A Fast Blind Channel Estimation Method For ZP-OFDM Systems

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***Abstract*— We develop an adaptive blind channel estimation method for an OFDM system using zero padding based on the minimum noise subspace. By applying the gradient method, a new adaptive algorithm is derived that have a number of attractive properties such as low computational complexity and good numerical stability. We extend the idea of spatial diversity for the proposed system to obtain high performance in the presence of additive channel noise. A suitable pre-FFT zero-forcing linear equalizer is also proposed. It is shown that the proposed method is computationally more efficient than existing systems and is consider as a powerful tools for the spatial diversity.**

I. Introduction

Multimedia Mobile Access Communication Systems (MMAC) and the future fourth-generation (4G) broadband wireless systems that will perform multimedia applications to mobiles and portable personal communications devices call for very high data rate transmissions. In order to accommodate this demand, Orthogonal Frequency Division Multiplexing (OFDM) and spatial diversity have recently emerged as two major commercial techniques [11], [12], [4]. In the OFDM system, the received signal is often corrupted by inter-symbol-interference (ISI). Such ISI is introduced by the channel. This increases the system bit-error-rate (BER) and therefore limits the achievable data transmission rate.

Classically, ISI could be mitigated by adding a time domain guard interval (GI) at the beginning of each OFDM symbol prior to its transmission [10], [15], [1]. This GI is also known as cyclic prefix (CP) [1] and the system CP-OFDM. The CP is chosen greater than or equal to the channel impulse response length. Thus ISI will only affect the redundant part, and the actual OFDM symbol will be received undistorted. Recently, zero-padded OFDM (ZP-OFDM), which pre-pends each OFDM symbol with zeros rather than replicating the last few samples, has been proposed [10], [1]. ZP-OFDM not only has all the advantages of CP-OFDM, but also guarantees symbol recovery and ensures finite impulse response (FIR) equalization. However, the implementation of a ZP-OFDM system involves transmitter modification and complicates the equalizer [4]. Additionally, CP- and ZP-OFDM have the same spectral efficiency if the CP samples equals to ZP.

A dynamic channel estimation is necessary before the demodulation of OFDM signals since the channel is frequency selective fading. It can be achieved by transmitting a training sequence periodically to the receiver to update the process.

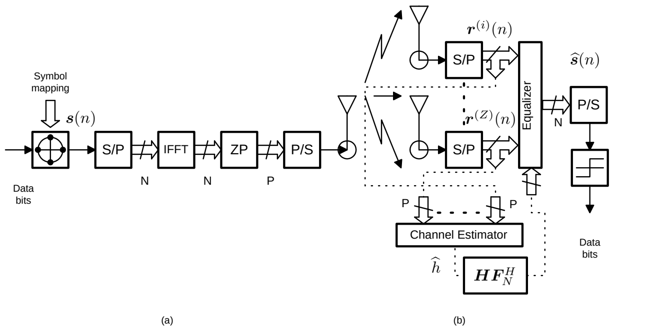

Fig. 1. OFDM system: (a) transmitter model with one antenna and multiple FIR channels, (b) receiver model with multiple antennas

There are practical situations where it is not feasible to utilize a training sequence such as in fast varying channels. In addition, a training sequence decreases the throughput, increases the system overhead, consumes the channel bandwidth, and reduces the effective channel rate [1]. These drawbacks make blind channel estimation methods more attractive. Among various known methods [9], [5], [7], [13], [8], [14], second-order-statistics (SOS) based methods are most attractive due to their useful properties [9], [13]. The main drawback of implementing SOS method, however, is their high computational cost for time varying multipath communication channels, since they need batch eigenvalue decomposition (EVD) to perform channel estimation. Therefore, there is still a need for low cost, and fast algorithms that can offer a lower computational complexity. To meet this demand, we propose a new fast adaptive blind channel estimation algorithm based on minimum noise subspace (MNS) [6], where the ZP-OFDM and not the CP-OFDM, is used.

Some notations are used throughout the paper. Superscripts ^{T} and ^{H} stand for transpose operator and Hermitian operator, respectively. $\boldsymbol{A}^\dagger$ denotes the Moore Penrose pseudo-inverse of $\boldsymbol{A}$ and $\boldsymbol{I}_c$ is the identity matrix of order c.

II. Data Model

Consider a baseband discrete-time OFDM system with a multiple FIR model arrangement as shown in Figure 1. Assume that there are Z sensors at the receiver and the maximum length of each of the FIR channels is $M+1$. We will generally choose N, the length of the OFDM symbol, to satisfy $N \geq M+1$. We also assume perfect synchronization of carriers and symbols. Then, in a noisy environment, the relation between the transmitted signals and the received signals, denoted $\boldsymbol{r}^{(i)}(n)$ of the ith channel ($i=1,\ldots,Z$) in time domain is described by [15]

$$\begin{aligned}\boldsymbol{r}^{(i)}(n) &= \boldsymbol{H}_0^{(i)}\boldsymbol{T}_{ZP}\boldsymbol{F}_N^H\boldsymbol{s}(n-1)\\ &\quad+\boldsymbol{H}_1^{(i)}\boldsymbol{T}_{ZP}\boldsymbol{F}_N^H\boldsymbol{s}(n)\\ &\quad+\boldsymbol{w}^{(i)}(n) \end{aligned} \quad (1)$$

where, the received signals are organized in vector form as

$$\boldsymbol{r}^{(i)}(n)=[r^{(i)}(n),\ldots,r^{(i)}(n+P-1)]^T.$$

$P=N+M$ represents the extended OFDM symbol. The transmitted signals, $\boldsymbol{s}(n)$, and the additive white Gaussian noise (AWGN), $\boldsymbol{w}^{(i)}(n)$, on the ith channel are assumed to be mutually uncorrelated and stationary and can be expressed as

$$\begin{aligned}\boldsymbol{s}(n) &= [s(n),\ldots,s(n+N-1)]^T\\ \boldsymbol{w}^{(i)}(n) &= [w^{(i)}(n),\ldots,w^{(i)}(n+P-1)]^T.\end{aligned}$$

The elements of $\boldsymbol{s}(n)$ are considered to be independent and identically distributed (i.i.d). We regard these elements to be in the frequency domain. These elements are modulated and converted into the time domain by an N-point IFFT matrix $\boldsymbol{F}_N^H$ with entires $f_{(n,k)}=\frac{1}{\sqrt{N}}exp(\frac{j2\pi nk}{N})$ where $k,n=0,\ldots,N-1$. The generalized $P\times P$ toeplitz matrices $\boldsymbol{H}_0^{(i)}$ and $\boldsymbol{H}_1^{(i)}$ of the $i$the channel are defined as [15]

$$\boldsymbol{H}_0^{(i)} = \begin{bmatrix} 0 & \ldots & 0 & h_M^{(i)} & \ldots & h_1^{(i)}\\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots\\ \vdots & \ddots & \ddots & \ddots & \ddots & h_M^{(i)}\\ 0 & \ldots & \ldots & \ldots & \ldots & 0\\ \vdots & \ddots & \ddots & \ldots & \ddots & \vdots\\ 0 & \ldots & \ldots & \ldots & \ldots & 0 \end{bmatrix}$$

$$\boldsymbol{H}_1^{(i)} = \begin{bmatrix} h_0^{(i)} & 0 & \ldots & \ldots & 0\\ \vdots & \ddots & \ddots & \ddots & \vdots\\ h_M^{(i)} & \ldots & h_0^{(i)} & \ldots & 0\\ 0 & h_M^{(i)} & \ldots & h_0^{(i)} & \vdots\\ \vdots & \ddots & \ddots & \ddots & \vdots\\ 0 & \ldots & h_M^{(i)} & \ldots & h_0^{(i)} \end{bmatrix}.$$

The first term in (1) represents the ISI introduced by the time variations of the channel. Using the transmit matrix $\boldsymbol{T}_{ZP}=[\boldsymbol{I}_N^T,\boldsymbol{0}_{N\times P-N}^T]^T$, the ISI part is compensated as long as the length of the channel impulse response is shorter than or equal to the GI, i.e.

$$\boldsymbol{H}_0^{(i)}\boldsymbol{T}_{ZP}=\boldsymbol{0}_{P\times N}. \quad (2)$$

From (2), it is straightforward to show that

$$\begin{aligned}\boldsymbol{r}^{(i)}(n) &= \boldsymbol{H}_1^{(i)}\boldsymbol{T}_{ZP}\boldsymbol{F}_N^H\boldsymbol{s}(n)+\boldsymbol{w}^{(i)}(n)\\ &= \boldsymbol{H}^{(i)}\boldsymbol{F}_N^H\boldsymbol{s}(n)+\boldsymbol{w}^{(i)}(n).\end{aligned} \quad (3)$$

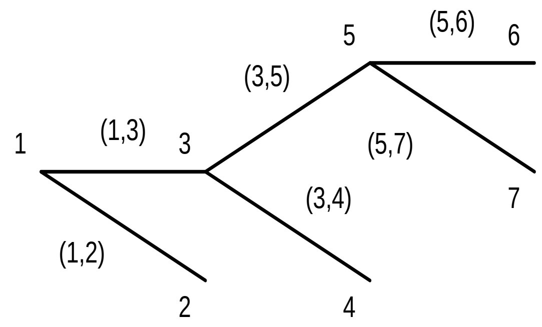

Fig. 2. Illustration of a tree connecting $Z=7$

Stacking the output of the Z channels gives the composite receive vector

$$\boldsymbol{r}(n)=\boldsymbol{H}\boldsymbol{F}_N^H\boldsymbol{s}(n)+\boldsymbol{w}(n) \quad (4)$$

where

$$\begin{aligned}\boldsymbol{r}(n) &= [\boldsymbol{r}^{(1)T},\boldsymbol{r}^{(2)T},\ldots,\boldsymbol{r}^{(Z)T}]^T\\ \boldsymbol{w}(n) &= [\boldsymbol{w}^{(1)T},\boldsymbol{w}^{(2)T},\ldots,\boldsymbol{w}^{(Z)T}]^T\\ \boldsymbol{H} &= [\boldsymbol{H}^{(1)T},\boldsymbol{H}^{(2)T},\ldots,\boldsymbol{H}^{(Z)T}]^T.\end{aligned}$$

Our problem consists of estimating the channel matrix $\boldsymbol{H}$ using only the observations and some statistical knowledge of the received signal $\boldsymbol{r}(n)$. For this reason, $\boldsymbol{H}$ is assumed to have full column rank, i.e., rank$(\boldsymbol{H})=P$ [1].

III. Channel estimation

The objective of this section is to design a blind channel estimation technique for the ZP-OFDM system based only on the second order statistics (SOS) of the received signals exploiting the MNS method. The proposed method reshape the received signals $\{\boldsymbol{r}^{(i)}(n), i=1,\ldots Z\}$ into $Z-1$ pairs. The $Z-1$ pairs can be designed on the relay of the tree pattern as shown in Figure 2 [6]. For each $\{q=(q_1,q_2)\}$ pair, the received signals can be expressed as follows

$$\boldsymbol{r}^{(q)}(n)=\boldsymbol{H}^{(q)}\boldsymbol{F}_N^H\boldsymbol{s}(n-1)+\boldsymbol{w}^{(q)}(n) \quad (5)$$

where

$$\boldsymbol{r}^{(q)}(n)=\begin{bmatrix}\boldsymbol{r}^{(q_1)}(n)\\ \boldsymbol{r}^{(q_2)}(n)\end{bmatrix}, \boldsymbol{w}^{(q)}(n)=\begin{bmatrix}\boldsymbol{w}^{(q_1)}(n)\\ \boldsymbol{w}^{(q_2)}(n)\end{bmatrix}$$

$$\boldsymbol{H}^{(q)}=\begin{bmatrix}\boldsymbol{H}^{(q_1)}\\ \boldsymbol{H}^{(q_2)}\end{bmatrix}.$$

We consider the covariance matrix of $\boldsymbol{r}^{(q)}(n)$ for $n=1,\ldots,K$

$$\boldsymbol{R}_{rr}^{(q)}=\frac{1}{K}\sum_{n=1}^{K}\boldsymbol{r}^{(q)}(n)\boldsymbol{r}^{(q)H}(n) \quad (6)$$

and as K becomes large, this matrix has the asymptotical structure

$$\boldsymbol{R}_{rr}^{(q)}=\boldsymbol{H}^{(q)}\boldsymbol{F}_N^H\boldsymbol{R}_{ss}\boldsymbol{F}_N\boldsymbol{H}^{(q)H}+\boldsymbol{R}_{ww}^{(q)} \quad (7)$$

where

$$\boldsymbol{R}_{ss} = \frac{1}{K}\sum_{n=1}^{K}\boldsymbol{s}(n)\boldsymbol{s}^H(n)$$

$$\boldsymbol{R}_{ww}^{(q)} = \frac{1}{K}\sum_{n=1}^{K}\begin{bmatrix}\boldsymbol{w}^{(q_1)}(n)\\ \boldsymbol{w}^{(q_2)}(n)\end{bmatrix}\begin{bmatrix}\boldsymbol{w}^{(q_1)}(n)\\ \boldsymbol{w}^{(q_2)}(n)\end{bmatrix}^H.$$

It is assumed that the noise is white ($\boldsymbol{R}_{ww}^{(q)} = \sigma_w^2\boldsymbol{I}_{2P}$) and the transmitted signal is rich enough so that it has full column rank, i.e. $rank(\boldsymbol{R}_{ss}) = N$. As [1], the EVD of $\boldsymbol{R}_{rr}^{(q)}$ is expressed as

$$\boldsymbol{R}_{rr}^{(q)} = \boldsymbol{S}^{(q)}diag(\lambda_1^{(q)},\ldots,\lambda_N^{(q)})\boldsymbol{S}^{(q)H} + \sigma_w^2\boldsymbol{G}^{(q)}\boldsymbol{G}^{(q)H} \quad (8)$$

where $\boldsymbol{S}^{(q)} = [\boldsymbol{S}_1^{(q)},\ldots,\boldsymbol{S}_N^{(q)}]$ is referred to as the signal subspace and $\boldsymbol{G}^{(q)} = [\boldsymbol{G}_1^{(q)},\ldots,\boldsymbol{G}_{2P-N}^{(q)}]$ is referred to the noise subspace. The columns of $\boldsymbol{H}^{(q)}$ also span the signal subspace, and thus by orthogonality we have

$$\boldsymbol{G}_j^{(q)H}\boldsymbol{H}^{(q)}\boldsymbol{F}_N^H = \boldsymbol{0}, \qquad j = 1,\ldots,2P-N. \quad (9)$$

The least dominant eigenvector, $\boldsymbol{G}_{2P-N}^{(q)}$ is selected from the noise subspace span. Divide $\boldsymbol{G}_{2P-N}^{(q)}$ into two subvectors as $\boldsymbol{G}_{2P-N}^{(q)} = [\breve{\boldsymbol{g}}^{(q_1)T}, \breve{\boldsymbol{g}}^{(q_2)T}]^T$, where each subvector has the dimension $P \times 1$. Then, form the zero-padded $ZP \times 1$ as follows

$$\boldsymbol{V}^{(q)} = \begin{bmatrix}\boldsymbol{g}^{(q)(1)}\\ \vdots\\ \boldsymbol{g}^{(q)(Z)}\end{bmatrix}, \boldsymbol{g}^{(q)(i)} = \begin{bmatrix}e^{(q)(i)}(1)\\ \vdots\\ e^{(q)(i)}(P)\end{bmatrix}$$

where

$$\boldsymbol{g}^{(q)(i)} = \begin{cases}\breve{\boldsymbol{g}}^{(q_1)(i)} & i = q_1\\ \breve{\boldsymbol{g}}^{(q_2)(i)} & i = q_2\\ 0 & otherwise\end{cases}$$

The channel is estimated by solving the orthogonality relation $\boldsymbol{V}^{(q)H}\boldsymbol{H}\boldsymbol{F}_N^H = \boldsymbol{0}$. In practice, since the received signals are noisy, this equation can be solved by minimizing the quadratic form

$$\boldsymbol{q}(\boldsymbol{h}) = \sum_{q=1}^{Z-1}\left\|\boldsymbol{V}^{(q)H}\boldsymbol{H}\boldsymbol{F}_N^H\right\|^2. \quad (10)$$

As [12], $\boldsymbol{V}^{(q)H}\boldsymbol{H}\boldsymbol{F}_N^H = \boldsymbol{h}^H\boldsymbol{E}^{(q)}\boldsymbol{F}_N^H$,where $\boldsymbol{E}^{(q)} = [\boldsymbol{E}^{(q)(1)T}, \ldots, \boldsymbol{E}^{(q)(Z)T}]^T$ is a $Z(M+1)\times N$ filtering matrix associated with $\boldsymbol{V}^{(q)}$ and comprising of Z Hankel matrices. Each $(M+1)\times N$ matrix is defined as

$$\boldsymbol{E}^{(q)(i)} = \begin{bmatrix} e^{(q)(i)}(1) & \cdots & \cdots & e^{(q)(i)}(N)\\ e^{(q)(i)}(2) & \cdots & \cdots & e^{(q)(i)}(N+1)\\ \vdots & \ddots & \ddots & \vdots\\ e^{(q)(i)}(M+1) & \cdots & \cdots & e^{(q)(i)}(P)\end{bmatrix}.$$

Therefore, (10) can be expressed as

$$\begin{aligned}\boldsymbol{q}(\boldsymbol{h}) &= \sum_{q=1}^{Z-1}\left\|\boldsymbol{V}^{(q)H}\boldsymbol{H}\boldsymbol{F}_N^H\right\|^2\\ &= \sum_{q=1}^{Z-1}\boldsymbol{h}^H\boldsymbol{E}^{(q)}\boldsymbol{F}_N^H\boldsymbol{F}_N\boldsymbol{E}^{(q)H}\boldsymbol{h}\\ &= \sum_{q=1}^{Z-1}\boldsymbol{h}^H\boldsymbol{Q}\boldsymbol{h} \quad (11)\end{aligned}$$

and the channel estimate can thus be formulated as

$$\widehat{\boldsymbol{h}} = \arg\min_{\|\boldsymbol{h}\|=1}\boldsymbol{h}^H\boldsymbol{Q}\boldsymbol{h}. \quad (12)$$

This quadratic optimization criterion allows unique estimation of $\boldsymbol{h}$ up to scale factor and $\boldsymbol{h}$ is thus obtained as the eigenvector associated with the minimum eigenvalue of $\boldsymbol{Q}$.

IV. Adaptive implementation

The proposed channel estimation technique in the previous section is linked to the equalization stage. This technique is accomplished via a standard EVD requiring $O(\overline{p}^3)$, where $\overline{p}$ is the dimension of the covariance matrix. Therefore, the computationally expensive EVD is unrealistic or too costly to acquire in adaptive applications. This limitation of the EVD can be resolved by deriving fast adaptive algorithm having linear complexity. Then, the implementation of this algorithm leads to a low complexity ZP-OFDM receiver. The new adaptive algorithm of the proposed ZP-OFDM receiver is outlined next as follows

- Step 1) Compute the covariance matrix $\boldsymbol{R}_{rr}^{(q)}(i_r)$ by its recursive version:

  $$\boldsymbol{R}_{rr}^{(q)}(i_r) = \kappa\boldsymbol{R}_{rr}^{(q)}(i_r-1) + \boldsymbol{r}^{(q)}(i_r)\boldsymbol{r}^{(q)H}(i_r).$$

  Intialize $\boldsymbol{R}_{rr}^{(q)}(i_r-1) = \boldsymbol{0}$ and choose the correlation matrix updating factor $0.9 \le \kappa < 1$.
- Step 2) Based on $\boldsymbol{R}_{rr}^{(q)}(i_r)$, estimate $\boldsymbol{G}_{2P-N}^{(q)}(i_r)$ through the subspace tracking algorithm.
- Step 3) Use the estimated $\boldsymbol{G}_{2P-N}^{(q)}$ to form $\boldsymbol{Q}$.
- Step 4) Compute gardient vector: $\boldsymbol{\nabla} = 2\boldsymbol{Q}\widehat{\boldsymbol{h}}_i$.
- Step 5) Update the channel coefficient: $\widehat{\boldsymbol{h}}_{i_r+1} = \widehat{\boldsymbol{h}}_{i_r} + \mu_h\boldsymbol{\nabla}$ where $0 < \mu_h < 1$.

The second step of the proposed algorithm is performed by employing a subspace tracking algorithm. In the literature, many subspace tracking algorithms have been proposed, which require $O(\overline{p}^2\,\overline{q})$, $O(\overline{p}\,\overline{q}^2)$, and $O(\overline{p}\,\overline{q})$ floating point operations where $\overline{q}$ is the dimension of the signal or noise subspace. In our adaptive implementation, we propose to track the MNS by an efficient subspace tracker: Fast Rayleigh's quotient-based adaptive noise subspace (FRANS), proposed by Attalah and Abed-Meraim [2]. The FRANS algorithm behaves much better than Oja's algorithm [3], while offering a comparable computational complexity $O(\overline{p}\,\overline{q})$. In addition, it can be implemented by less calculations than the normalized orthogonal Oja (NOOja) algorithm [3]. The FRANS algorithm is outlined as follows

- Step 1) Initialization of the algorithm: $\boldsymbol{G}_{2P-N}^{(q)}(0)$= any arbitrary orthogonal matrix such that $\boldsymbol{G}_{2P-N}^{(q)H}\boldsymbol{G}_{2P-N}^{(q)} = 1$ or noise subspace which is drived from EVD of the initial channel covariance matrix and injected for initialization.
- Step 2) At iteration i_r:

$$
\begin{aligned}
\boldsymbol{y}^{(q)}(i_r) &= \boldsymbol{G}_{2P-N}^{(q)H}(i_r)\boldsymbol{r}^{(q)}(i_r) \\
\beta^{(q)}(i_r) &= \alpha(\left\|\boldsymbol{r}^{(q)}(i_r)\right\|^2 + \zeta) \\
\delta^{(q)}(i_r) &= 4\beta^{(q)}(i_r)(1-\beta^{(q)}(i_r) \\
&\quad \times \left\|\boldsymbol{r}^{(q)}(i_r)\right\|^2) \left\|\boldsymbol{y}^{(q)}(i_r)\right\|^2 \\
\rho^{(q)}(i_r) &= \begin{cases} \sqrt{1-\delta^{(q)}(i_r)}, \delta^{(q)}(i_r) \le 1 \\ \sqrt{\delta^{(q)}(i_r)-1}, otherwise \end{cases} \\
\boldsymbol{p}^{(q)}(i_r) &= \frac{-\tau^{(q)}(i_r)\boldsymbol{G}_{2P-N}^{(q)}(i_r)\boldsymbol{y}^{(q)}(i_r)}{\beta^{(q)}(i_r)} \\
&\quad +2\boldsymbol{r}^{(q)}(i_r)(1+\tau^{(q)}(i_r)) \\
\boldsymbol{G}_{2P-N}^{(q)}(i_r+1) &= \boldsymbol{G}_{2P-N}^{(q)}(i_r) - \beta^{(q)}(i_r) \\
&\quad \times \boldsymbol{p}^{(q)}(i_r)\boldsymbol{y}^{(q)H}(i_r)
\end{aligned}
$$

In this algorithm ζ is a small positive constant which improves the stability, and α is a learning parameter where $0 < \alpha < 1$.

V. Linear equalizer

In this section, we design an equalizer based on one FFT operation at the receiver as shown in Figure 1. As a consequence, a considerable reeducation in hardware complexity is expected. From Maximum Likelihood (ML) estimation theory, the estimate of $s(n)$ is given by

$$\hat{\boldsymbol{s}}(n) = \boldsymbol{E}\boldsymbol{r}(n) \tag{13}$$

where $\boldsymbol{E}$ is the pre-FFT zero forcing-linear equalizer given by $\boldsymbol{E} = (\hat{\boldsymbol{H}}\boldsymbol{F}_N^H)^\dagger$ and $\hat{\boldsymbol{H}}$ denotes the estimate of $\boldsymbol{H}$.

VI. Numerical results

i	1	2	3	4
$\boldsymbol{h}^i(0)$	-0.0490+0.3590i	0.4430-0.03640i	-0.2110-0.3220i	0.4170+0.0300i
$\boldsymbol{h}^i(1)$	0.4820-0.5690i	1.000	-0.199+0.9180i	1.000
$\boldsymbol{h}^i(2)$	-0.5560+0.5870i	0.9210-0.1940i	1.000	0.8730+0.1450i
$\boldsymbol{h}^i(3)$	1.000	0.1890-0.2080	-0.2840-0.5240i	0.2850+0.3090i
$\boldsymbol{h}^i(4)$	-0.1710+0.0610	-0.087-0.054i	0.1360-0.1900i	-0.0490+0.1610i

TABLE I

IMPULSE RESPONSES OF THE Z CHANNEL SYSTEM

We provide simulation results which illustrate the performance of MNS ZP-OFDM receiver. As a comparison, we include the results obtained with noise subspace (NS) ZP-OFDM receiver described in [1]. The user symbols were randomly generated using a BPSK modulation scheme. We restricted the simulation to $Z = 4$ FIR channels, and the degree of ISI or channel impulse response is $M = 4$. The channel coefficients are given in Table 1. The performance of the receiver can be examined by utilizing the normalized root mean square error (NRMSE) with 100 Monte Carlo runs. This is defined as

$$NRMSE = \frac{1}{||h||}\sqrt{\frac{1}{N_t}\sum_{i_r=1}^{N_t}||\hat{h}_{i_r} - h||^2} \tag{14}$$

where N_t is the number of Monte Carlo runs and $\hat{h}_{i_r}$ is the estimate of the channel. In the first simulation study, we fixed the number of OFDM symbols at 500, varied the SNR from 0-50 dB and the number of sub-carriers is set to $N = 20$. Figure 3 shows the NRMSE performance of the receivers as a function of SNR. We observe that the estimate of the true channel responses by both receivers improves with increasing SNR. It is clear that the NS ZP-OFDM has better performance than the MNS ZP-OFDM and gives superior performance at low SNR.

Figure 4 displays the overall BER performance corresponding to SNR range of 0-18 dB. It is seen that the NS ZP-OFDM receiver has slightly better performance in terms of BER than the MNS ZP-OFDM receiver at low SNR. However, at moderate to high SNR, both receivers achieve the same performance.

Obviously, the NS ZP-OFDM receiver obtains better results than the MNZ ZP-OFDM receiver, but we would remark the difference in computational cost between both receivers. The NS ZP-OFDM receiver requires an EVD of an $ZP \times ZP$ covariance matrix [1]. In contrast, the proposed MNS ZP-OFDM receiver requires an EVD of an $2P \times 2P$ covariance matrix. This means that the computational cost of the proposed MNS ZP-OFDM is lower than that of the NS ZP-OFDM. Additionally, the NS ZP-OFDM receiver creates a noise subspace spanned by $ZP - N$ vectors [1] against $Z - 1$ vectors in case of the MNS ZP-OFDM.

The reduced noise subspace dimension in the MNS based channel estimator makes the ZP-OFDM receiver less robust to channel noise and thus performance degradation is obvious [5]. To prevent this degradation, additional spatial diversity can be included at the expense of increased number of antennas.

For further complexity reduction in the MNS ZP-OFDM receiver, the proposed adaptive algorithm is employed. In the simulations, the eigen components of the noise subspace are obtained by applying EVD to the covariance matrix of the first 500 data vectors. Another EVD is required in the same iteration to resolve (12). Then, the role of the adaptive algorithm is started for tracking the channel. The computational complexity of the new receiver is evaluated as shown in Figure 5. The computational complexity of the original receivers are also shown. It is clear that the complexity increases as the number of sub-carriers increases. We remark that the implementation without fast adaptive algorithm can be considered as a real computational burden.

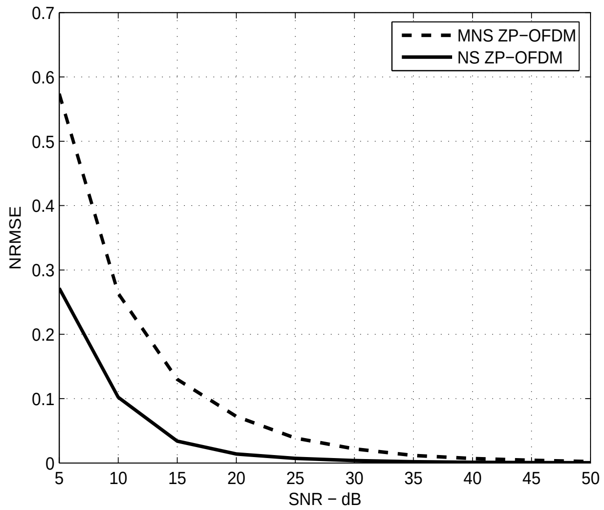

Fig. 3. SNR v/s NRMSE comparison of ZP-OFDM estimators with $K = 500$, $Z = 4$, $M = 4$, $N = 20$, $P = 24$ and $N_t = 100$

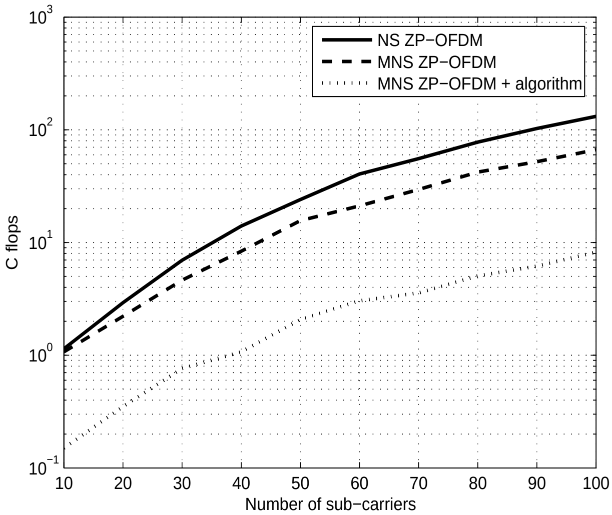

Fig. 5. Comparison of computational complexity with $K = 500$, $Z = 4$, $M = 4$, $SNR = 25$, $\kappa = 0.9$, $\mu_h = 0.0001$, $\zeta = 0.01$, $\alpha = 0.05$

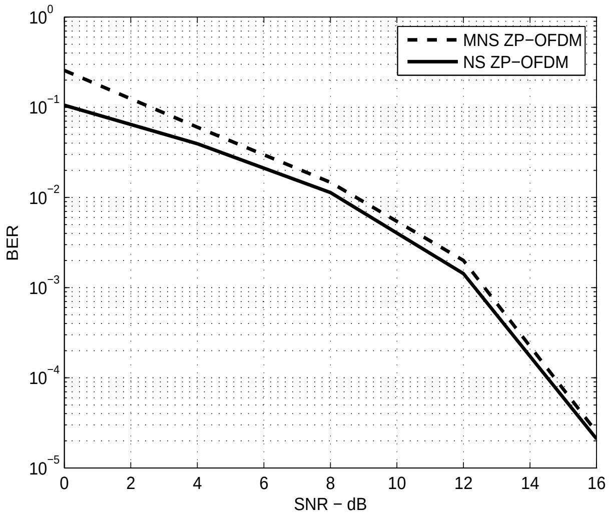

Fig. 4. SNR v/s BER comparison of ZP-OFDM receivers with $K = 500$, $Z = 4$, $M = 4$, $N = 20$, $P = 24$ and $N_t = 100$

VII. Conclusion

In this paper we have proposed a fast adaptive blind channel estimation method based on minimum noise subspace method exploiting spatial diversity for zero-padded OFDM system. The resulting method has two distinct advantages: it is computationally efficient and has a good performance at moderate to high SNR.

VIII. Acknowledgment

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