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A Novel Adaptive Method For The Blind Channel Estimation And Equalization Via Sub Space Method

Pradyumna Ku. Mohapatra[1], Pravat Ku.Dash[2] , Jyoti Prakash Swain[3] , Jibanananda Mishra[4]

[1,2,4]Asst.Prof .Orissa Engg.College,BPUT,Bhubaneswar,Odisha.

ABSTRACT

In this paper, we present a systematic study of the subspace-based blind channel estimation and equalization method. We first formulate a general signal model of multiple simultaneous signals transmitted through a channels, which can be applied to a modern digital communication systems QAM. Based on this model, we then propose a generalized subspace-based channel estimator by minimizing a novel cost function. We investigate the asymptotic performance of the proposed estimator, i.e. bias, mean square error (MSE), NRMSE and also estimate the channel performance

Keywords:- OFDM, semi-blind, space-time coding, subspace based channel estimation.

1.INTRODUCTION

In wireless communication estimation of channel become a tough task where multiple independent signals are transmitted simultaneously though a channels. In accurate channel information is important to recover the original transmitted signals by signal processing techniques, e.g. combining, deconvolution, detection, etc. [6]. Blind identification and equalization of wireless communication channels have attracted considerable interest during the past few years because they avoid training and thus make efficient use of the available bandwidth. A wireless communication channel usually introduces inter symbol interference (ISI) due to multipath propagation. At the receiver, channel equalization is necessary to mitigate ISI for successful symbol detection [1]. Blind methods rely mainly on the channel outputs instead of requiring system to transmit training sequences. Second-order statistics (SOS) based methods can yield fast convergence and acceptable performance [2] which are used in all blind methods.. Subspace methods are very efficient and widely studied. They apply subspace decomposition to the data covariance matrix to obtain either signal subspace or noise subspace first [3], [4]. In this paper, we propose a generalized blind subspace channel estimator within the framework of the general signal model . We also study the asymptotic performance of the proposed estimator with a large number of observed data. We identified a generalized subspace-based channel estimator by minimizing a novel cost function, which incorporates the set of kernel matrices of the signals sharing the target channel via a weighted sum of errors. We investigate the asymptotic performance of the proposed estimator, i.e. bias, covariance, mean square error (MSE) for large numbers of independent observations. We show that the performance of the estimator can be optimized by increasing the number of kernel matrices and by using a special set of weights in the cost function. Therefore, low-complexity algorithms based on the SOS are desirable. Certainly, subspace tracking technique can be applied to adaptively obtain subspaces [7].

2. SYSTEM MODEL

In modern communication, if duration of transmitted symbol w(n) is T , then received baseband signal follows a model [4]

$$y(t) = \sum_{n=-\infty}^{\infty} w(n)h(t-nT) + v(t) \qquad (1)$$

where h(t) is the overall channel impulse response including the effects of transmitter filter, propagation channel and receiver filter, v(t) is a white Gaussian stationary process. For diversity reception and channel estimation purposes, we assume P sub-channels are available. They can be obtained from either oversampling a single sensor at a rate of multiples of symbol rate, or employing multiple sensors sampling at the symbol rate at the receiver [4]. In either case, all sub channels are assumed to have finite duration support with maximum order q. The discrete-time output of the p th sub channel can be written by

$$y_p(n) = \sum_{l=0}^{q} w(n-l)h_p(l) + v_p(n) \qquad (2)$$

If we collect $y_p(n)$ for p = 1, ..., P in a vector and then stack L such vectors corresponding to L current/past successive symbol intervals in a vector y_n of length $v = LP$, then we obtain a vector/matrix representation [4]

$$y_n = Hw_n + v_n \qquad (3)$$

Where H is a block Toeplitz channel matrix of size $v \times (L+q)$, $W_n = [w(n), \ldots, w(n-L-q+1)]^T$ is an input vector, v_n is a noise vector. Assume input and noise have zero mean and variance $\sigma_w^{\,2}$ and $\sigma_v^{\,2}$ respectively.

3. SUBSPACE CHANNEL ESTIMATION[11]

Using subspace technique channel parameters H can be estimated . For ease, collect all $P(q+1)$ un known parameters in a vector g_d

$$g_d = [h_1(q), \ldots, h_p(q), \ldots, h_1(0), \ldots, h_p(0)]^T$$

Also denote the (j+q+1) th column $(j = -q, \ldots, 0 \ \ldots, L-1)$ of H by h_j. Then $h_0 = [g_d^{\,T}, 0, \ldots, 0]^T$ If we define $v \times P(q+1)$ matrix $S = [I_{P(q+1)}, 0]^T$ Where I is an identity matrix, then $h_0 = Sg_d$. Other columns h_j also contain partial/full copies of vector g_d jointly with some possibly leading/trailing zeros. We introduce a shift matrix J with all 1's in the first sub-diagonal to conveniently explore this relationship. Use the symbol j^{-1} to denote j^T although J is singular: $J^{-1} = J^T$ and define j^0 as an identity matrix. Then h_j can be obtained by shifting all elements of h_o up or down by $|jP|$ positions

$$h_j = J^{jp} h_o = J^{jp} S_{g_d} \qquad (4)$$

If the data covariance matrix R is decomposed $R = E\{y_n y_n^{\,H}\}$ by EVD as

$$R = [U_s \quad U_n]\begin{pmatrix} \square_s + \sigma_v^{\,2} & 0 \\ 0 & \sigma_v^{\,2} I \end{pmatrix} \qquad (5) \quad \text{Where} \quad \square_s = diag\{\lambda_1^{\,2}, \ldots, \lambda_{L+q}^{\,2}\},$$

Where U_s and U_n represent the signal and noise subspaces respective, then $U_n^{\,H} h_j = 0$ for all possible j. It is found that the rank of U_s is equal to the rank of H which is $L+q$ under some assumptions on all sub channels [4]. Denote it by $\xi_s = L+q$. Then the rank of U_n becomes $\xi_n = v - L - q$. Therefore considering (4), the subspace channel estimation criterion can be described as follows [4]

$$\hat{g} = arg \min_{\|x\|=1} \sum_{j=-q}^{L-1} x^H S^H J^{-jP} U_n U_n^{\,H} J^{jP} S_x \qquad (6)$$

Under some identifiability conditions, (6) gives a unique channel vector up to a multiplicative scalar. In the subspace technique, the U_n can be estimated from EVD of the data covariance matrix estimated from N data vectors

$$\hat{R} = \frac{1}{N}\sum_{n=1}^{N} y_n y_n^{\,H} \qquad (7)$$

From the above definition we will propose a subspace approximation (SA) technique to approximate the noise subspace component $U_n U_n^{\,H}$ in (6) from which g_d can be estimated.

4. SUBSPACE DECOMPOSITION

Let 'r' denote the covariance matrix of received signal vector r in (8).We consider the following model of an L-dimensional received signal vector in a communication system:

$$r = \sum_{i=1}^{N} \gamma_i \ b_i \ C_i h_i + e \qquad (8)$$

Where N is the number of individual symbols that comprise the received signal vector, γ_i is a real-value channel gain, bi is the ith information symbol, C_i is defined as a kernel matrix with size L × M, hi is an M×1 normalized channel vector, and e is an L × 1 additive noise vector. We assume that the information symbols bi, for $i = 1, \ldots, N$ are independent and identically distributed with zero mean and equal variance. If we define the i-th element of the vector e as e_i then

$$E[e_i] = 0 \qquad i = 1, \ldots, L \qquad E[e_i e_j^{\,*}] = \delta^2 \delta_{i,j} \quad i,j = i = 1, \ldots, L$$

$$E[e_i e_j] = 0 \quad i \neq j, \ \ i,j = 1, \ldots, L$$

We define an $N \times 1$ data vector b, an $N \times N$ amplitude matrix $\mathbf{\Gamma}$,and an $L \times N$ signature waveform matrix W ,respectively, as follows:

$$b \triangleq [b_1, \ \ldots, b_N]$$

$$\mathbf{\Gamma} \triangleq \mathrm{diag}[\gamma_1, \ \ldots, \gamma_N]$$

$$W = [w_1, \ \ldots, w_N]$$

$$W_i \triangleq C_i h_i \qquad i = 1, \ \ldots \qquad , N \qquad (9)$$

is the effective signature waveform of the i-th information symbol, i.e. combined effect of channel and kernel matrix as seen by the receiver. Using the above matrix notations, the signal model (8) can be expressed more compactly as

$$r = W\Gamma b + e = x + e \quad (10)$$

Where we define $X \triangleq W\Gamma b$

Let R denote the covariance matrix of received signal vector r in (8):

$$R = E[rr^H] = W\Gamma^2 W^H + \sigma^2 I_L \quad (11)$$

Blind subspace methods exploit the special structure of R to estimate the channel parameters. Specifically, let us express the Eigen Value Decomposition (EVD) (see[10]) of R in the form

$$R = U\Lambda U^H \quad (12)$$

Where $\Lambda = \mathrm{diag}[\lambda_1, \ldots \lambda_L]$ denotes the eigen value matrix, with the eigenvalues in a non-increasing order, and U is a unitary matrix that contains the corresponding eigenvectors. Since the rank of matrix $W\Gamma^2 W^H$ in (11) is N, it follows that

$$\lambda_1 \geq \ldots \geq \lambda_N > \lambda_{N+1} = \ldots = \lambda_L = \sigma^2 \quad (13)$$

Thus, the eigenvalues can be separated into two distinct groups, the signal eigen values and the noise eigenvalues, respectively represented by matrices

$$\Lambda_S \triangleq \mathrm{diag}[\lambda_1, \ldots, \lambda_N] \quad (14)$$

Accordingly, the eigenvectors can be separated into the signal and noise eigenvectors, as represented by matrices Us and Un with dimensions L×N and L×(L − N), respectively. With this notation, the EVD in (11) can be expressed in the form

$$R = [U_S \quad U_n]\begin{bmatrix}\Lambda_s & 0 \\ 0 & \Lambda_n\end{bmatrix}\begin{bmatrix}U_s^H \\ U_n^H\end{bmatrix} \quad (15)$$

The columns of Us span the so-called signal subspace with dimension N, while those of Un span its orthogonal omplement, i.e. the noise subspace.

5. ADAPTIVE SUBSPACE CHANNEL ESTIMATION

Here, we consider the signal model (8) in a dynamic signal environment, where the M× 1 channel vector $h^m(t)$is assumed to be a time varying parameter.

Define the following variables for convenience:

$$\bar{A} \triangleq \mathrm{diag}\left[\sqrt{\alpha^1}, \ldots, \sqrt{\alpha^p}\right] \otimes I_L \quad (16)$$

$$\bar{w}(t) \triangleq \bar{A}\ \mathrm{vec}\left[\bar{W}(t)\right] \quad (17)$$

$$\bar{C} \triangleq \bar{A}C \quad (18)$$

where $\bar{A}$ is a PL × PL matrix, $\bar{W}(t)$ is the time varying version of $\bar{W}$ i.e, Construct a matrix

$$\bar{W} \triangleq [W^{m,1}, \ldots, W^{m,p}] \quad (19)$$

To estimate the target channel vector h^m, which is shared by the signal component in the m-th group we select $1 \leq P \leq K^m$ effective signature waveforms from the m-th group, say $W^{m,j}(j = 1, \ldots, P)$ without loss of generality $\bar{W}$

$$\bar{W} \triangleq [w^{m,1}, \ldots, w^{m,p}] \quad (20)$$

in (20) with size L× P, C is defined in (3.14)

$$C^T \triangleq [(C^{m,1})^T, \ldots, C^{m,1})^T] \quad (21)$$

with size PL×M and $\bar{C}$ has the same size as C .The proposed subspace channel estimation algorithm in estimates the target channel by calculating the eigenvector corresponding to the smallest eigenvalue of $C^H\hat{u}_n A A \hat{u}_n^H C$, which can be reformed as follows:

$$C^H\hat{u}_n A A\hat{u}_n^H C = \sum_{i=1}^{P} \alpha^i\, (C^{m,i})^H \hat{u}_n \hat{u}_n^H C^{m,i} = \bar{C}^H \hat{u}_n \hat{u}_n^H \bar{C} \quad (22)$$

6. SIMULATION

- Take SNR=15dB&sample amount=1000
- Take length of the antenna ,channel length, smoothing &equalization delay
- Take channel coefficients
- Generate 16 QAM symbols
- Find received signals
- Apply sub space method
- Calculate correlation matrix and SVD to find null subspace
- check rank of null subspace and display rank
- Remove noise and Construct matrix A (in Q)
- solve equation Ah=0 by SVD
- Compare channel estimation MSE
- Plot MSE and bias of the Channel Estimation
- Plot channels and equalization results

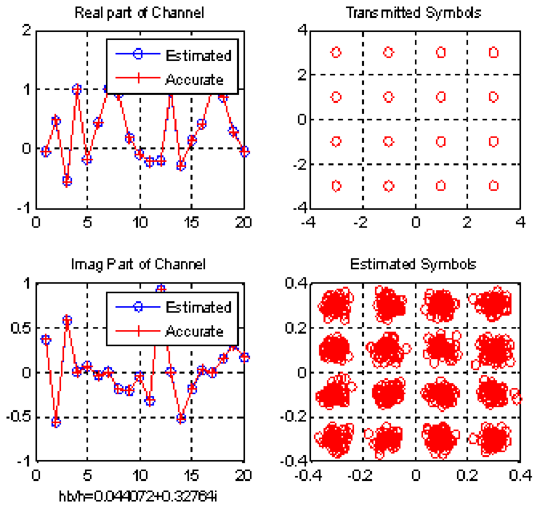

Figure 1 Transmitted &Estimated Symbols

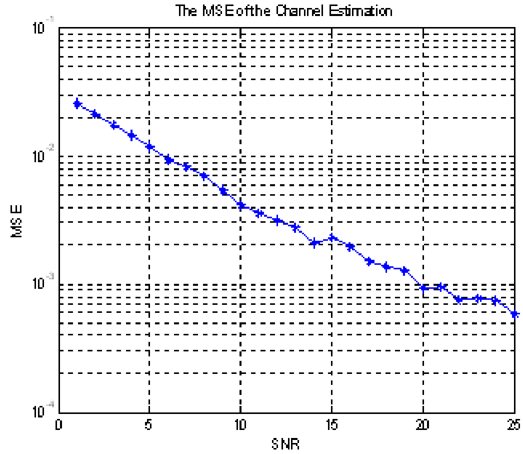

Figure 2: MSE Of Channel Estimation

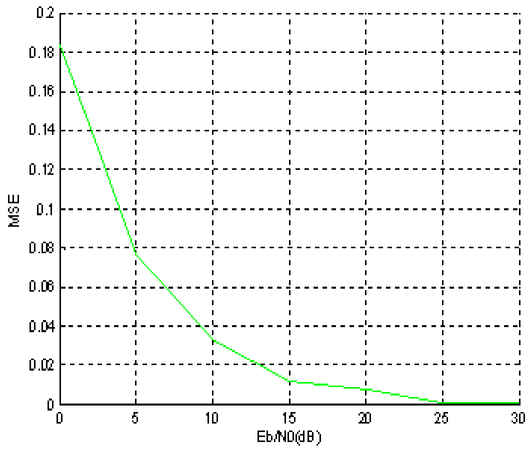

Figure 3: OFDM blind channel estimation for **sub-space algorithm, with better MSE**

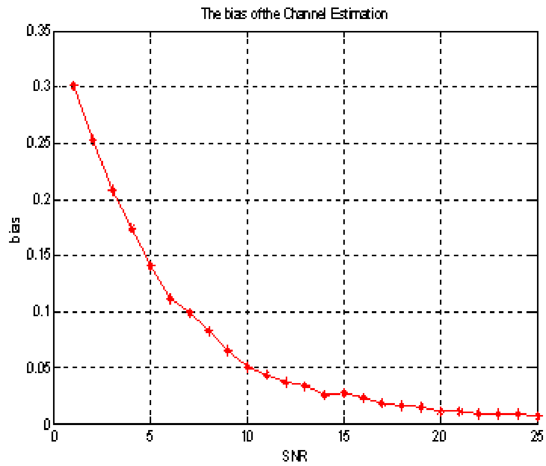

Figure 4: Bias Of Channel Estimation

7 . SIMULATION FOR NRMSE

- The number of transmitting antenna is 1&receiving antennas are 4
- The number of subcarrier =48
- Number of symbol N =200
- length of CP(P)=12
- The totle length of an OFDM symbol Q=N+P

- Collect J consecutively received OFDM symbols
- The order of channel L=4
- Go through the channel

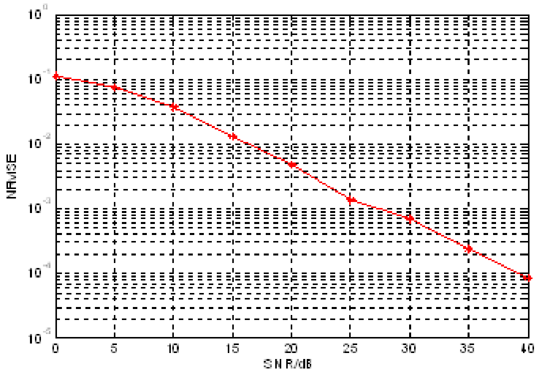

Figure 5: NRMSE Of Channel Estimation

Conclusion: This paper has shown that blind channel estimation and equalization using sub space method. We investigated the asymptotic performance of the proposed estimator when the number of independent observations is large. We derive its bias, mean square error (MSE)and NRMSE. The performance of the estimator can be optimized by increasing the number of kernel matrices and by using a special set of weights in the cost function.

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