\sqrt{N_f}} \sum_{k=1}^{N_f} b_i(k) e^{j \frac{2\pi n (k-1)}{N_f}}$$

here $b_i(k)$ is the modulated signals. some of the subcarriers are allocated to the PU for its usage. Since we only consider $N_{f'}$ subcarriers are used, there are only $N_{f'}$ non-zero elements in \mathbf{b}_i . The transmitted signal on i th antennas is expressed as

$$x_i = F_{N_f}^{-1} N_{f'}$$

where $F_{N_f}^{-1}$ stands for the IFFT matrix. We set channel impulse response vector which between the i th transmit antenna and the j th receive antenna as $\mathbf{h}_{i,j}$. We consider there are L multipath among the wireless channels between the transmitter and the receiver. $\mathbf{h}_{i,j}$ can be expressed as

$$h_{i,j} = \begin{pmatrix} h_{i,j}^{(0)} \\ \vdots \\ h_{i,j}^{(L-1)} \end{pmatrix}$$

Thus, the signal received at the receiver can be expressed as.

$$y_{i,j} = H_{i,j} x_i$$

where $y_{i,j}$ stands for the signals which are transmitted from i th antenna and received by j th antenna. $H_{i,j}$ stands for the matrix which is the result of the cyclic convolution with $h_{i,j}$. Since there are N_p transmit antennas and N_s receive antennas in the MIMO-OFDM system, the signals which are transmitted from all NP antennas and received on j th antenna is denoted by y_j . Here we express it as

$$y_j = \sum_{i=1}^{N_p} y_{i,j} \quad j = 1, \dots, N_s$$

Thus, the received signals from all receive antenna can be expressed as a vector-matrix format, which is shown as the following, and where V stands for noise vector

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{N_s} \end{pmatrix} = \begin{pmatrix} H_{1,1} & \dots & H_{N_p,1} \\ H_{1,2} & \ddots & H_{N_p,2} \\ \dots & \dots & \dots \\ H_{1,N_s} & \dots & H_{N_p,N_s} \end{pmatrix} \begin{pmatrix} x \\ x_2 \\ \vdots \\ x_{N_s} \end{pmatrix} + V$$

To the convenience, we express the above equation as,

$$y = Hx + V$$

To the receiver in conventional MIMO-OFDM system, after sampled by ADC, the received signal will be sent to a FFT unit, where signals can be transformed to Fourier domain. Then the transmitted symbols are demodulated by MIMO detector.

B. Sparse Signal Model

Traditional MIMO-OFDM system is considered to be power consuming for multiple ADC need to be used. Thus, we introduce a sparse signal model for the MIMO-OFDM based CR scheme. The received signals are mixed together and then sampled by a single ADC. The sampled signal can be expressed as

$$y_r = \sum_{j=1}^{N_s} d_j y_j^r$$

where y_j^r stands for the signal received on j th antenna before sampled by ADC and d_j is a vector, which is used to modulate the received signal on each antenna. Usually, we will select a pseudo-random sequence to modulate the received signals at each antenna, In practice, the random sequence can be generated by using Gold or Kasami sequences. Then, we mix all modulated signals together and send to the DSP. Above equation can be re-expressed as follows. In that equation D_j stands for diagonal matrix where its diagonal element are picked sequentially from the vector d_j .

$$y_r = \begin{bmatrix} D_1 & D_2 & \dots & D_{N_s} \end{bmatrix} \begin{pmatrix} y_1^r \\ y_2^r \\ \vdots \\ y_{N_s}^r \end{pmatrix}$$

Vector d_j expressed as

$$D_j = \begin{bmatrix} d_j(1) & 0 & \dots & 0 \\ 0 & d_j(2) & \vdots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \dots & 0 & d_j(N_f) \end{bmatrix}$$

Besides, we just define the set of matrix D_j in above equation as D for the convenience, which is expressed as

$$D = \begin{bmatrix} D_1 & D_2 & \dots & D_{N_s} \end{bmatrix}$$

Thus the receiving sample process can be expressed as,

$$y_r = DHF^{-1}b + v \\ = Ab + v$$

where v stands for the equivalent noise, F^{-1} is the matrix by consisting of the set of IFFT matrix $F_{N_f}^{-1}$, b_i is the OFDM symbols transmitted on i th antenna and b is a concatenation of b_i . Since only a finite subcarriers are used, b_i is sparse for only a finite number of nonzero elements on the vector. Besides, the sensing matrix is defined as

$$A = D H F^{-1}$$

Thus, our target is how to detect the subcarriers symbols b from the sampled signals y_r and sensing matrix A .

C. Sparse Signal Reconstruction in DSP Block

In our scheme, the compressively sampled signals are separated and reconstructed in the DSP block by exploiting the sparsity model. Thus, the reconstruction of the sampled signals is equivalent to the compressive sensing problem, also called as sparse signal recovery problem. This problem has been widely studied and a variety of algorithms.

III. SPECTRUM SENSING SCHEME

The conventional mathematical model for compressive sensing is expressed as

$$\min \|b\|_1 \\ \text{s.t. } y_r = Ab + v$$

But we prefer to use the l_p diversity measure instead of the l_1 diversity measure for the better performance that l_p diversity measure will lead to.

$$j(p, b) \triangleq \text{sgn}(p) \sum_{j=1}^{N_p N_s} |b(j)|^p$$

Thus, the target problem can be formed as:

$$b^* = \arg \min G(b)$$

where

$$G(b) = \|\Phi b - y_b\|_{l_2}^2 + \gamma j(p, b), \text{ with } \gamma = \frac{2\lambda}{|p|}$$

we need the algorithm which has the feature of sparsity adaptive. Besides, consider the application in the dynamic and complex wireless environment, the reconstruction

algorithm need faster speed with lower computation complexity. Based on the above reasons, we introduce the R-FOCUSS algorithm to detect the activity of subcarriers.

Algorithm: Spectrum Usage Detection Algorithm

Input: A, y_r

initialize $\lambda = \delta, j \in [1, 2 \dots N_s], k = 1$

repeat

$$W_k = \text{diag}(b_{k-1}(j)^{1-p/2})$$

$$q_k = W_k(A_K^T A_K + \lambda I)^{-1} A_r y_r$$

Where $A_k = A W_k$ with $\lambda \geq 0$

$$b_k = W_k q_k$$

Until $\|b_k - b_{k-1}\| < \theta$

Compute: $\Omega = \text{argmax}(|b_k|, S), b^* = b_k$

where S stands for the number of now-zero elements in b_k

output: Ω, b^*

The Algorithm 1 given in the following, k denotes the iterative step index. From the algorithm, we can find the outputs are estimated signals and the estimated support Ωb . Since the support stands for the indices of nonzero entries, which also stands for the location of the occupied frequency points, usually we can detect the activity of subcarriers by only analyzing the support of the sparse signals. Besides, from the table we also can find this algorithm is suitable for the application in spectrum detection when the prior information of subcarriers is unknown. In our experiments, we choose θ as 0.005. In next section, we will discuss the choice of parameters which are involved in our algorithm

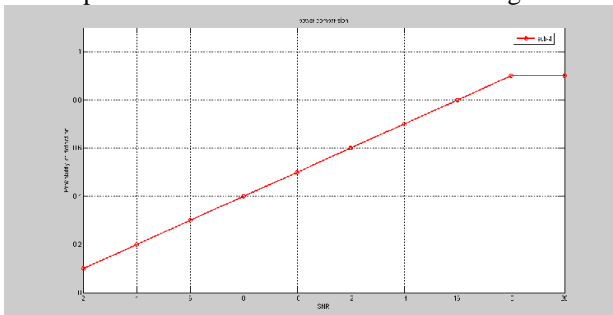


Fig 1: Probability of spectrum detection versus different SNR in 2×2 MIMO system

IV. SIMULATION EVALUATION

This section will present the simulation results and performance analysis of our proposed scheme

A. Simulation Settings.

In our simulation, we consider there are 64 subcarriers for all users on the given spectrum channel. The probability of spectrum detection is defined as the average rate of number of nonzero entries in b which are used in forming the measurement that are correctly identified over the number of the overall nonzero entries. Since the used entries stand for the subcarriers which have been occupied by the PUs, the probability of detection is equal to the probability of successfully detecting the spectrum usage. We consider three multi paths are among the MIMO transmission channels and

the channel state information (CSI) is known to the SU receiver.

B. Spectrum Usage Detection

This section will validate the proposed compressive spectrum sensing for MIMO-OFDM based CR network. For convenience, we label the active subcarriers as Sub in the following figures. In Fig. 1, we present the probability of spectrum detection versus different SNR with different number of active subcarriers. We consider 2 transmit antennas and 2 receive antennas are set in our system model. From the figure, we can find when less subcarriers are occupied, higher detection probability can be obtained. Besides, we also can find higher SNR can lead to better recovery performance. We present the relative mean squared error versus different number of active subcarriers under different number of SNR in Fig. 2. We still consider that there are 2 transmit antennas and 2 receive antennas in our system. From the figure, we can see when less subcarriers are occupied, less relative mean square error will be obtained. However, if more subcarriers are active in the CR network at same time, the mean square error will increase. In Fig. 3, we show the bit error rate versus different SNR under different number of active subcarriers. There are 4 transmit antennas and 4 receive antennas considered in this experiment. From the figure, we can find that less active subcarriers will lead to lower data recovery error. Besides, higher SNR will also increase the recovery performance. We also find when the number of subcarriers is larger than 8, the BER is less sensitive to the change of the SNR. This also shows our scheme is more effective for the situation when only a small number of subcarriers are occupied.

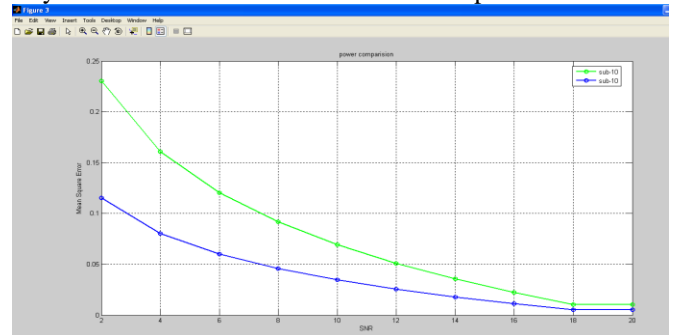


Fig. 2. Probability of relative mean square error versus different SNR in 2×2 MIMO system.

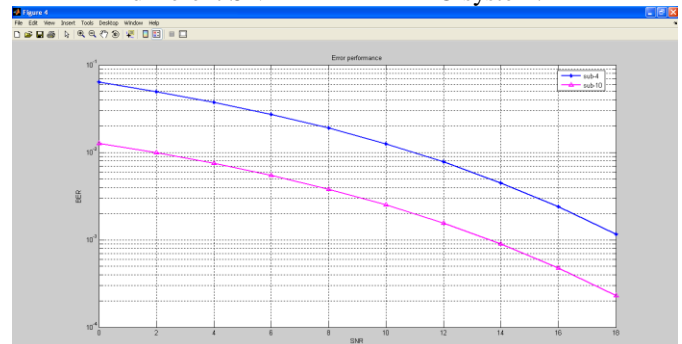


Fig. 3. Probability of bit error rate versus different SNR in 4×4 MIMO system.

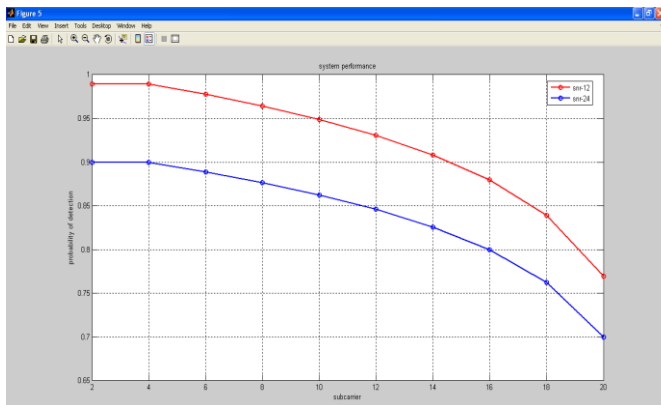


Fig. 4. Probability of spectrum detection versus different number of occupied subcarriers in 4×4 MIMO system

In Fig. 4, we present the probability of spectrum detection versus different number of occupied subcarriers under different SNR. We still consider the situation that 4 transmit antennas and 4 receive antennas are equipped in the system. From the figure, we can see for all SNR environment, when smaller number of subcarriers were occupied, the detection probabilities are almost higher compared to other situation. Besides, when SNR is larger, the SU can detect more active subcarriers.

V. CONCLUSIONS

We proposed a novel scheme for spectrum sensing in MIMO-OFDM based Cognitive Radio system in this paper. Compared with traditional MIMO-OFDM system, where the signals received in each antenna are sampled by a individual analog-to-digital converter (ADC), our scheme can mix the received signals from multiple receiving antennas together and sample the mixed signal through a single ADC by exploiting the sparsity model of the subcarriers allocated in transmission signals, which can lead to a significantly reduction of hardware cost. Since usually there is a finite number of subcarriers are occupied in the CR network, the transmission signals can be reconstructed through the compressive sensing algorithms in our model. Furthermore, the spectrum sensing algorithm introduced in this paper can efficiently estimate the spectrum usage but without the prior information of sparsity, which makes it suitable for the application in the real wireless environment.

REFERENCES

- [1] J. Mitola III and G. Q. Maguire Jr, "Cognitive radio: making software radios more personal," IEEE Personal Communications, vol. 6, no. 4, pp. 13–18, 1999.
- [2] D. L. Donoho, "Compressed sensing," IEEE Transactions on Information Theory, vol. 52, no. 4, pp. 1289–1306, 2006.
- [3] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," IEEE Transactions on Information Theory, vol. 52, no. 2, pp. 489–509, 2006.
- [4] Y. Kim, W. Guo, B. V. Gowreesunker, N. Sun, and

A. H. Tewfik, "Multichannel sparse data conversion with a single analog-to-digital converter." IEEE J. Emerg. Sel. Topics Circuits Syst., vol. 2, 2012.

- [5] E. J. Candes and T. Tao, "Decoding by linear programming," IEEE Transactions on Information Theory, vol. 51, no. 12, pp. 4203–4215, 2005.
- [6] J. A. Tropp, "Greed is good: Algorithmic results for sparse approximation," IEEE Transactions on Information Theory, vol. 50, no. 10, pp. 2231–2242, 2004.
- [7] W. Dai and O. Milenkovic, "Subspace pursuit for compressive sensing signal reconstruction," IEEE Transactions on Information Theory, vol. 55, no. 5, pp. 2230–2249, 2009.