Iterative Semi-blind Beamforming Algorithm in MIMO-OFDM Systems

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Abstract

A new frequency domain semi-blind beamforming algorithm is proposed in this paper for multiple input multiple output (MIMO) systems in which orthogonal frequency division multiplexing (OFDM) technique is employed. Based on singular value decomposition (SVD) technique, the semi-blind beamforming algorithm eliminates space interference in an iterative manner by shaping antenna patterns in transmitter and receiver sides. The performance of the new algorithm is evaluated for a 16-QAM MIMO-OFDM system by computer simulations under different scenarios. The results show the superiority of the proposed algorithm in comparison with semi-blind subspace method.

1. Introduction

A receiver is completely blind to the channel state information and the data signal. The training methods benefit from more accurate estimation, faster convergence and stability while suffer from bandwidth inefficiency. On the contrary the blind methods have commonly very low speed of convergence and yet there is no guarantee to reach to the optimum point. The key advantage of blind methods is their preservation of bandwidth that is a crucial issue in current band-limited systems. By coupling the training and blind techniques, another method called semi-blind is derived that benefits from the advantages of both methods [1]-[3]. The semi-blind method can be designed to preserve the bandwidth efficiency while its performance is very close to that of the training technique.

Signal subspace partitioning is one of the most popular approaches that can be used for blind and semi blind beamforming methods [1],[2]; however this method needs a large amount of data to reach to near the optimum point. In [1] a blind method based on signal subspace partitioning is proposed. In this method , some feedback data should be sent to the transmitter in order to eliminate the beamforming weights accurately. In [3] the blind estimation of mutual beamforming weights is suggested to be done separately at the transmitter and receiver when signal subspace partitioning approach is used for reciprocal channels; however there is a phase ambiguity in SVD estimation that requires to be removed by some feedback data.

In this paper, we propose a beamforming technique that employs the channel SVD matrices as transmit/receive beamforming weights. The channel SVD is a way which is used to transform the channel matrix to a diagonal matrix by some mathematical manipulations. Thus the interference can be omitted by mapping each distinct transmit antenna to a distinct receive antenna. Using this method, the beamforming weights can be computed in a straightforward manner.

The channel SVD matrices can be obtained directly from the channel matrix estimation, however because of the nonlinear operation of taking SVD, if the channel matrix is not precise enough, it may create more errors. Apart from this, taking SVD for each subchannel needs a huge amount of computations which is a cumbersome task. One good solution to this problem is to estimate the SVD matrices directly from the received signal [4],[5]. In this paper, we follow the proposed approach for iterative channel SVD estimation and develop our semi-blind beamforming algorithm based on the Constrained Maximum Likelihood (CML) criterion [5]. Computer simulations show that our proposed beamforming algorithm outperforms the signal subspace based semi-blind approaches without using coding.

The organization of this paper is in the following order: after introduction, in section 2 the system model of a MIMO-OFDM channel is explained briefly based on the SVD method [4] . In section 3, the iterative semi-blind beamforming algorithm is presented. Computer simulations are given in section 4 and section 5 concludes the paper.

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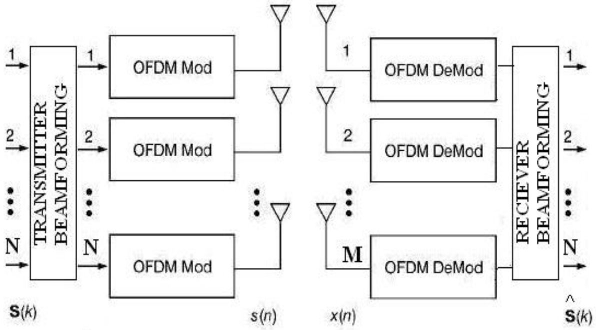

Figure 1. MIMO – OFDM system model.

2. System model

The model of the MIMO-OFDM system has been depicted in Fig.1. The system has N transmitter antennas and M receiver antennas. We define

$$\mathbf{s}^{(m)}(k) = [s_1^{(m)}(k),...,s_N^{(m)}(k)]^T \quad (1)$$

$$\mathbf{H}_f = \begin{bmatrix} \mathbf{H}^{(1)} & 0 & & \\ 0 & \mathbf{H}^{(2)} & 0 & \\ & \ddots & \ddots & \ddots \\ & & & \mathbf{H}^{(L)} \end{bmatrix} \quad (2)$$

Where $\mathbf{s}^{(m)}(k)$ is the transmitted vector of the mth subcarrier at time index k. The matrix $\mathbf{H}$ is a block diagonal matrix obtained by taking FFT of the channel impulse response where the FFT block length is L. Each block of $\mathbf{H}_f$ represents a subcarrier channel matrix.

After removing the cyclic prefix in receiver, the received vector is given as

$$\mathbf{x}^{(m)}(k) = \mathbf{H}^{(m)}\mathbf{s}^{(m)}(k) + \mathbf{n}^{(m)}(k) \quad m = 1,...,L \quad (3)$$

such that $\mathbf{x}^{(m)}(k) = [x_1^{(m)}(k),\ldots,x_M^{(m)}(k)]^T$ is the $M \times 1$ received vector of the mth subcarrier. $\mathbf{n}^{(m)}(k)$ is the $M \times 1$ additive white Gaussian noise with zero mean and autocorrelation matrix $\mathbf{R}_\mathbf{n} = \sigma_n^2 \mathbf{I}_M$.

The SVD of $\mathbf{H}^{(m)}$ can be written as

$$\mathbf{H}^{(m)} = \mathbf{U}^{(m)}\mathbf{\Sigma}^{(m)}\mathbf{V}^{(m)^H} \quad (4)$$

$\mathbf{U}^{(m)}$ and $\mathbf{V}^{(m)}$ are $M \times P$ and $N \times P$ unitary matrices where P is the rank of $\mathbf{H}^{(m)}$ such that $P \le \min(M,N)$. $\mathbf{\Sigma}^{(m)} = diag(\sigma_1^{(m)},\sigma_2^{(m)},...,\sigma_P^{(m)})$ is a diagonal matrix and $(.)^H$ denotes transposed complex conjugate.

We intend to estimate the SVD of the sub channels directly at the receiver. First a rough estimation is obtained by a short training sequence after which the estimation is performed blindly using Decision Feedback (DF) method. This will be an iterative procedure that improves the estimation as it proceeds through data sequence. As we see later, this process leads to an improved beamforming by canceling interference.

3. Iterative beamforming

The process of iterative semi-blind beamforming can be divided into two parts referred to as training and blind. The training part is mostly based on the proposed method in [5] and the blind part is developed based on DF approach.

For the ease of derivation of formulas and without loss of generality, we can omit the index m in (3)

$$\mathbf{H} = \mathbf{U\Sigma V}^H = \mathbf{W}_1\mathbf{V}^H = \mathbf{UW}_2^H \quad (5)$$

where

$$\mathbf{W}_1 = \mathbf{U\Sigma} \quad (6)$$

$$\mathbf{W}_2 = \mathbf{V\Sigma} \quad (7)$$

If $\mathbf{u}_i$, $\mathbf{v}_i$ are defined as the ith column of $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{w}_{1i}$, $\mathbf{w}_{2i}$ as the ith column of $\mathbf{W}_1$, $\mathbf{W}_2$, we have

$$\mathbf{w}_{1i} = \mathbf{Hv}_i = \sigma_i\mathbf{u}_i \quad (8)$$

$$\mathbf{w}_{2i}^H = \mathbf{u}_i^H\mathbf{H} = \sigma_i\mathbf{v}_i^H \quad (9)$$

For each subchannel, we can write

$$\mathbf{x}(k) = \mathbf{W}_1\mathbf{V}^H\mathbf{s}(k) + \mathbf{n}(k) \quad (10)$$

Following the procedure of CML estimation [5] that maintains the orthogonality of $\mathbf{W}_1$ we obtain $\mathbf{u}_i^{(l)}$

$$\hat{\mathbf{w}}_{1i}^{(l)} = [\mathbf{I}_M - \widehat{\mathbf{W}}_{1i}^{(l)}(\widehat{\mathbf{W}}_{1i}^{(l)^H}\widehat{\mathbf{W}}_{1i}^{(l)})^{-1}\widehat{\mathbf{W}}_{1i}^{(l)^H}]\widehat{\mathbf{y}}_{1i}^{(l-1)}(k) \quad i = 1,...,P \quad (11)$$

where

$$\widehat{\mathbf{y}}_{1i}^{(l-1)}(k) = \mathbf{X}(k)\mathbf{S}^H(k)\mathbf{\Phi}_s(k)\widehat{\mathbf{v}}_i^{(l-1)} \quad (12)$$

$$\mathbf{\Phi}_s(k) = (\mathbf{S}(k)\mathbf{S}(k)^H)^{-1} \quad (13)$$

$$\mathbf{S}(k) = [\mathbf{s}(0), s(1),..., \mathbf{s}(k)] \qquad M \times (k+1) \quad (14)$$
$$\mathbf{X}(k) = [\mathbf{x}(0), \mathbf{x}(1),..., \mathbf{x}(k)] \qquad P \times (k+1) \quad (15)$$

After normalizing, we have

$$\hat{\mathbf{u}}_i^{(l)} = (\hat{\mathbf{w}}_{1i}^{(l)H} \hat{\mathbf{w}}_{1i}^{(l)})^{-\frac{1}{2}} \hat{\mathbf{w}}_{1i}^{(l)} \qquad i = 1,..., P \quad (16)$$

while l is the iteration index. A similar approach yields $\mathbf{v}_i^{(l)}, \hat{\sigma}_i^{(l)}$ as follows

$$\hat{\mathbf{w}}_{2i}^{(l)} = [\mathbf{I}_N - \mathbf{\Phi}_s(k)\hat{\mathbf{W}}_{2i}^{(l)}(\hat{\mathbf{W}}_{2i}^{(l)H}\mathbf{\Phi}_s(k)\hat{\mathbf{W}}_{2i}^{(l)})^{-1}\hat{\mathbf{W}}_{2i}^{(l)H}] \times \hat{\mathbf{y}}_{2i}^{(l)}(k) \qquad i = 1,...,P \quad (17)$$

$$\hat{\mathbf{y}}_{2i}^{(l)}(k) = \mathbf{\Phi}_s(k)\mathbf{S}(k)\mathbf{X}^H(k)\hat{\mathbf{u}}_i^{(l)} \quad (18)$$

$$\hat{\mathbf{v}}_i^{(l)} = (\hat{\mathbf{w}}_{2i}^{(l)H} \hat{\mathbf{w}}_{2i}^{(l)})^{-\frac{1}{2}} \hat{\mathbf{w}}_{2i}^{(l)} \qquad i = 1,..., P \quad (19)$$

$$\hat{\sigma}_i^{(l)} = (\hat{\mathbf{w}}_{2i}^{(l)H} \hat{\mathbf{w}}_{2i}^{(l)})^{-\frac{1}{2}} \qquad i = 1,...,P \quad (20)$$

Having a limited number of training symbols (preferably one) we estimate the channel SVD as explained above.

The rest of this work concerns with employing the above strategy for beamforming in a semi-blind approach. In this part, we start from the training SVD estimation as the initial transmit/receive beamforming matrices, then assuming a specific time interval, the estimated transmit beamforming matrix, $\hat{\mathbf{V}}$, is sent to the transmitter side. Notice that similar to a feedback process, this routine uses the data channel, so the interval should be large enough not to waste the channel bandwidth while it must be chosen in such a way that throughout each interval, channel variation is negligible. The received signal is then multiplied in the estimated receive beamforming matrix $\hat{\mathbf{U}}^H$. For blind beamforming part, we use DF approach in order to estimate the transmitted symbols as follows.

We denote the transmitted weighted signal with $\mathbf{p}_s(k)$

$$\mathbf{p}_s(k) = \hat{\mathbf{V}}\mathbf{s}(k) \quad (21)$$

and similar to (14) we define signal sampling matrix

$$\mathbf{P}_s(k) = [\mathbf{p}_s(0), \mathbf{p}_s(1), \dots \mathbf{p}_s(k)] \qquad N \times (k+1) \quad (22)$$

According to (3) the received signal can be written as

$$\mathbf{y}(k) = \mathbf{H}\mathbf{p}_s(k) + \mathbf{n}(k) \quad (23)$$

From (23), the Least Squares (LS) estimation of $\mathbf{p}_s(k)$ is given as

$$\tilde{\mathbf{p}}_s(k) = (\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H\mathbf{y}(k) \quad (24)$$

This is a soft decision estimation of the transmitted signal. To improve the channel estimation, we use the estimation of $\mathbf{H}$ in each iteration ($\hat{\mathbf{H}}^{(l)}$) and $\hat{\mathbf{V}}$ for the corresponding interval to make a hard decision.

$$\hat{\mathbf{s}}^{(l)}(k) = map(\hat{\mathbf{V}}^H\tilde{\mathbf{p}}_s^{(l)}(k)) = map\left(\hat{\mathbf{V}}^H(\hat{\mathbf{H}}^{(l)(H)}\hat{\mathbf{H}}^{(l)})^{-1}\hat{\mathbf{H}}^{(l)H}\mathbf{y}(k)\right) \quad (25)$$

Where $\tilde{\mathbf{p}}_s^{(l)}(k)$ denotes the soft estimation of $\mathbf{p}_s(k)$ in iteration l and the *map* function, maps the signal on the constellation space based on the minimum Euclidian distance criterion. As a result, the estimation of $\mathbf{p}_s(k)$ in each iteration is given as

$$\hat{\mathbf{p}}_s^{(l)}(k) = \hat{\mathbf{V}}\hat{\mathbf{s}}^{(l)}(k) \quad (26)$$

The SVD estimation is then performed by replacing the estimation of $\mathbf{P}_s(k)$ in each iteration ($\hat{\mathbf{P}}_s^{(l)}(k)$) instead of $\mathbf{S}(k)$ in (12), (13), (17), (18).

4. Simulations and results

A MIMO-OFDM system with 64 subcarriers has been considered in simulations. A sequence of independent, identically distributed 16-QAM signal vector $\mathbf{s}(k)$ with $\mathbf{R_s} = \mathbf{I}_N$ is sent from transmitter antennas. To evaluate the performance of the algorithm the Normalized Mean Square Error (NMSE) criterion [4] along with Bit Error Rate (BER) are employed. The channel has an exponential delay spread profile with utmost 16 paths [4]. The length of training and data packets are denoted by NT and ND respectively. Note that each packet consists of N individual OFDM symbols .

Fig. 2 and Fig. 3, present the performance of the MIMO-OFDM system with N=M=2,4 in terms of SNR. The interval of sending $\hat{\mathbf{V}}$ is 5 OFDM packets while NT=1, 2 and ND=30. Closer inspection reveals that the performance of the system is improved by increasing NT. Fig.4 shows BER of the system in terms of number of iterations. As illustrated, the performance of the system is significantly improved when the number of iterations is increased from 1 to 2 and reaches to a rather steady state in iteration 4 and over. Fig. 5 and Fig.6 compare the performance of the signal subspace based semi-blind method [1] with the performance of our proposed algorithm. As can be seen, our scheme outperforms signal subspace method especially at high SNRs. Fig. 7 depicts the BER of the system in terms of ND. Notice that ND=0 is equivalent to training sequence estimations. We can see clearly that the more data symbols are sent, the better estimation is obtained, however the rate of improvement becomes negligible at ND=25 and over. It should be mentioned that because of updating the estimated $\mathbf{U},\mathbf{V}$ after each 5-packet interval, the BER remains constant until the next $\mathbf{U},\mathbf{V}$ estimations are employed.

5. Conclusions

This paper proposed a novel semi-blind beamforming method for MIMO-OFDM systems based on channel SVD estimation using Decision Feedback (DF) approach. As illustrated, with just one or two training packets the convergence of the DF algorithm is achieved; furthermore, utilizing the data packets, the algorithm improves the performance of beamformer. Simulations results also demonstrated that the proposed method outperforms the previous subspace based semi blind approaches.

6. Acknowledgement

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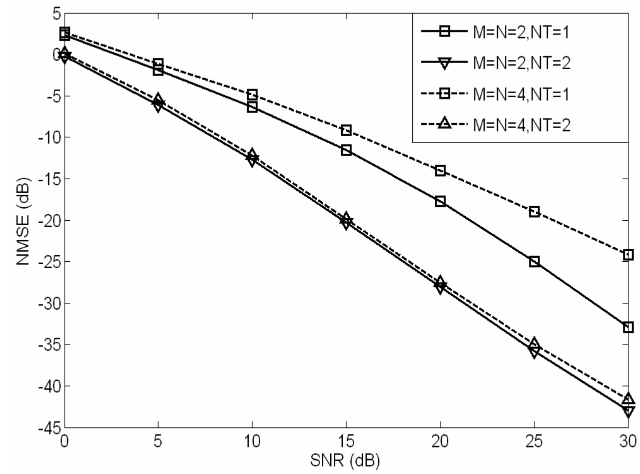

Figure 2. NMSE versus SNR for ND =30, M=2,4 and NT=1,2 .

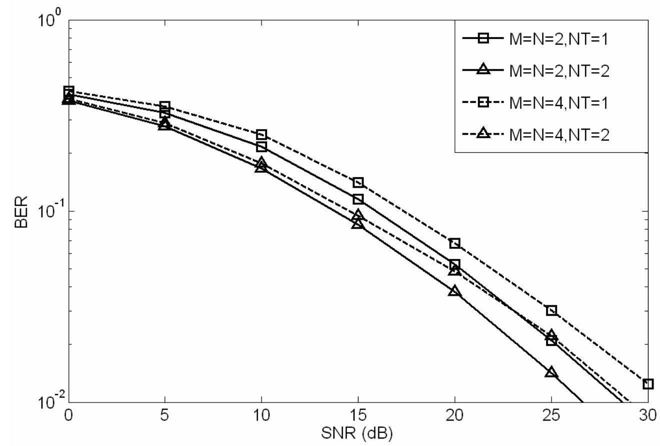

Figure 3. BER versus SNR for ND =30 , M=2,4 and NT=1,2.

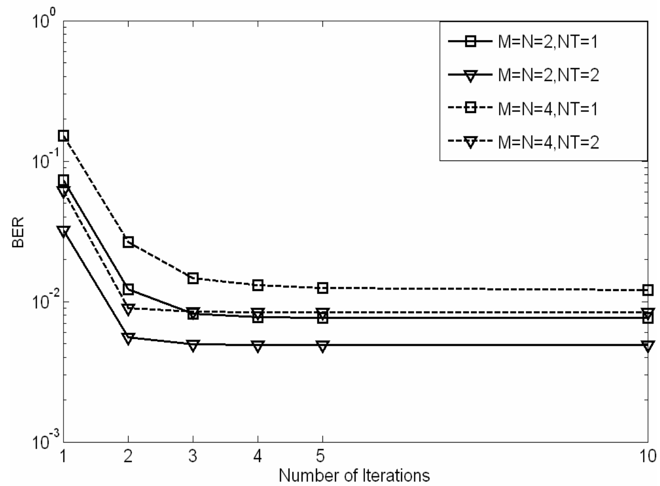

Figure 4. BER versus iteration number for ND=30, SNR=30 , M=2,4 and NT=1,2.

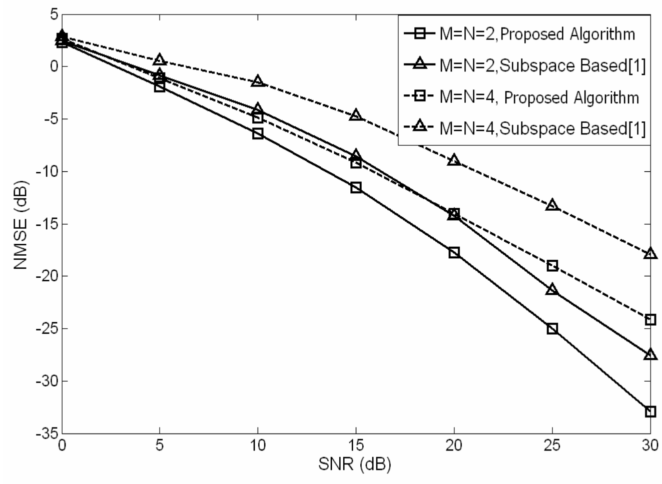

Figure 5. NMSE versus SNR, comparing the proposed SVD based beamforming algorithm with signal subspace approach, NT=1 and ND=30.

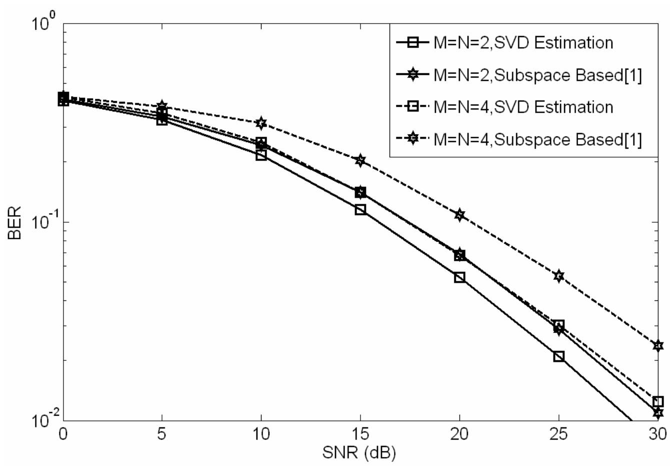

Figure 6. BER versus SNR, comparing the proposed SVD based beamforming algorithm with signal subspace approach, NT=1 and ND=30.

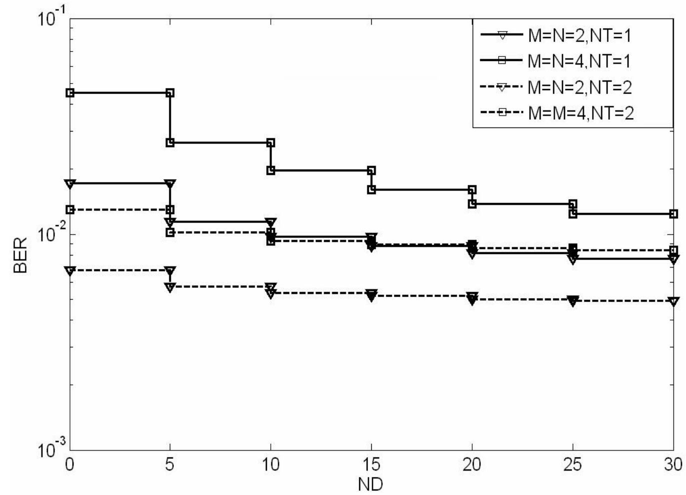

Figure 7. BER versus ND for SNR=30, iteration number =5, NT=1,2 and M=2,4.

7. References

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