

Low Complexity Algorithm for Frequency Offset and Channel Estimation in MIMO-OFDM Systems

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Abstract—In this study, we present a new reduced-complexity scheme for maximum-likelihood (ML) estimate of both carrier-frequency offset (CFO) and channel coefficients in multi antenna OFDM transmission, assuming that a training sequence is available. Our scheme is also capable to accommodate any space-time coded (STC) transmission. Moreover, to benchmark the performance of the proposed scheme, the Cramer-Rao bounds (CRBs) are derived for both CFO and channel estimators. Simulation results show that the proposed scheme achieves almost ideal performance compared with the CRBs in all ranges of signal-to-noise ratios (SNR) for both channel and frequency offset estimates.

Keywords—Carrier frequency offset, channel impulse response, maximum-likelihood (ML) estimation, multiple-input multiple-output (MIMO), orthogonal frequency division multiplexing (OFDM).

1. Introduction

High data-rate wireless access is demanded by many applications. Traditionally, more bandwidth is required for higher data-rate transmission. However, due to spectral limitations, it is often impractical or sometimes very expensive to increase bandwidth. In this case, using multiple transmit and receive antennas for spectrally efficient transmission is an alternative solution. Multiple transmit antennas can be used either to obtain transmit diversity, or to form multiple-input multiple-output (MIMO) channels.

The combination of MIMO signal processing with orthogonal frequency-division multiplexing (OFDM) has gained considerable interest in recent years [1], [2]. MIMO offers extraordinary throughput without additional power consumption or bandwidth expansion [3], and OFDM introduces overlapping but orthogonal narrowband sub-channels to convert a frequency selective fading channel into a non-frequency selective one. Moreover, OFDM avoids inter-symbol interference (ISI) by means of cyclic prefix (CP) [4].

Like single antenna OFDM, MIMO-OFDM is very sensitive to frequency synchronization and channel estimation errors [5]. Several carrier frequency synchronization schemes for MIMO-OFDM systems are reported in the literature

[6]-[10]. Moreover, the coherent detection of MIMO-OFDM signals requires channel estimation to mitigate amplitude and phase distortions in a fading channel. Various channel estimation algorithms are also proposed for MIMO-OFDM systems (see, e.g., [5]; [11]; [12] and references therein). In dealing with channel estimation, most investigators assume zero frequency offset between the carrier and the local reference at the receiver. In practice, this means that the offset is so small that the demodulated signal incurs only negligible phase rotations. Using stable oscillators is not a viable route to meet such conditions for; in general, the stability requirements would be too stringent. Furthermore, even ideal oscillators would be inadequate in a mobile communication environment experiencing significant Doppler shifts. The only solution is to measure the CFO accurately [13]. The combination of CFO and channel estimation leads to particularly complex problems in MIMO-OFDM systems due to the number of unknowns [5].

In this paper, we present a new reduced-complexity scheme for ML estimate of both CFO and CIR in multi antenna OFDM transmission, assuming that a training sequence is available. As we shall see, the solution consists of two separate steps: a CFO estimator and a channel estimator. It is known that the expectation-maximization (EM) algorithm [14] can provide the ML solutions in an iterative manner for ML estimation problems [15], [16]. Therefore, to overcome the difficulty of ML estimation of CFO, we resort to the EM algorithm and propose a novel EM-based CFO estimator (first step). The CFO estimates are then exploited in the second step to estimate the MIMO channel coefficients. Moreover, to benchmark the performance of the proposed scheme, the Cramer-Rao bounds (CRBs) are derived for both CFO and CIR estimators.

The rest of the paper is organized as follows. In the next section, we describe the MIMO-OFDM signal model in the presence of CFO. Section 3, is devoted to the description of the ML estimation of CFO and CIR via the EM algorithm. The CRBs for both channel and frequency offset estimators are derived in section 4 to characterize the accuracy of the estimators. Simulation results for the MSE performance of the proposed scheme are given in section 5 and conclusion summarizes the main results in section 6.

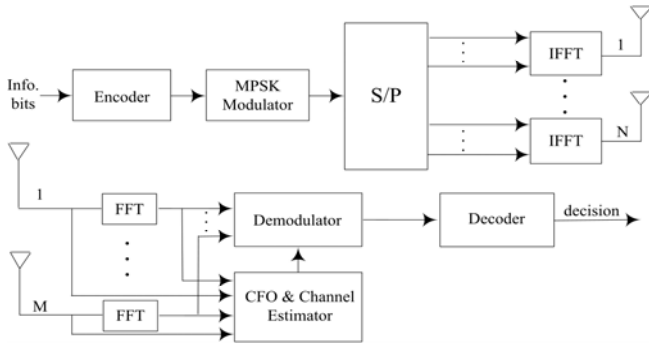


Figure 1. MIMO-OFDM system model

2. MIMO-OFDM Signal Model

We consider a MIMO-coded OFDM communication system with K subcarriers, N transmit and M receive antennas, signaling through frequency-selective fading channels in the presence of frequency offset. The system model is illustrated in Fig. 1. It is assumed that the fading channel processes are slowly time variant, such that the fading coefficients are assumed to remain constant during each OFDM block (one time slot) but it varies from one OFDM block to another, and the fading processes associated with different transmit–receive antenna pairs are uncorrelated.

At the receiver, the signals are received from M receive antennas. Accordingly, the MIMO-OFDM system model subject to CFO is given as [7]–[9]:

$$\mathbf{y}_i[p] = \mathbf{F}(\varepsilon) \mathbf{W}_K^H \mathbf{X}[p] \mathbf{W} \mathbf{h}_i[p] + \mathbf{z}_i[p] \quad (1)$$

$i = 1, 2, \dots, M, p = 1, \dots, P$

where the normalized frequency offset ε is presented in the matrix $\mathbf{F}(\varepsilon)$ given by:

$$\mathbf{F}(\varepsilon) = \text{diag}(1, e^{j(2\pi\varepsilon/K)}, \dots, e^{j(2\pi\varepsilon(K-1)/K)})_{K \times K} \quad (2)$$

and

$$\mathbf{y}_i[p] = [y_i[p, 0], \dots, y_i[p, K-1]]_{K \times 1}^T \quad (3)$$

$$[\mathbf{W}_K^H]_{r,s} = \frac{1}{\sqrt{K}} e^{j(2\pi rs/K)} (r, s = 0, \dots, K-1) \quad (4)$$

$$\mathbf{X}[p] = [\mathbf{X}_1[p], \mathbf{X}_2[p], \dots, \mathbf{X}_N[p]]_{K \times N \times K} \quad (5)$$

$$\mathbf{X}_j[p] = \text{diag}[x_j[p, 0], \dots, x_j[p, K-1]]_{K \times K} \quad (6)$$

$$\mathbf{W} = \text{diag}[\mathbf{w}, \dots, \mathbf{w}]_{NK \times NL} \quad (7)$$

$$[\mathbf{w}]_{r,s} = e^{-j(2\pi/K)rs} (r = 0, \dots, K-1; s = 0, \dots, L-1) \quad (8)$$

$$\mathbf{h}_i[p] = [\mathbf{h}_{i,1}^T[p], \dots, \mathbf{h}_{i,N}^T[p]]_{NL \times 1}^T \quad (9)$$

$$\mathbf{h}_{i,j}[p] = [h_{i,j}(p, 0), \dots, h_{i,j}(p, L-1)]_{L \times 1}^T \quad (10)$$

Note that in (1) the additive white Gaussian noise (AWGN) vector $\mathbf{z}_i[p]$ contains independent zero-mean complex Gaussian random variables with power $\sigma_{z_i}^2$.

As practical applications, data transmission is carried out in a burst manner. Each data burst spans $P+1$ OFDM blocks, with the first block (preamble) containing known training symbols. The remaining P OFDM blocks are containing data symbols. Our idea is to simultaneously make use of training symbols for both CFO and CIR estimation. Therefore, in the sequel to this study, we concentrate on the preamble (corresponding to $p=0$) and omit the temporal index p for notation simplicity.

3. EM-Based ML Estimation of CFO and Channel

The transmission model in (1) contains two unknown parameters: the CFO ε and the channel parameters $\mathbf{h}_i$ ($i=1, \dots, M$). The ML estimates of ε and $\mathbf{h}_i$ are given by minimizing the following quadratic cost function:

$$\min_{\varepsilon, \mathbf{h}_i} \left\{ \sum_{i=1}^M \|\mathbf{y}_i - \mathbf{F}(\varepsilon) \mathbf{V} \mathbf{h}_i\|^2 \right\} \quad (11)$$

where

$$\mathbf{V} = \mathbf{W}_K^H \mathbf{X}_{\text{training}} \mathbf{W} \quad (12)$$

Problem of (11) lies in the fact that we have to estimate two parameters with only one cost function. We propose at first to estimate the parameter ε . The ML estimation of ε leads to the following mathematical development:

$$\begin{aligned} \tilde{\varepsilon} &= \arg \max_{\varepsilon} \sum_{i=1}^M \log p(\mathbf{y}_i | \varepsilon) \\ &= \arg \max_{\varepsilon} \sum_{i=1}^M \log \int p(\mathbf{y}_i | \varepsilon, \mathbf{h}_i) p(\mathbf{h}_i) d\mathbf{h}_i \end{aligned} \quad (13)$$

It is seen in (13) that the direct computation of the optimal ML detection involves multiple-dimensional integral over the unknown random vector $\mathbf{h}_i$ and, hence, is of prohibitive complexity. Instead of direct computation of (13), EM-type algorithms provide an iterative and more easily implementable solution. The basic idea of the EM algorithm is to solve problem (13) iteratively according to the following two steps

-Step 1: Expectation (E)-step: Compute

$$Q(\varepsilon | \varepsilon^{(k)}) = E \left\{ \sum_{i=1}^M \log p(\mathbf{y}_i | \varepsilon, \mathbf{h}_i) \middle| \mathbf{y}_i, \varepsilon^{(k)} \right\} \quad (14)$$

-Step 2: Maximization (M)-step: Solve

$$\varepsilon^{(k+1)} = \arg \max_{\varepsilon} Q(\varepsilon | \varepsilon^{(k)}) \quad (15)$$

where $\varepsilon^{(k)}$ denotes the estimated CFO value at the k th EM iteration. It is known that the likelihood function $\sum_{i=1}^M \log p(\mathbf{y}_i | \varepsilon^{(k)})$ is non-decreasing as a function of k and under regularity conditions the EM algorithm converges to a local stationary point [7, 8].

In the E-step, the expectation is taken with respect to the hidden channel response $\mathbf{h}_i$ conditioned on $\mathbf{y}_i$ and $\varepsilon^{(k)}$. It is easily seen that, conditioned on $\mathbf{y}_i$ and $\varepsilon^{(k)}$, $\mathbf{h}_i$ is complex Gaussian distributed as [17]

$$\mathbf{h}_i | (y_i, \varepsilon^{(k)}) \sim N_c(\hat{\mathbf{h}}_i, \hat{\Sigma}_{\mathbf{h}_i}), \quad i = 1, \dots, M \quad (16)$$

with

$$\hat{\Sigma}_{\mathbf{h}_i} = (\mathbf{V}^H \mathbf{F}^H(\varepsilon^{(k)}) \Sigma_{z_i}^{-1} \mathbf{F}(\varepsilon^{(k)}) \mathbf{V} + \Sigma_{\mathbf{h}_i}^\dagger)^{-1} \quad (17)$$

$$\hat{\mathbf{h}}_i = \hat{\Sigma}_{\mathbf{h}_i} \mathbf{V}^H \mathbf{F}^H(\varepsilon^{(k)}) \Sigma_{z_i}^{-1} \mathbf{y}_i \quad (18)$$

where Σ_{z_i} and $\Sigma_{\mathbf{h}_i}$ denote respectively the covariance matrix of the ambient white Gaussian noise $\mathbf{z}_i$ and channel responses $\mathbf{h}_i$. According to the assumptions in Section 2, both of them are diagonal matrices as

$$\Sigma_{z_i} = E(\mathbf{z}_i \mathbf{z}_i^H) = \sigma_{z_i}^2 \mathbf{I} \quad (19)$$

$$\Sigma_{\mathbf{h}_i} = E(\mathbf{h}_i \mathbf{h}_i^H) = \text{diag}[\sigma_{i,j,0}^2, \dots, \sigma_{i,j,L-1}^2, \dots, \sigma_{i,N,0}^2, \dots, \sigma_{i,N,L-1}^2] \quad (20)$$

where $\sigma_{i,j,l}^2$ is the average power of the l -th tap between the j -th transmit and i -th receive antennas; $\sigma_{i,j,l}^2 = 0$ if the channel response at this tap is zero. Assuming $\Sigma_{\mathbf{h}_i}$ is known, $\Sigma_{\mathbf{h}_i}^\dagger = \text{diag}[\gamma_{i,1,0}, \dots, \gamma_{i,1,L-1}, \dots, \gamma_{i,N,0}, \dots, \gamma_{i,N,L-1}]$ is defined as the pseudo inverse of $\Sigma_{\mathbf{h}_i}$ as

$$\gamma_{i,j,l} = \begin{cases} \frac{1}{\sigma_{i,j,l}^2} & \sigma_{i,j,l}^2 \neq 0 \\ 0 & \sigma_{i,j,l}^2 = 0 \end{cases} \quad (21)$$

As depicted in Fig. 2, the diagonal elements of $\mathbf{V}^H \mathbf{V}$ are equal to K/N . K/N is much larger than $\sigma_{z_i}^2 / \sigma_{i,j,l}^2$, which is inversely proportional to the signal-to-noise ratio of the fading channel. Therefore, we can simplify (17) and (18) to

$$\hat{\Sigma}_{\mathbf{h}_i} \approx \sigma_{z_i}^2 (\mathbf{V}^H \mathbf{V})^{-1} \quad (22)$$

$$\hat{\mathbf{h}}_i \approx (\mathbf{V}^H \mathbf{V})^{-1} \mathbf{V}^H \mathbf{F}^H(\varepsilon^{(k)}) \mathbf{y}_i \quad (23)$$

Hence, (14) reduces to

$$\begin{aligned} Q(\varepsilon | \varepsilon^{(k)}) &= -\sum_{i=1}^M \left\{ E_{\mathbf{h}_i} \left(\mathbf{y}_i, \varepsilon^{(k)} \right) \left\| \mathbf{y}_i - \mathbf{F}(\varepsilon) \mathbf{V} \mathbf{h}_i \right\|^2 \right\} + \text{const.} \\ &= -\sum_{i=1}^M \left\{ \left\| \mathbf{y}_i - \mathbf{F}(\varepsilon) \mathbf{V} \hat{\mathbf{h}}_i \right\|^2 + \text{trace}(\mathbf{V} \hat{\Sigma}_{\mathbf{h}_i} \mathbf{V}^H) \right\} + \text{const.} \end{aligned} \quad (24)$$

The second term is independent of ε , and hence has no contribution to the detector. Developing (24) and dropping terms irrelevant of ε , we obtain:

$$\begin{aligned} Q(\varepsilon | \varepsilon^{(k)}) &= 2 \text{Re} \left(\sum_{i=1}^M \mathbf{y}_i^H \mathbf{F}(\varepsilon) \mathbf{V} \hat{\mathbf{h}}_i \right) + \text{const.} \\ &= 2 \text{Re} \left(\sum_{i=1}^M \left\{ \sum_{n=0}^{K-1} y_i^*(n) M_i(n) e^{j \frac{2\pi n \varepsilon}{K}} \right\} \right) + \text{const.} \end{aligned} \quad (25)$$

By denoting $r_i(n) = y_i^*(n) M_i(n)$, the final expression for $(k+1)$ -th estimate of ε is obtained as follows:

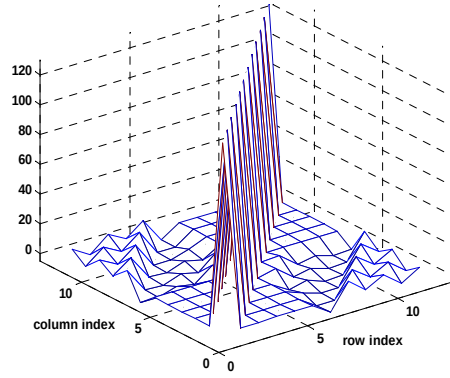


Figure 2. Evaluation of matrix products $\mathbf{V}^H \mathbf{V}$ ($K=128, N=2$)

$$\varepsilon^{(k+1)} = \arg \max_{\varepsilon} \left\{ \text{Re} \left(\sum_{i=1}^M R_i(\varepsilon) \right) \right\} \quad (26)$$

where $R_i(\varepsilon) = \sum_{n=0}^{K-1} r_i(n) e^{j \frac{2\pi n \varepsilon}{K}}$ can be easily computed using the FFT algorithm. Better frequency resolution can be achieved by zero-padding to effectively increase the length of the symbol sequence.

When $\tilde{\varepsilon}$ has been obtained, it is straightforward, using (23), to estimate $\mathbf{h}_i$. The LS solution of (23) is also the ML channel estimate. The ML solution can be determined by:

$$\tilde{\mathbf{h}}_i = (\mathbf{V}^H \mathbf{V})^{-1} \mathbf{V}^H \mathbf{F}^H(\tilde{\varepsilon}) \mathbf{y}_i \quad (27)$$

4. Cramer-Rao Bounds

To benchmark the performance of our estimators, we evaluate the CRBs for the estimation of CFO and CIR. Remember that for each received antenna we have: $\mathbf{y}_i = \mathbf{F}(\varepsilon) \mathbf{V} \mathbf{h}_i + \mathbf{z}_i$ ($i = 1, \dots, M$). Stacking all the different vectors $\mathbf{y}_i$ in column to form the vector $\mathbf{y}$ and doing the same thing with vectors $\mathbf{h}_i$ to obtain $\mathbf{h}$, we add together the contributions of all received antennas:

$$\mathbf{y} = (\mathbf{I}_M \otimes \mathbf{F}(\varepsilon) \mathbf{V}) \mathbf{h} + \mathbf{z} \quad (28)$$

with $\otimes$ denoting the Kronecker product.

Let $\boldsymbol{\eta} = [\varepsilon \mathbf{h}_R \mathbf{h}_I]^T$ denote the parameter vector of interest where $\mathbf{h}_R$ and $\mathbf{h}_I$ stand for the real and imaginary parts of $\mathbf{h}$, respectively. Under all the made assumptions, the received signal $\mathbf{y}$ is a complex-valued circularly symmetric Gaussian vector with mean $\boldsymbol{\mu} = (\mathbf{I}_M \otimes \mathbf{F}(\varepsilon) \mathbf{V}) \mathbf{h}$ and covariance matrix $\mathbf{C}_z = \sigma_z^2 \mathbf{I}_{M \cdot K}$. For this type of problem, the Fisher Information Matrix (FIM) for estimation of $[\boldsymbol{\eta}^T \sigma_z^2]$ is block diagonal i.e., the estimation of σ_z^2 is decoupled from that of $\boldsymbol{\eta}$. Therefore, we only consider the FIM for $\boldsymbol{\eta}$, which we denote by $\mathbf{F}$. The latter is given by:

$$\mathbf{F} = \frac{2}{\sigma_z^2} \text{Re} \left(\frac{\partial \boldsymbol{\mu}^H}{\partial \boldsymbol{\eta}} \frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\eta}^T} \right) \quad (29)$$

The CRB is obtained as the inverse of the FIM $\mathbf{F}$. Using the same principle as those given in [17], we obtain the final expression for CRB as:

$$\text{CRB}(\epsilon) = (K^2 \sigma_z^2 / 8\pi^2) [\mathbf{h}^H (\mathbf{I}_M \otimes \mathbf{V}^H \mathbf{D} \mathbf{I} \mathbf{D} \mathbf{V}) \mathbf{h}]^{-1} \quad (30)$$

with the following definitions:

$$\mathbf{D} = \text{diag}(0, 1, \dots, K-1) \quad (31)$$

$$\mathbf{\Pi} = \mathbf{I}_K - \mathbf{V} [\mathbf{V}^H \mathbf{V}]^{-1} \mathbf{V}^H \quad (32)$$

For the derivation of CRB for channel parameter estimation, we obtain [17]:

$$E[(\hat{\mathbf{h}} - \mathbf{h})(\hat{\mathbf{h}} - \mathbf{h})^H] \geq \frac{\sigma_z^2}{2} (2\lambda + \gamma^{-1} \beta \beta^H) = \text{CRB}(\mathbf{h}) \quad (33)$$

where

$$\lambda = \mathbf{I}_M \otimes (\mathbf{V}^H \mathbf{V})^{-1} \quad (34)$$

$$\gamma = \mathbf{h}^H \mathbf{I}_M \otimes [\mathbf{V}^H \mathbf{D} \mathbf{I} \mathbf{D} \mathbf{V}] \mathbf{h} \quad (35)$$

$$\beta = \mathbf{I}_M \otimes \left[(\mathbf{V}^H \mathbf{V})^{-1} \mathbf{V}^H \mathbf{D} \mathbf{V} \right] \mathbf{h} \quad (36)$$

5. Simulation Results

In this section, we provide computer simulation results to illustrate the performance of the proposed ML estimator. The characteristics of the fading channels are described in Section 2, specifically; the system performance is simulated in typical urban (TU) channel with 6 taps. In the following simulations, the available bandwidth is 1 MHz and is divided into 128 subcarriers. These correspond to a subcarrier symbol rate of 7.8 KHz and OFDM word duration of 128 μs . In each OFDM word, a cyclic prefix interval of 32 μs is added to combat the effect of ISI, hence, the duration of one OFDM word 160 μs . For all simulations, two transmitter antennas and two receiver antennas are used. The modulator uses quaternary phase-shift keying (QPSK) constellation. The system transmits in a burst manner. A preamble is applied at the beginning of each burst for synchronization purposes. MIMO channel estimates are also drawn from the preamble. The performance of the CFO estimator is evaluated with the MSE of the estimated frequency offset. In the case of channel estimation, $E(\|\hat{\mathbf{h}} - \mathbf{h}\|^2)$ is plotted.

$E(\|\hat{\mathbf{h}} - \mathbf{h}\|^2)$ is plotted.

Example 1 (Performance of CFO Estimator): First, we test the effect of the number of EM iterations on CFO estimation. The CFO is randomly selected in the range $[-0.25, 0.25]$. To start the iteration of proposed algorithm, we set the initial estimate $\epsilon^{(0)} = 0$. In Fig. 3, the MSE performance of the CFO estimator versus the number of EM iterations is depicted. As it can be seen the MSE performance of the proposed estimator converges after three iterations at the SNR of 5 dB, while it is improved continually until the number of iterations increases to eleven for the SNR values greater than 20 dB.

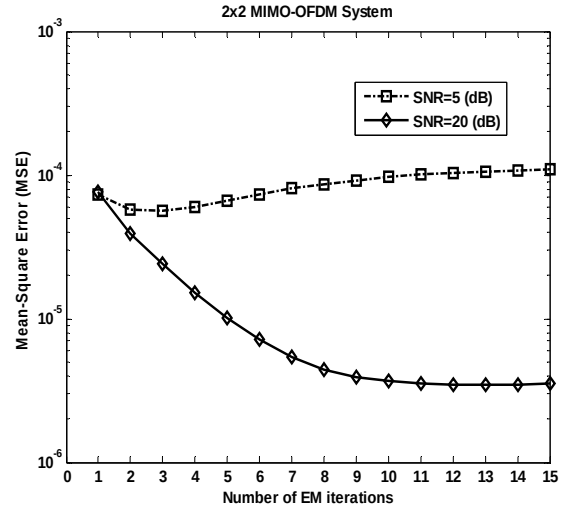


Figure 3. MSE performance of the CFO estimator versus number of EM iterations for a 2x2 MIMO-OFDM communication system

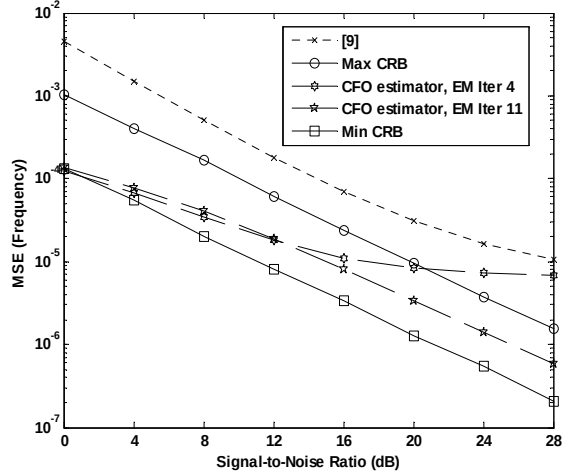


Figure 4. Comparisons of MSE performance for frequency offset estimate versus SNR.

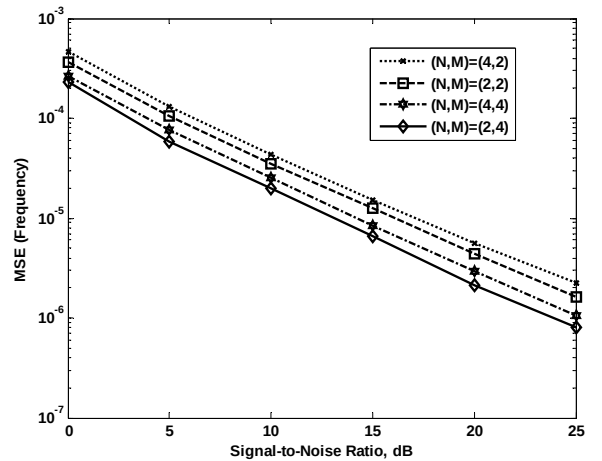


Figure 5. Comparison of the performance of the MLE#2 for different antenna configurations

In Fig. 4, we depict the MSE performance versus SNR. The curves denoted by “EM Iter#4” and “EM Iter#11” show the CFO estimator performance after the fourth and eleventh EM iteration, respectively. The CRB derived in (30) is also shown as a bench mark. As indicated in (30), CRB values are varying according to the channel state [13], and for a given SNR, the solid lines labeled “Min/Max CRB” indicate the minimum and maximum CRB obtained in 10^5 simulation runs. However, in high SNR above 20 dB, the proposed scheme needs eleventh iterations to maintain the improved performance between CRBs in all ranges of SNR. From Fig. 4, it is also deduced that proposed frequency estimator outperforms the one in [9] in all ranges of SNR.

We also test the effect of the number of antennas on CFO estimation. The CFO is randomly selected in the range $[-0.25, 0.25]$. In Fig. 5, we plot the MSE of CFO estimator when $(N,M)=(2,2)$, $(N,M)=(4,2)$, $(N,M)=(2,4)$, and $(N,M)=(4,4)$. It is observed that in MIMO-OFDM systems with equal number of transmit antennas, as the number of receive antennas increases; the performance of CFO estimation improves, since the receive-diversity gain increases accordingly.

Example 2 (Performance of Channel Estimator): In this example, we test the performance of MIMO channel estimation with $(N,M)=(2,2)$, and CFO being also randomly selected in the range $[-0.25, 0.25]$. In Fig. 6, the simulated MSE performances of channel estimator in (27) are presented and compared with the CRB in (33) and “ideal case,” where the CFO is perfectly known. It is seen that the channel estimator of the proposed algorithm shows almost ideal performance in all ranges of SNR. Especially for high SNR values greater than 24 dB, at least eleven iterations are required to achieve almost ideal MSE performance.

6. Conclusions

The problem of estimating the frequency offset and channel coefficients in multi antenna OFDM transmission was investigated in this paper. The frequency estimates were obtained using an ML approach, and the EM algorithm was employed to reduce the computational complexity of ML solution. The CFO estimates were then exploited to estimate the MIMO channel responses. The performance of our estimators was benchmarked with CRBs, and investigated by computer simulation. Simulation results show that the proposed algorithm achieves almost ideal performance compared with the CRBs for both channel and frequency offset estimations.

REFERENCES

- [1] G.L. Stuber, S.W. McLaughlin, Y. Li, M. Ingram, and T.G. Pratt, “Broadband MIMO-OFDM Wireless Communications,” *IEEE Proceeding*, vol. 92, no. 2, pp. 271-294, Feb. 2004.
- [2] Y. Li, J. H. Winters, and N. R. Sollenberger, “MIMO-OFDM for wireless communications, signal detection with enhanced channel estimation,” *IEEE Transactions on Communication*, vol. 50, no. 9, pp. 1471-1477, Sep. 2002.

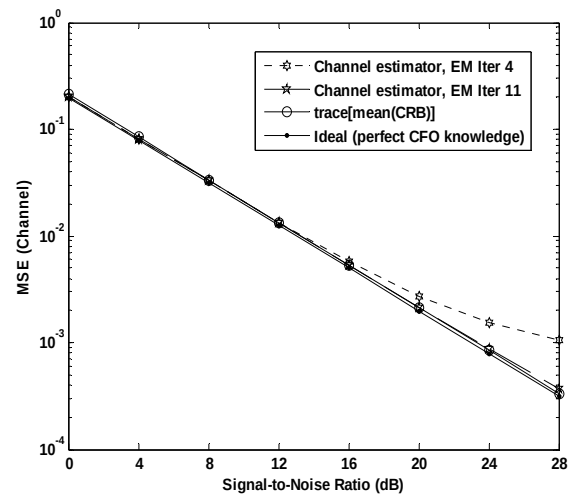


Figure 6. Channel estimation performance of a 2x2 MIMO-OFDM communication system.

- [3] H. Bolckei, D. Gesbert, and A. Paulraj, “On the capacity of OFDM based spatial multiplexing systems,” *IEEE Transactions on Communication*, vol. 50, pp. 225-234, Feb. 2002.
- [4] M. Engels, *Wireless OFDM Systems: How to make them work?* Newton, MA: Kluwer Academic Publishers, 2002.
- [5] X. Ma, M.K. Oh, G. B. Giannakis, and D.J. Park, “Hopping Pilots for Estimation of Frequency-Offset and Multiantenna Channels in MIMO-OFDM,” *IEEE Transactions on Communication*, vol. 53, no. 1, pp. 162-172, Jan. 2005.
- [6] Schenk, and A. van Zelst, “Frequency Synchronization for MIMO OFDM Wireless LAN Systems,” in *Proceedings of the IEEE VTC*, Oct. 2003, Orlando (FL), pp. 781-785.
- [7] S. Salari, M. Ahmadian, M. Ardebilipour, J. P. Cances, and V. Meghdadi, “EM-Based Turbo Receiver Design for LDPC Coded MIMO-OFDM Systems with Carrier-Frequency Offset,” *IET Commun.*, Vol. 2, No. 1, Jan. 2008, pp. 107-112.
- [8] S. Salari, M. Ardebilipour, M. Ahmadian, “Frequency Offset Synchronization and Channel Estimation for MIMO-OFDM Systems,” in *Proceedings of the 9th International Conference on Advanced Communication Technology (ICACT'07)*, Phoenix Park, Republic of Korea, pp. 1474-1478, Feb. 2007.
- [9] Y. Sun, Z. Xiong, and X. Wang, “EM-based iterative receiver design with carrier frequency offset estimation for MIMO OFDM systems,” *IEEE Transactions on Communication*, vol. 53, no. 4, pp. 581-586, Apr. 2005.
- [10] P. Priotti, “Frequency synchronization of MIMO OFDM systems with frequency selective weighting,” in *Proceedings of the IEEE VTC*, 2004, vol. 2, pp. 1114-1118.
- [11] Z. Jane Wang, Z. Han, and K. J. Ray Liu, “A MIMO-OFDM Channel Estimation Approach Using Time of Arrivals,” *IEEE Transactions on Wireless Communications*, vol. 4, no. 3, pp. 1207-1213, May 2005.
- [12] H. Minn, and N. Al-Dhahir, “Optimal training signals for MIMO-OFDM channel estimation,” *IEEE Transactions on Wireless Communications*, vol. 5, no. 5, pp. 1158-1168, May 2006.
- [13] M. Morelli and U. Mengali, “Carrier-frequency estimation for transmissions over selective channels,” *IEEE trans. Commun.* vol. 48, Sept 2000, pp.1580-1589.
- [14] T. Moon, “The expectation-maximization algorithm,” *IEEE Signal Process. Mag.*, vol. 13, 1996, pp. 47-60.
- [15] M. Feder and E. Weinstein, “Parameter estimation of superimposed signals using the EM algorithm,” *IEEE Trans. ASSP*, vol. 36, Apr. 1998, pp. 477-489.
- [16] Y. Xie and C. N. Georgiades, “Two EM-type channel estimation algorithm for OFDM with transmitter diversity,” *IEEE Trans. Commun.*, vol. 51, Jan. 2003, pp. 106-115.
- [17] P. Stoica and O. Besson, “Training sequence design for frequency offset and frequency selective channel estimation,” *IEEE Trans. Commun.*, vol. 51, Nov. 2003, pp. 1910-1917.