EM-BASED H-INF CHANNEL ESTIMATION IN MIMO-OFDM SYSTEMS

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ABSTRACT

A robust and reduced-complexity H-infinity (H-inf) channel estimator for multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems is addressed. The proposed estimator is realized by taking the following procedures: first, a simplified objective function is considered to guarantee the design simplicity of the H-inf channel estimator. Second, an expectation maximization (EM) algorithm is adopted to make the problem less complex. Third, an equivalent signal model (ESM) is utilized to relieve the non-Gaussian noise (NGN) features of practical channels, which are due to various natural or man-made impulsive sources. According to the simulation results, it is shown that the H-inf estimator has almost the same mean square error (MSE) performance as an optimal maximum a posteriori (MAP) estimator. Moreover, during implementing H-inf estimator via EM process, only few iterations are needed. Compared to traditional signal models (TSM), ESM can improve the robustness of the estimator substantially, especially in case of NGN channels.

Index Terms**—**channel estimation, MIMO-OFDM, H-inf, expectation maximum, equivalent signal model

1. INTRODUCTION

Nowadays, to further improve system performance, the MIMO-OFDM technique was proposed and it has been considered to be an attractive candidate technically [1]. However, the performance of MIMO-OFDM systems critically depends on the quality of the channel state information (CSI) available at the receiver, which is often obtained through channel estimation.

Pilot-based channel estimators in MIMO-OFDM systems have been extensively studied for many years. A Least squares (LS) estimator, without requiring any priori knowledge, is usually considered as an initial estimator [2]. EM-type estimator, given in [3], is an effective solution by iterative computing, which converts a MIMO channel estimation problem into a series of single-input single-output (SISO) channel estimation problems. By using the prior information, a MAP estimator can supply optimal performance, however, the complexity is prohibitively high [4]. Although the use of EM process reduces the computational load, its complexity is still high [4]. To deal with this conundrum, we will introduce an H-infinity (H-inf) estimator, which has both remarkably good performance and much less complexity.

To the best of our knowledge, H-inf estimator has never been used for MIMO-OFDM systems. Up to now, there are a limited number of literatures applied for wireless communication systems, which is mainly about adaptive equalization [5, 6]. In this paper, an H-inf estimator is firstly introduced to MIMO-OFDM systems. To ensure the simplicity and real-time property of receivers, we adopt the simplified objective function. Next, the EM iterative process will be adopted to lower the large matrix calculations for each received OFDM symbol from different transmit antennas. The other contribution of this paper is on the derivation of a robust EM-based H-inf estimator by using ESM over NGN channels. It is well known that the channel is always corrupted by NGN due to the impulsive nature of man-made electromagnetic interferences and of a great deal of natural noise. To relieve the effect of NGN on the estimate, an ESM which decomposes additive white Gaussian noise (AWGN) into two part Gaussian noises is introduced. One Gaussian noise is assigned to wireless fading channel, and the other belongs to the receiver. By adjusting the proportion of these two parts of noises, an obviously improved robustness against NGN channels will appear.

This paper is structured as follows. In Section 2, the signal model is discussed. In Section 3, an H-inf estimator is introduced and the EM process is proposed for reducing the complexity of H-inf estimator. Next, a robust estimator by using ESM is presented. After the performance analysis of ESM is discussed, the effectiveness of the proposed approach is evaluated via computer simulations in Section 4. Finally, we come to conclusions in Section 5.

2. SIGNAL MODEL

In what follows, we will consider MIMO-OFDM systems with K subcarriers, N_t transmitting antennas and N_r receiving antennas. L is time span of MIMO channel, $\boldsymbol{h}_{r,t}(l)$ represents the tap gain of path l for the sub-channel from the tth transmitting antenna to the rth receiving antenna. The received signal vector from the rth receiving antenna can be expressed as below

$$\boldsymbol{Y}_r = \boldsymbol{D}\boldsymbol{H}_r + \boldsymbol{Z}_r \tag{1}$$

where $\boldsymbol{Y}_r = [\boldsymbol{Y}_r(0),...,\boldsymbol{Y}_r(K-1)]^T$, $\boldsymbol{D} = [\boldsymbol{D}_1,...,\boldsymbol{D}_{N_t}]$, $\boldsymbol{D}_t = diag[d_t(0),...,d_t(K-1)]$, $d_t(k)$ is the signal from the tth transmit antenna at the kth subcarrier,

This work is supported by the National Natural Science Foundation of China (Grant no. 61004052, 61104005), the Natural Science Foundation of Liaoning and Heibei Province of China (Grant no. 20102064 and F2011501052), the Research Fund for the Doctoral Program of Higher Education of China (Grant no. 20110042120015).

$\boldsymbol{H}_r = [\boldsymbol{H}_{r,1}^T, ..., \boldsymbol{H}_{r,N_t}^T]^T$ is the channel vector, $\boldsymbol{H}_{r,t} = \boldsymbol{F}\boldsymbol{h}_{r,t}$, $\boldsymbol{h}_{r,t} = [\boldsymbol{h}_{r,t}(0), ..., \boldsymbol{h}_{r,t}(L-1)]^T$, $\boldsymbol{F} = (1/\sqrt{K})\exp(-j2\pi kl/K)$, $\boldsymbol{Z}_r = [\boldsymbol{Z}_r(0), ..., \boldsymbol{Z}_r(K-1)]^T$ is zero-mean AWGN vector, $f(\boldsymbol{Z}_1) \sim CN(0, \sigma^2 \boldsymbol{I}_K)$.

3. EM-BASED H-INF CHANNEL ESTIMATOR

3.1 H-inf channel estimator

An H-inf estimator is often carried out based on multiple-order AR model [7], implying the channel corresponding to the current OFDM symbol is estimated by using estimated channel corresponding to previous OFDM symbols. In MIMO-OFDM systems, this generally makes the design more complicated and the estimation less reliable. To avoid the disadvantages above, we consider the H-inf estimator without AR model, which applies (1) solely. Consequently, the objective function can be simplified as

$$\sup_{\boldsymbol{Z}_r} \frac{\left\|\hat{\boldsymbol{h}}_r - \boldsymbol{h}_r\right\|_{\boldsymbol{Q}}^2}{\left\|\boldsymbol{Z}_r\right\|^2} < s \tag{2}$$

where s is a given positive scalar which could be adopted as [7], $\hat{\boldsymbol{h}}_r$ is the estimation of $\boldsymbol{h}_r$, $\boldsymbol{h}_r = [\boldsymbol{h}_{r,1}^T, ..., \boldsymbol{h}_{r,N_t}^T]^T$, $\left\|\hat{\boldsymbol{h}}_r - \boldsymbol{h}_r\right\|_{\boldsymbol{Q}}^2 = \left(\hat{\boldsymbol{h}}_r - \boldsymbol{h}_r\right)^H \boldsymbol{Q}\left(\hat{\boldsymbol{h}}_r - \boldsymbol{h}_r\right)$, $\boldsymbol{Q} > 0$, is a weighting matrix. (2) can casted into an indefinite quadratic form

$$J_r = \left(\begin{bmatrix} \boldsymbol{Y}_r \\ \hat{\boldsymbol{h}}_r \end{bmatrix} - \begin{bmatrix} \boldsymbol{T}_r \\ \boldsymbol{I}_{LN_t} \end{bmatrix} \boldsymbol{h}_r\right)^H \begin{bmatrix} \boldsymbol{I}_K & 0 \\ 0 & -s^{-1}\boldsymbol{Q} \end{bmatrix} \left(\begin{bmatrix} \boldsymbol{Y}_r \\ \hat{\boldsymbol{h}}_r \end{bmatrix} - \begin{bmatrix} \boldsymbol{T}_r \\ \boldsymbol{I}_{LN_t} \end{bmatrix} \boldsymbol{h}_r\right) > 0 \tag{3}$$

where $\boldsymbol{T}_r = \left[\boldsymbol{T}_{r,1}, ..., \boldsymbol{T}_{r,N_t}\right]$, $\boldsymbol{T}_{r,t} = \boldsymbol{D}_t \boldsymbol{F}$. According to [7], H-inf estimator for MIMO-OFDM systems can be described as

$$\hat{\boldsymbol{h}}_r = \boldsymbol{\eta}_r \boldsymbol{\varepsilon}_r^{-1} \ \boldsymbol{T}_r^\dagger \boldsymbol{Y}_r \tag{4}$$

where $\boldsymbol{\varepsilon}_r = \boldsymbol{\Theta}_{r,1} + \boldsymbol{\Theta}_{r,2}\xi_r$, $\boldsymbol{\eta}_r = \boldsymbol{\Theta}_{r,3} + \boldsymbol{\Theta}_{r,4}\xi_r$, $\left\|\xi_r\right\|_\infty = \max\left(\left|\xi_1\right|, \left|\xi_2\right|, ..., \left|\xi_{LN_t}\right|\right) < 1$. $\boldsymbol{\Theta}_{r,t}$, $1 \le t \le 4$, can be given as

$$\begin{aligned} &\boldsymbol{\Theta}_{r,1} = \boldsymbol{\Omega}\boldsymbol{R}_T^{1/2} + \boldsymbol{R}_T^{-1/2}, \ \boldsymbol{\Theta}_{r,2} = s^{-1/2}\boldsymbol{\Omega}\boldsymbol{Q}^{1/2}, \\ &\boldsymbol{\Theta}_{r,3} = \boldsymbol{\Omega}\boldsymbol{R}_T^{1/2}, \ \boldsymbol{\Theta}_{r,4} = s^{-1/2}\boldsymbol{\Omega}\boldsymbol{Q}^{1/2} - s^{1/2}\boldsymbol{Q}^{-1/2}. \end{aligned} \tag{5}$$

where $\boldsymbol{R}_T = \boldsymbol{T}_r^\dagger \boldsymbol{T}_r$, $\boldsymbol{\Omega} = \boldsymbol{\Lambda}\boldsymbol{\Delta}^{1/2} - \boldsymbol{\Delta}$, $\boldsymbol{\Delta} = \left(\boldsymbol{R}_T - s^{-1}\boldsymbol{Q}\right)^{-1}$ and $\boldsymbol{\Lambda}$ can be easily calculated by the canonical factorization of $\boldsymbol{I}_{LN_t} + \boldsymbol{\Delta}$.

Considering (4), the complexity of the H-inf estimator which is in the order of $\mathcal{O}(L^3 N_t^3)$ is slightly larger than LS estimator.. However, the optimal MAP needs to invert an $KN_t \times KN_t$ matrix, which is in the order of $\mathcal{O}(K^3 N_t^3)$. Obviously, the complexity of the H-inf estimator is much less than MAP.

3.2 Reduced-complexity H-inf channel estimator

The H-inf estimator, despite its apparent simplicity, may be intractable for the large values of L, N_t. It is more convenient to write the received vector in (1) as $\boldsymbol{Y}_r = \sum_{t=1}^{N_t} \boldsymbol{Y}_{r,t}$, $\boldsymbol{Y}_{r,t} = \boldsymbol{D}_t \boldsymbol{H}_{r,t} + \boldsymbol{Z}_{r,t}$. Since the EM algorithm converts a MIMO problem into a series of SISO problems [3], the dimension of $\boldsymbol{\Omega}$, $\boldsymbol{\Phi}_r$, $\boldsymbol{W}$ involved in the computation of $\boldsymbol{\varepsilon}_r$, $\boldsymbol{\eta}_r$ can be reduced correspondingly. Therefore, $\boldsymbol{\varepsilon}_{r,t}$, $\boldsymbol{\eta}_{r,t}$ of dimension $L \times L$ can be considered as the simplified version of $\boldsymbol{\varepsilon}_r$, $\boldsymbol{\eta}_r$. The EM-based H-inf estimator can be efficiently implemented as follows.

- E-step: for $t = 1, ..., N_t$

$$\hat{\boldsymbol{Y}}_{r,t}^{(i)} = \boldsymbol{T}_{r,t}\boldsymbol{\varepsilon}_{r,t}\boldsymbol{\eta}_{r,t}^{-1}\hat{\boldsymbol{h}}_{r,t}^{(i)} \tag{6}$$

$$\hat{\boldsymbol{\Pi}}_{r,t}^{(i)} = \hat{\boldsymbol{Y}}_{r,t}^{(i)} + \mu_t[\boldsymbol{Y}_r - \sum_{t=1}^{N_t} \hat{\boldsymbol{Y}}_{r,t}^{(i)}] \tag{7}$$

where superscript i represents the ith sub-iteration, μ_t s meet $\sum_{t=1}^{N_t} \mu_t = 1$ and are usually chosen as $\mu_1 = ... = \mu_{N_t} = 1/N_t$, initial value of $\hat{\boldsymbol{h}}_{r,t}^{(0)}$ is 1_L, where 1_L is an $L \times 1$ vector whose elements are 1s only.

- M-step: for $t = 1, ..., N_t$, compute

$$\hat{\boldsymbol{h}}_{r,t}^{(i+1)} = \arg\min_{\boldsymbol{h}_{r,t}} \left\{\left\|\hat{\boldsymbol{\Pi}}_{r,t}^{(i)} - \boldsymbol{T}_{r,t}\boldsymbol{\varepsilon}_{r,t}\boldsymbol{\eta}_{r,t}^{-1}\boldsymbol{h}_{r,t}\right\|^2\right\} \tag{8}$$

$$\hat{\boldsymbol{h}}_{r,t}^{(i+1)} = \boldsymbol{\eta}_{r,t}\boldsymbol{\varepsilon}_{r,t}^{-1} \ \boldsymbol{T}_{r,t}^\dagger \hat{\boldsymbol{\Pi}}_{r,t}^{(i)} \tag{9}$$

3.3 Robust H-inf channel estimation via ESM

For TSM-based algorithms, $\boldsymbol{Z}_{r,t}$ is often considered as AWGN, which assumes that noise is mainly from the receiver side. However, in wireless systems, channels always suffer from the impact of NGN, which is due to the impulsive nature of man-made electromagnetic interferences and of a great deal of natural noise. By taking this effect into account, we take advantage of ESM to decompose $\boldsymbol{Z}_{r,t}$ into two independent Gaussian noises. One noise is assigned to the receiver, and the other is assigned to the observed wireless fading channel. The observed noisy channel coefficient can be described as: $\widehat{\boldsymbol{H}}_{r,t} = \boldsymbol{H}_{r,t} + \boldsymbol{Z}_1$, $f(\boldsymbol{Z}_1) \sim CN(0, \sigma_1^2 \boldsymbol{I}_K)$. Then, the TSM can be transformed into [8]

$$\begin{cases} \boldsymbol{Y}_{r,t} = \boldsymbol{D}_t \widehat{\boldsymbol{H}}_{r,t} + \boldsymbol{Z}_2 \\ \widehat{\boldsymbol{H}}_{r,t} = \boldsymbol{F}\boldsymbol{h}_{r,t} + \boldsymbol{Z}_1 \end{cases} \tag{10}$$

where $\boldsymbol{Z}_2 = \boldsymbol{Z}_{r,t} - \boldsymbol{D}_t \boldsymbol{Z}_1$. Moreover, we will have $f(\boldsymbol{Z}_2) \sim CN(0, (\sigma^2 - \sigma_1^2 \boldsymbol{I}_K)$ if normalized QPSK symbols are used. This kind of decomposition allows the introduction of new complete data set $\left\{\boldsymbol{Y}_{r,t}, \widehat{\boldsymbol{H}}_{r,t}\right\}$ estimator. The EM algorithm is often used to maximize the expectation of the posterior distribution over all possible missing data and hidden variables, performing estimation by alternatingly employing E and M steps.

- **E-step:** Compute the conditional expectation of the log-likelihood of $\left\{\boldsymbol{Y}_{r,t}, \widehat{\boldsymbol{H}}_{r,t}\right\}$. For given $\boldsymbol{Y}_{r,t}$ and the current estimate $\hat{\boldsymbol{h}}_{r,t}^{(i)}$ obtained by the EM algorithm in TSM, the Q-function can be expressed as

$$Q(\boldsymbol{h}_{r,t} \left| \hat{\boldsymbol{h}}_{r,t}^{(i)}\right.) = \mathrm{E}\left[\log f(\boldsymbol{Y}_{r,t}, \widehat{\boldsymbol{H}}_{r,t} \mid \boldsymbol{h}_{r,t}) \middle| \boldsymbol{Y}_{r,t}, \hat{\boldsymbol{h}}_{r,t}^{(i)}\right] \tag{11}$$

- **M-step:** Updates the estimate based on

$$\hat{\boldsymbol{h}}_{r,t}^{(i+1)} = \arg\max_{\boldsymbol{h}_{r,t}} \left\{ Q(\boldsymbol{h}_{r,t} \,|\, \hat{\boldsymbol{h}}_{r,t}^{(i)}) \right\} \tag{12}$$

According to [8], after some derivation, the improved channel estimator via ESM can be given by

$$\hat{\boldsymbol{h}}_{r,t}^{(i+1)} = (1-R)\hat{\boldsymbol{h}}_{r,t}^{(i)} + R(\boldsymbol{D}_t\boldsymbol{F})^H \boldsymbol{Y}_{r,t} \tag{13}$$

where $R = \sigma_1^2 / \sigma^2$ denotes the proportion of noise in observed wireless fading channel that is assigned to $\boldsymbol{Z}_1$.

For simplicity, the superscript $^{(i)}$ is neglected. In order to distinguish the estimators via ESM and TSM in (13), $\hat{\boldsymbol{h}}_{r,t}^{(i+1)}$ and $\hat{\boldsymbol{h}}_{r,t}^{(i)}$ are replaced by $\hat{\boldsymbol{h}}_{r,t}^{\mathrm{ESM}}$ and $\hat{\boldsymbol{h}}_{r,t}^{\mathrm{TSM}}$, respectively. So, (13) can be simplified to

$$\hat{\boldsymbol{h}}_{r,t}^{\mathrm{ESM}} = (1-R)\hat{\boldsymbol{h}}_{r,t}^{\mathrm{TSM}} + R(\boldsymbol{D}_t\boldsymbol{F})^H \boldsymbol{Y}_{r,t} \tag{14}$$

To evaluate the performance by using $\hat{\boldsymbol{h}}_{r,t}^{\mathrm{ESM}}$ and $\hat{\boldsymbol{h}}_{r,t}^{\mathrm{TSM}}$, $\boldsymbol{h}_{r,t}$ is subtracted from both sides of (14). We obtain

$$\hat{\boldsymbol{h}}_{r,t}^{\mathrm{ESM}} - \boldsymbol{h}_{r,t} = (1-R)(\hat{\boldsymbol{h}}_{r,t}^{\mathrm{TSM}} - \boldsymbol{h}_{r,t}) + R(\boldsymbol{D}_t\boldsymbol{F})^H \boldsymbol{Z}_{r,t} \tag{15}$$

The expectation of Euclidean norm of (15) is given by

$$\mathrm{MSE}_0 = (1-R)^2\,\mathrm{MSE}_1 + R^2\Xi \tag{16}$$

where $\mathrm{MSE}_0 = \mathrm{E}\left\{ \left\| \hat{\boldsymbol{h}}_{r,t}^{\mathrm{ESM}} - \boldsymbol{h}_{r,t} \right\|^2 \right\}$, $\mathrm{MSE}_1 = \mathrm{E}\left\{ \left\| \hat{\boldsymbol{h}}_{r,t}^{\mathrm{TSM}} - \boldsymbol{h}_{r,t} \right\|^2 \right\}$, $\Xi = \mathrm{E}\left\{ \left\| (\boldsymbol{D}_t\boldsymbol{F})^H \boldsymbol{Z}_{r,t} \right\|^2 \right\}$. In [2], $\mathrm{MSE}_1 = \sigma^2/\rho$, ρ is the power of each subcarrier, $\Xi = L\sigma^2$. By subtracting MSE_1 from both sides of (16), we obtain

$$\Delta_{\mathrm{MSE}} = \left[(L+1)R^2 - 2R \right]\sigma^2 \tag{17}$$

where $\Delta_{\mathrm{MSE}} = \mathrm{MSE}_0 - \mathrm{MSE}_1$. According to (17), we can draw the conclusions as follows.

① When $R=0$ or $R=2/(L+1)$, i.e. $\Delta_{\mathrm{MSE}} = 0$, $\mathrm{MSE}_0 = \mathrm{MSE}_1$, the performance of the ESM-based estimator is equal to the TSM-based estimator.

② When $0<R<2/(L+1)$, i.e. $\Delta_{\mathrm{MSE}} < 0$, $\mathrm{MSE}_0 < \mathrm{MSE}_1$, the performance of ESM-based estimator outperforms the TSM-based estimator.

③ When $2/(L+1) < R \le 1$, i.e. $\Delta_{\mathrm{MSE}} > 0$, $\mathrm{MSE}_0 > \mathrm{MSE}_1$, the performance of ESM-based estimator is worse than the TSM-based estimator.

4. SIMULATION RESULTS

To compare different algorithms, a lot of simulations have been implemented. All of the results are averaged over up to 5000 independent runs. The system parameters are assigned as follows: 4×4 MIMO systems, Rayleigh multipath fading channel with a delay of $L=8$, OFDM symbol size $K=128$ with each subcarrier modulated by QPSK, using phase shifted orthogonal pilot sequences, the power of each subcarriers $\rho=1$, cyclic prefix length of $K/16$, bandwidth of 20MHz, 15KHz subcarriers spacing, 1GHz center frequency of modulation, 50Hz Doppler frequency shift, $s=0.1$ for all simulation experiments.

First, we study the MSE performance of EM-based H-inf estimators over AWGN channel under TSM as a function of number of iterations. As depicted in Figure 1, the MSE performance begin to converge after 6 times of iterations, which is mainly due to the superior convergence property of EM iterative algorithm. Due to the general convergent property of the EM algorithm, the EM-based H-inf estimator converges to the local minimum of J_r rather than the global minimum, which can account for performance degradation, compared to the H-inf estimator.

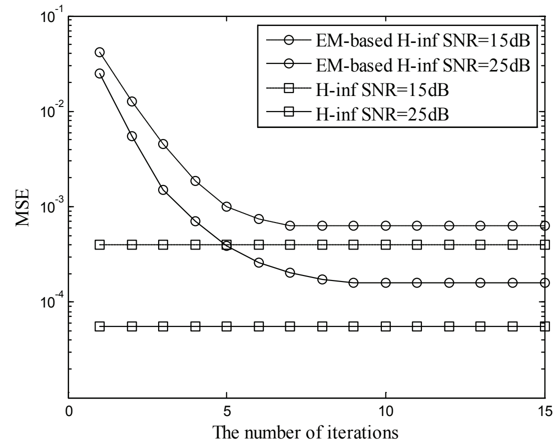

Fig. 1 The effect of the number of iterations

In Figure 2, we compare the MSE performance of the proposed estimators over AWGN channels with the LS [2] and MAP [4] estimators as a function of SNRs. As shown in the figure, both proposed H-inf and EM-based H-inf estimators have obvious improvements compared with the LS estimator. It is also noticeable that as SNR becomes larger, the MSE of H-inf estimator approaches to optimal MAP estimator. Therefore, the H-inf estimator, in terms of the advantage of low complexity, can be considered as an effective substitute for MAP estimator.

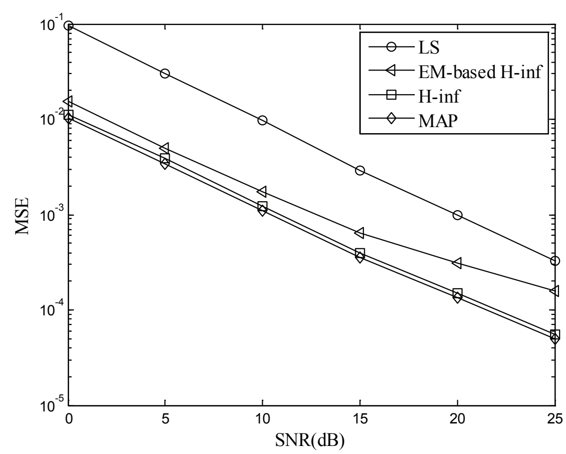

Fig. 2 MSE from four estimators with respect to SNRs

In many wireless channels, estimation algorithms often suffer from the non-Gaussian features. In our discussions, the widely used two-term Gaussian mixture model is adopted [9]. In Figure 3, we study the performance influenced by the value of R for EM-based H-inf estimator using ESM at SNR=15, 20, 25dB. It is easily shown that setting $R=0$ will lead to $\boldsymbol{Z}_1=0$ and equivalently work with the TSM. It is intuitive to find that if the observed channel coefficient is noisy, that is, $R\neq 0$, the channel estimation error will be large by using TSM. On the contrary, it is more reasonable for ESM to consider the noisy observed channel, which decreases the modeling error. The results presented in this figure demonstrate a better performance can be obtained by changing the value of R.

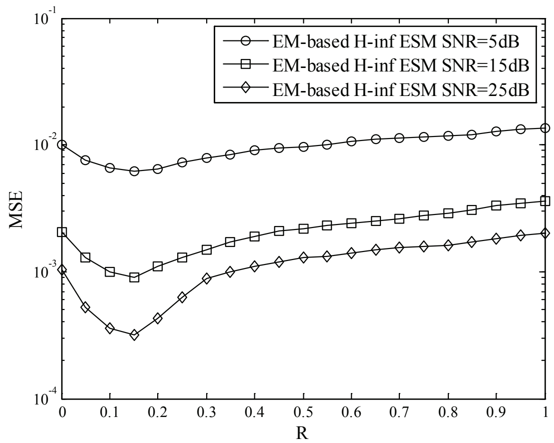

Fig. 3 The effect of different value of R under NGN

The performance of EM-based H-inf estimators regarding different signal and noise models as a function of SNR is depicted in Figure 4. It is seen that the estimator via TSM is vulnerable against the NGN condition, which will lead to performance degradation and suffer from an error floor of MSE. So no matter how the power of signal is increased, there is no improvement to the MSE performance. Moroever, the result becomes more robust in case of $R=0.15$. For example, compared to the estimator by using TSM over NGN channels, a merit of exceeding 10 dB is obtained at $\mathrm{MSE}=10^{-3}$. Therefore, by using ESM, the proposed scheme could effectively save the waste of signal power in NGN channels.

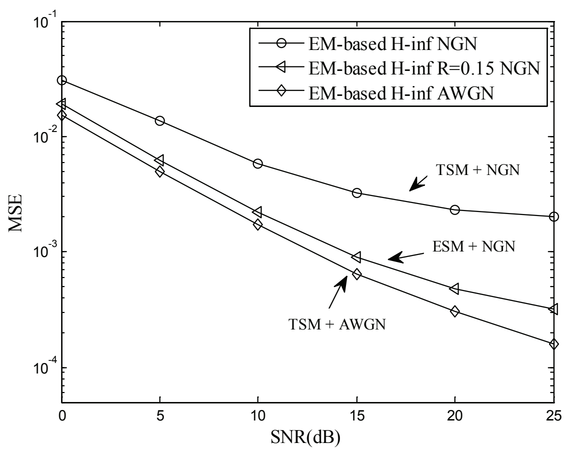

Fig. 4 MSE performance under two noise model with respect to different SNRs

5. CONCLUSIONS

In this paper, we have proved that the complexity of the H-inf estimator can be significantly reduced by using the EM process and the ESM is introduced as an effective approach to deal with error floor due to NGN. Simulation results have confirmed that the proposed H-inf estimator has almost the same MSE performance with the optimal MAP estimator, but with much less complexity. Hence, the H-inf estimator renders itself as a substitute for the optimal MAP estimator. It also has been shown that the EM-based H-inf estimator has obviously lower MSE than the LS estimator, and it generally converges after 6 iterations. Moreover, the EM-based H-inf estimator based on ESM exhibits good robust performance against NGN channels by adjusting the value of R. To sum up, we believe that the proposed estimator by employing ESM can be useful in MIMO-OFDM systems, especially for NGN channels.

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