적응 고유값 분해 알고리듬을 이용한 새로운 블라인드 채널 인식

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New Blind Channel Identification Based on Adaptive Eigenvalue Decomposition Algorithm

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요 약

통신 채널에서 블라인드 채널 인식은 매우 중요한 문제이다. 블라인드 채널 인식은 고차 통계를 이용하면 구할 수 있으나 최근에는 오버샘플링한 수신신호를 이용하거나 수신측의 안테나 어레이를 이용한 신호의 2차 통계값을 이용한 방법에 관한 많은 연구가 진행되고 있다. 기존의 알고리듬은 잡음이 없는 환경에서 LS 방법에 기반을 두고 있기 때문에 잡음이 강한 채널에서는 원하는 성능을 얻을 수 없는 단점이 있다. 수신신호의 상관행렬의 최소 고유값에 대응하는 고유벡터는 채널의 임펄스 응답에 관한 정보를 포함하고 있다. 본 논문에서는 이러한 고유벡터를 매 시간마다 갱신시키면서 구하는 적응 알고리듬을 제안하고 이를 이용하여 블라인드 채널 인식 알고리듬을 제안한다. 제안한 알고리듬은 잡음에 강인한 특성을 보일 뿐만 아니라 기존의 알고리듬들 보다 우수한 채널 추정 성능을 보임을 모의실험을 통하여 검증하였다.

ABSTRACT

Blind adaptive channel identification of communication channels is a problem of important current theoretical and practical concerns. Recently proposed solutions for this problem exploit the diversity induced by antenna array or time oversampling, leading to the so-called, second order statistics techniques. And adaptive blind channel identification techniques based on a off-line least-squares approach have been proposed but this method assuming noise-free case. The method resorts to an adaptive filter with a linear constraint. In this paper, a new approach is proposed that is based on eigenvalue decomposition. Indeed, the eigenvector corresponding to the minimum eigenvalue of the covariance matrix of the received signals contains the channel impulse response. And we present a adaptive algorithm to solve this problem. The performance of the proposed technique is evaluated over real measured channel and is compared to existing algorithms.

Ⅰ. 서 론

In recent years, the interest in blind channel identification problem has received considerable attention. The basic blind channel identification problem involves a channel model where only the observation signal is available for processing in the identification channel. Earlier blind channel identification approaches mostly depend on higher order statistics (HOS), because the second order statistics (SOS) does not contain phase information for stationary signal[1]-[4]. In

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HOS-based methods, because the performance index as the optimization criterion is nonlinear with respect to estimation parameters and these methods require a large amount of data samples. These methods have the disadvantage that their computational complexity may be large. See, for example, [3] and references therein. Since the seminal work by Tong *et al.* the problem of estimating the channel response of multiple FIR channel driven by an unknown input symbol has interested many researchers in signal processing and communication fields. This is achieved by exploiting assumed cyclostationary properties, induced by oversampling or antenna array at the receiver part[3][4]. Up to date, the implementation of the SOS based methods have been mostly block based algorithm rather than adaptive algorithms. Most communication channels are time-varying in practice. Therefore, the algorithms should be able to track the change of the channel impulse response. Moreover, in a fast fading channel, the multipath channels in wireless communications vary rapidly, and we only have a few data samples corresponding to the same channel characteristics. The adaptive algorithms for blind adaptive channel identification based on SOS have been shown. Blind channel identification technique has been developed in adaptive algorithm based on vector-correlation method[7]-[9]. But most algorithms neglected the effect of channel noise.

In this paper, a novel adaptive blind identification algorithm is proposed by exploiting a constrained adaptive filter in noisy environment. We show that the minimization of the error variance, subject to a specific constant norm constraint, permits the derivation of asymptotically noise-free case. And it can be implemented adaptively at low cost using LMS-like algorithm.

Most notations are standard: vectors and matrices are boldface small and capital letters, respectively; the matrix transpose, the complex conjugate, the Hermitian, the Moore-Penrose inverse, and convolution are denoted by $(.)^T$, $(.)^*$, $(.)^H$, $(.)^+$, and $\otimes$, respectively; $\mathbf{I}_P$ is the $P \times P$ identity matrix; $E[\cdot]$ is the statistical expectation. This paper is organized as follows. In section II, we review the multichannel blind identification problem and block LS approach. And the existing adaptive algorithms of the block LS methods are described also. A novel blind channel identification technique based on eigenvlaue decomposition and adaptive implementation are proposed in section III. Simulation results with real measured channel are performed in section VI. Section V concludes our results.

Ⅱ. PROBLEM FORMULATION AND LS APPROACH

1. Channel Model and Assumptions

Let $x(t)$ be the signal at the output of a noisy channel

$$x(t) = \sum_{k=-\infty}^{\infty} s(k)h(t-kT) + v(t) \tag{1}$$

where $s(k)$ denotes the transmitted symbol at time kT, $h(t)$ denotes the continuous-time channel impulse response, and $h(t)$ is additive noise. The fractionally-spaced discrete-time model can be obtained either by time oversampling or by the sensor array at the receiver. As shown in [3], the single channel system can be considered as the multichannel system by the sampling the received signal at a rate faster than the input symbol rate. The source signal $s(n)$ then passes through M equivalent symbol rate linear filters. And as shown in Fig. 1, $x_i(n)$ denotes the output from the ith channel with the noisy FIR channel impulse response $h_i(n)$, which is driven by the same input $s(n)$. Clearly, for linearly modulated communication signals, $x_i(n)$, $a_i(n)$, $s(n)$, $v_i(n)$, and $h_i(n)$ are related as follows:

$$\begin{aligned} x_i(n) &= \sum_{k=0}^{L} h_i(k)s(n-k) + v_i(n) \\ &= a_i(n) + v_i(n), \quad i = 1, \Lambda, M \end{aligned} \tag{2}$$

where L is the maximum order of the M channels.

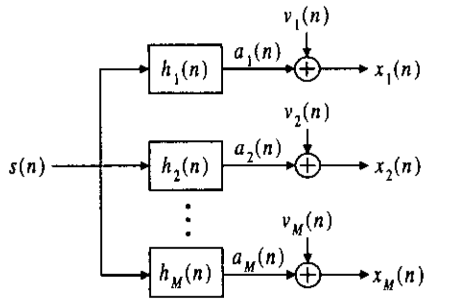

Fig. 1 SIMO model with M subchannels.

The blind identification problem can be stated as follows: Given the observation of channel output, determine the channels and further recover the input signals. As in classical system identification problems, certain conditions about the channel and the source must be satisfied to ensured identifiability. In the multichannel blind identification case, three conditions are shared by many different approaches. We assume the following throughout in this paper about the channel and source conditions.

A1) Subchannels do not share common zeros, or in other words, they are coprime.

A2) The noise is zero mean, white with known covariance, no cochannel correlation, and uncorrelated with source signal.

A3) The channel has known order L.

Assumption 1 provides the necessary and sufficient condition to the unique solution for the blind channel identification problem. This condition has been regarded as the major difficulty of blind algorithms using the SOS[6].

The assumption that L is known may be practical. To address this problem, there are three approaches[6]. First, channel order detection and parameter estimation can be performed separately. There are well-known order detection schemes that can be used in practice such as Akaike's information criterion. Second, some statistical subspace methods require only upper bound of L. Third, channel order detection and parameter estimation can be performed jointly. Similarly, the noise variance 2 may not be known in practice, but it can be estimated in many ways. For example, the noise variance estimation and channel order detection can be performed using singular values of the estimated covariance matrix.

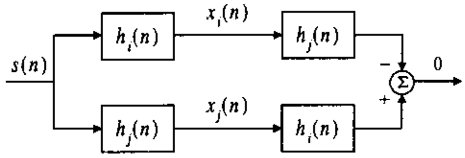

Fig. 2 The cross-relation between two subchannels.

2. LS Approach to Blind Channel Identification

In this paper, consider a special case, when the channel output is two times oversampled or there are two antennas at the receiver, this is equivalent to two channel representation (M=2). From the Fig. 2, in the absence of noise, it is apparent that the output of each subchannel is

$$x_1(n) = h_1(n) \otimes s(n)$$
$$x_2(n) = h_2(n) \otimes s(n) \tag{3}$$

Then

$$\begin{aligned} h_2(n) \otimes x_1(n) &= h_2(n) \otimes [h_1(n) \otimes s(n)] \\ &= h_1(n) \otimes [h_2(n) \otimes s(n)] \\ &= h_1(n) \otimes x_2(n) \end{aligned} \tag{4}$$

Obviously, the above equation is not applicable for a single channel system. We can write (4) as

$$[\mathbf{X}_1(L) \ \ \text{-}\mathbf{X}_2(L)] \begin{bmatrix} \mathbf{h}_2(n) \\ \mathbf{h}_1(n) \end{bmatrix} = 0 \tag{5}$$

where $h_m=[h_m(L),\cdots,h_m(L)]^T$, m=1,2, and

$$\mathbf{X}_m(L) = \begin{bmatrix} x_m(0) & \Lambda & x_m(L) \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ x_m(N-L) & \Lambda & x_m(N) \end{bmatrix} \tag{6}$$

Let us define as follows:

$$\mathbf{h} = [\mathbf{h}_2^T \ \ \mathbf{h}_1^T]^T, \ \mathbf{X} = [\mathbf{X}_1 \, \mathrm{M} \mathbf{X}_2]^T \tag{7}$$

In the noise free context, $\mathbf{h}$ is the null space of

X, and equivalently (5) can be written as follows[5]

$$\mathbf{X}(L)\mathbf{h}=0 \tag{8}$$

Equation (8) provides the unique solution for the identification problem if and only if subchannels are coprime, i.e., they do not share any common zeros. When the channel is corrupted by additive noise, we can estimate h by solving the following LS problem

$$\min_{\hat{\mathbf{h}}} \| \mathbf{X}(L)\hat{\mathbf{h}} \|^2 \tag{9}$$

where $\hat{\mathbf{h}}$ is subject to nontrivial constraints, e.g., $\|\hat{\mathbf{h}}\|=1$ or $\mathbf{c}^*\hat{\mathbf{h}}=1$ for a constant vector **c**. Although the treatment of the noise is in (9) may be statistically optimal, it is perhaps a natural simple way of formulating this problem.

3. Existing Algorithms

It is well known that all blind identification methods suffer from a possible scale ambiguity[5]. Therefore, some constraint must be imposed while minimizing (9), as discussed earlier. In this section, we review existing adaptive channel identification algorithms that use linear constraint.

3.1 Heath's Algorithm[8]

In [8], the algorithm has been developed by firstly assuming that $h_1(0)=1$. This implies that a linear constraint. This is reasonable because in practice, the unknown scale factor is typically overcome by employing automatic gain control and/or differential encoding. With this assumption, the last column of $\mathbf{X}_2(L)$ is removed, forming, $\tilde{\mathbf{X}}_2(L)$, and place this column on the order side, thus (5) becomes

$$\left[\mathbf{X}_1(L) \quad -\tilde{\mathbf{X}}_2(L)\right]\begin{bmatrix}\mathbf{h}_2\\ \tilde{\mathbf{h}}_1\end{bmatrix}=\begin{bmatrix}x_2(L)\\ \mathrm{M}\\ x_2(L)\end{bmatrix}$$
$$\Rightarrow \mathbf{X}_{N-1}\hat{\mathbf{h}}=\hat{\mathbf{x}} \tag{10}$$

where $\tilde{\mathbf{h}}_1=[h_1(L),\cdots,h_1(1)]^T$

The batch LS formulation in (10) leads naturally to a recursive formulation, since the channels are coprime and assuming $N\text{-}L+1\geq 2L+1$, the $(N\text{-}L+1)\times(2L+1)$ matrix $\mathbf{X}_{N\text{-}1}$ is full rank. With this assumption, we can write the following LS batch method for finding estimated channel

$$\hat{\mathbf{h}}=(\mathbf{X}^H\mathbf{X})^{-1}\mathbf{X}^H\hat{\mathbf{x}} \tag{11}$$

Let $\mathbf{X}(n)=[x_1(n\text{-}L),\cdots,x_1(n),-x_2(n\text{-}L),\cdots,-x_2(n+1)]^T$ be the regression vector at each time n and let $x_2(n)$ be the addition to $\hat{\mathbf{x}}$. Following similar derivation for the LMS algorithm in [1], (11) can be solved in an adaptive manner using a stochastic gradient descent algorithm. An error can be formed the difference between the predicted and the actual value of the $(n+1)$th data point $x_2(n)$ from the other channel as in

$$e(n+1)=x_2(n+1)-\mathbf{X}^H(n+1)\hat{\mathbf{h}}(n) \tag{12}$$

This weighted error is then used to update the channel estimate

$$\hat{\mathbf{h}}(n+1)=\hat{\mathbf{h}}(n)+\mu e^*(n)\mathbf{X}(n+1) \tag{13}$$

3.2 Yoshito's Algorithm[9]

In [9], it has been shown that the cost function is a quadratic form and has the unique solution. To achieve a blind system identification, a cost function as mean square error (MSE) of output signal $x_1(n)$ and $x_2(n)$ as follows:

$$\begin{aligned} J &= E[|e(n)|^2] \\ &= E[|x_1(n)-x_2(n)|^2] \end{aligned} \tag{14}$$

Let M=2 in (1) and substituting (1) into (14), we get

$$J=E\left[\left|\sum_{k=0}^{L}h_1(k)x_1(n-k)-\sum_{k=0}^{L}h_2(k)x_2(n-k)\right|^2\right] \tag{15}$$

To avoid trivial solution as described in Heath's algorithm early, we also assume that $h_1(0)=1$ which implies that a linear constraint. Then we get

$$J = E\left[\left|x_1(n) + \sum_{k=1}^{L} h_1(k)x_1(n-k) - \sum_{k=0}^{L} h_2(k)x_2(n-k)\right|^2\right] \quad (16)$$

We now rewrite (16) in matrix and vector form as follows:

$$J = E[|x_1(n) + \mathbf{h}_1^H \bar{\mathbf{x}}_1(n) - \mathbf{h}_2^H \mathbf{x}_2(n)|^2] \quad (17)$$

where

$$\begin{aligned} \bar{\mathbf{x}}_1(n) &= [x_1(n-1), \Lambda, x_1(n-L)]^T \\ \mathbf{x}_2(n) &= [x_2(n), \Lambda, x_2(n-L)]^T \\ \mathbf{h}_1 &= [h_{1,1}, \Lambda, h_{1,L}]^T \\ \mathbf{h}_2 &= [h_{2,0}, \Lambda, h_{2,L}]^T \end{aligned} \quad (18)$$

We denote $\mathbf{x}(n)$ and $\mathbf{h}$ as follows:

$$\mathbf{x}(n) = [-\bar{\mathbf{x}}_1^T(n) \quad \mathbf{x}_2^T(n)]^T, \ \mathbf{h} = [\mathbf{h}_1 \quad \mathbf{h}_2]^T \quad (19)$$

Therefore, we may write (17) as

$$\begin{aligned} J &= E[|x_1(n) - \mathbf{h}^T \bar{\mathbf{x}}|^2] \\ &= E[x_1^2(n) - 2x_1(n)\mathbf{h}^T \mathbf{x}(n) + \mathbf{h}^T \mathbf{x}(n)\mathbf{x}^T(n)\mathbf{h}] \\ &= \sigma_{x_1}^2 - 2\mathbf{h}^T E[x_1(n)\mathbf{x}(n)] + \mathbf{h}^T E[\mathbf{x}(n)\mathbf{x}(n)]\mathbf{h} \end{aligned} \quad (20)$$

Equation (12) has same form as a cost function with ordinary adaptive filters. In order to minimize (20), let partial derivative with respect to $\mathbf{h}$ to be zero. Then we get the Wiener solution. Then it directly leads to the LMS algorithm as follows:

$$\mathbf{h}(n+1) = \mathbf{h}(n) + \mu e^*(n)\mathbf{x}(n) \quad (19)$$

Ⅲ. PROPOSED METHOD

As described earlier, to avoid the trivial solution to minimization problem a proper condition must be selected. In this section, a new approach is proposed that is based on eigenvalue decomposition. Indeed, the eigenvector corresponding to the minimum eigenvalue of the covariance matrix of the received signals contains the channel impulse response. This approach is based on the unit norm constraint that is apart from the linear constraint introduced in the previous section.

1. Principle of the Proposed Algorithm

We assume that the channel is linear and time invariant within small time interval; therefore, we have the following relation as described in (4)

$$\mathbf{x}_1^H(n)\mathbf{h}_2 = \mathbf{x}_2^H(n)\mathbf{h}_1 \quad (22)$$

where

$$\mathbf{x}_i(n) = [x_i(n), \Lambda, x_i(n-L+1)]^T, i = 1,2 \quad (23)$$

and the channel impulse response vector of length L are defined as

$$\mathbf{h}_i = [h_{i,0}\ h_{i,1} \Lambda\ h_{i,L-1}]^T, i = 1,2 \quad (24)$$

This linear relation follows from (5). The covariance matrix of the two received signals is given by

$$\mathbf{R}_\mathbf{x} = \begin{bmatrix} \mathbf{R}_{\mathbf{x}1\mathbf{x}1} & \mathbf{R}_{\mathbf{x}1\mathbf{x}2} \\ \mathbf{R}_{\mathbf{x}2\mathbf{x}1} & \mathbf{R}_{\mathbf{x}2\mathbf{x}2} \end{bmatrix} \quad (25)$$

where $\mathbf{R}_{\mathbf{x}i\mathbf{x}j}$=E[$\mathbf{x}_i(n)\mathbf{x}_j^H(n)$], i, j=1,2
Consider the $2L \times 1$ vector as follows:

$$\mathbf{h} = \begin{bmatrix} \mathbf{h}_2 \\ -\mathbf{h}_1 \end{bmatrix} \quad (26)$$

From (22) and (25), it can be seen that $\mathbf{R}_\mathbf{x}\mathbf{h}$=0 which means that the vector $\mathbf{h}$ is the eigenvector of the covariance matrix $\mathbf{R}_\mathbf{x}$ corresponding to the eigenvalue 0. Moreover, if the two channel impulse response $\mathbf{h}_1$ and $\mathbf{h}_2$ have no common zeros and the autocorrelation matrix of the source signal $s(n)$ is full rank, which is assumed in the rest of this paper, the covariance matrix $\mathbf{R}_\mathbf{x}$ has one and only one eigenvalue equal to zero. Consider the noisy channel case as described in (2) and let M=2. It follows from (1) that

$$\begin{aligned} \mathbf{x}^H(n)\mathbf{h} &= \sum_{k=0}^{L} x_2^*(n-k)h_1(k) - \sum_{k=0}^{L} x_1^*(n-k)h_2(k) \\ &= \sum_{k=0}^{L} v_2^*(n-k)h_1(k) - \sum_{k=0}^{L} v_1^*(n-k)h_2(k) \\ &= \mathbf{v}^H(n)\mathbf{h} \end{aligned} \quad (27)$$

where $\mathbf{x}(n)=[\mathbf{x}_1^T\ \mathbf{x}_2^T\ ]^T$, $\mathbf{v}(n)=[\mathbf{v}_1^T\ \mathbf{v}_2^T\ ]^T$
If the correlation matrix of the vector **x** is denotes by $\mathbf{R}_x$, a direct of conclusion of (27) will be

$$\mathbf{R}_x\mathbf{h} = E[\mathbf{x}(n)\mathbf{x}(n)^T]\mathbf{h} = E[\mathbf{x}(n)\mathbf{v}(n)^T]\mathbf{h} \\ = E[\mathbf{v}(n)\mathbf{v}(n)^T]\mathbf{h} = \mathbf{R}_v\mathbf{h} = \sigma_v^2\mathbf{h} \tag{28}$$

We note from (28) that **h** is the eigenvector of the correlation matrix $\mathbf{R}_x$ and σ_v^2 is the corresponding eigenvalue of $\mathbf{R}_x$ The knowledge of σ_v^2 is not require in the practical case, but it can be obtained as a by product if wanted

$$\sigma_v^2 = \frac{\mathbf{h}^H\mathbf{R}_x\mathbf{h}}{\mathbf{h}^H\mathbf{h}} \tag{29}$$

2. Adaptive Implementation

In practice, it is saimple to estimate iteratively the eigenvector corresponding to the minimum eigenvalue of $\mathbf{R}_x$, by using an algorithm similar to the Frost algorithm that is a simple constrained LMS algorithm[11]. In the following, we show how to apply these techniques to out problem. Minimizing the quantity $\mathbf{h}^H\mathbf{R}_x\mathbf{h}$ with respect to **h** and subject to $\|\mathbf{h}\|^2=\mathbf{h}^H\mathbf{h}=1$ will give us the optimum weight $\mathbf{h}_{opt}$.

Let us define the error signal

$$e(n) = \frac{\mathbf{h}^H(n)\mathbf{x}(n)}{\|\mathbf{h}(n)\|} \tag{30}$$

where $\mathbf{x}(n)=[\mathbf{x}_1^T\ \mathbf{x}_2^T\ ]^T$. Note that minimizing the mean square value of $e(n)$ is equivalent to solving the above eigenvalue problem. Taking the graidient of $e(n)$ with respect to $\mathbf{h}(n)$ gives

$$\nabla e(n) = \frac{1}{\|\mathbf{h}(n)\|}\left(\mathbf{x}(n) - e(n)\frac{\mathbf{h}(n)}{\|\mathbf{h}(n)\|}\right) \tag{31}$$

and we obtain the gradient-descent constrained LMS algorithm

$$\mathbf{h}(n+1) = \mathbf{h}(n) - \mu e^*(n)\nabla e(n) \tag{32}$$

where μ, the adaptation step-size, is a positive constant.

Substituting (30) and (31) into (32) gives

$$\mathbf{h}(n+1) = \mathbf{h}(n) - \mu\frac{1}{\|\mathbf{h}(n)\|}\cdot \\ \left(\mathbf{x}(n)\mathbf{x}^H(n)\frac{\mathbf{h}(n)}{\|\mathbf{h}(n)\|} - |e(n)|^2\frac{\mathbf{h}(n)}{\|\mathbf{h}(n)\|}\right) \tag{33}$$

and taking statistical expectation after convergence, we get

$$\mathbf{R}_x\frac{\mathbf{h}(\infty)}{\|\mathbf{h}(\infty)\|} = E[|e(n)|^2]\frac{\mathbf{h}(\infty)}{\|\mathbf{h}(\infty)\|} \tag{34}$$

which is what is desired: the eigenvector $\mathbf{h}(\infty)$ corresponding to the smallest eigenvalue $E[|e(n)|^2]$ of the covariance matrix $\mathbf{R}_x$. In practice, it is advantageous to use the following adaptation scheme

$$\mathbf{h}(n+1) = \frac{\mathbf{h}(n) - \mu e^*(n)\nabla e(n)}{\|\mathbf{h}(n) - \mu e^*(n)\nabla e(n)\|} \tag{35}$$

The algorithm (35) presented above is a little bit complicated and is very general to find the eigenvector corresponding to the smallest eigenvalue of any matrix $\mathbf{R}_x$. If the smallest eigenvalue is equal to zero, which is the case here, the algorithm can be simplified as follows:

$$e(n) = \mathbf{h}^H(n)\mathbf{x}(n) \tag{36}$$

$$\mathbf{h}(n+1) = \frac{\mathbf{h}(n) - \mu e^*(n)\mathbf{x}(n)}{\|\mathbf{h}(n) - \mu e^*(n)\mathbf{x}(n)\|} \tag{37}$$

Note that this algorithm can be seen as an approximation of the previous one by neglecting the terms is $e^2(n)$, which is reasonable since the smallest eigenvalue is equal to zero. In this application, the two algorithms (35) and (37) should have the same performance after convergence even with low SNRs.

Ⅳ. SIMULATION RESULTS

Computer simulations were conducted to evaluate the performance of the proposed algorithm in comparison with existing algorithms.

Table 1. Channel coefficients for simulations.

	Channel 1	
	i=1	i=2
$h_i(0)$	+0.7	−0.0326−j0.0022
$h_i(1)$	+0.1657−j0.0443	+1.0259+j0.0060
$h_i(2)$	+0.0333+j0.0184	+0.0145+j0.0013
$h_i(3)$	+0.0152+j0.0005	−0.1020−j0.0180
$h_i(4)$	+0.8451−j0.0331	+0.4411+j0.0236
	Channel 2	
	i=1	i=2
$h_i(0)$	+0.2636−j0.0113	−0.0276−j0.0073
$h_i(1)$	−0.0186−j0.0059	+0.0350−j0.0067
$h_i(2)$	−0.0065+j0.0039	+0.0147+j0.0020
$h_i(3)$	+0.0236−j0.0035	+0.8760+j0.0329
$h_i(4)$	+0.7826−j0.0113	−0.2025−j0.0015
$h_i(5)$	+0.0754−j0.0090	−0.0225+j0.0073
$h_i(6)$	+0.0134+j0.0010	+0.0134−j0.0023
$h_i(7)$	+0.0042−j0.0012	+0.0042−j0.0128

In all the simulations, two channel SIMO model is assumed. This means two times oversampling or two sensors at the receiver in real situation. The input signal is 4-QAM. For simplicity of comparison, we assumed that the channel order L is known. The performance index is achieved by examination the root mean square error (RMSE) that is defined as [5].

$$\mathrm{RMSE} = \frac{1}{\|\mathbf{h}\|^2}\sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\|\hat{\mathbf{h}}_{(i)} - \mathbf{h}\|^2} \tag{38}$$

where N_t is number of Monte Carlo trials, and $\hat{\mathbf{h}}_i$ is the estimate of the channels from the ith trials. We used two different channels to test our algorithm. The first one (denotes channel 1) has order L=3 and the coefficients were chosen randomly, whereas the second channel (denotes channel 2) is a length-16 version of an empirically measured $T/2$-spaced digital microwave radio channel (M=2) with 230 taps, which we truncated to obtain a channel with L=7. The microwave channel *chan1.mat* is founded in [13] The shortened version is derived by linear

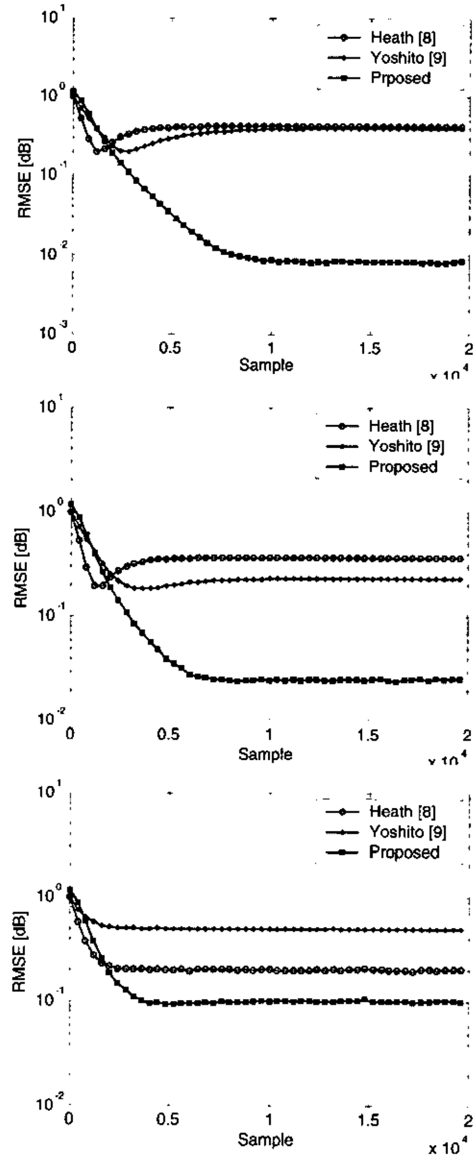

Fig. 3 RMSE comparison of the proposed and existing algorithms for channel 1 under SNR=30dB, 20dB, and 10dB.

decimation of the FFT of the full-length $T/2$-spaced impulse response and taking the IFFT of the decimated version (see [12] for more details on this channel). The channel coefficients for both sets of channels are listed in Table 1. A total number of 50 independent trials were performed. All algorithms were initiated at $\mathbf{h}(0) = [1, 0, \cdots, 0, 1, 0, \cdots, 0]^T$ with the step size, μ =0.01.

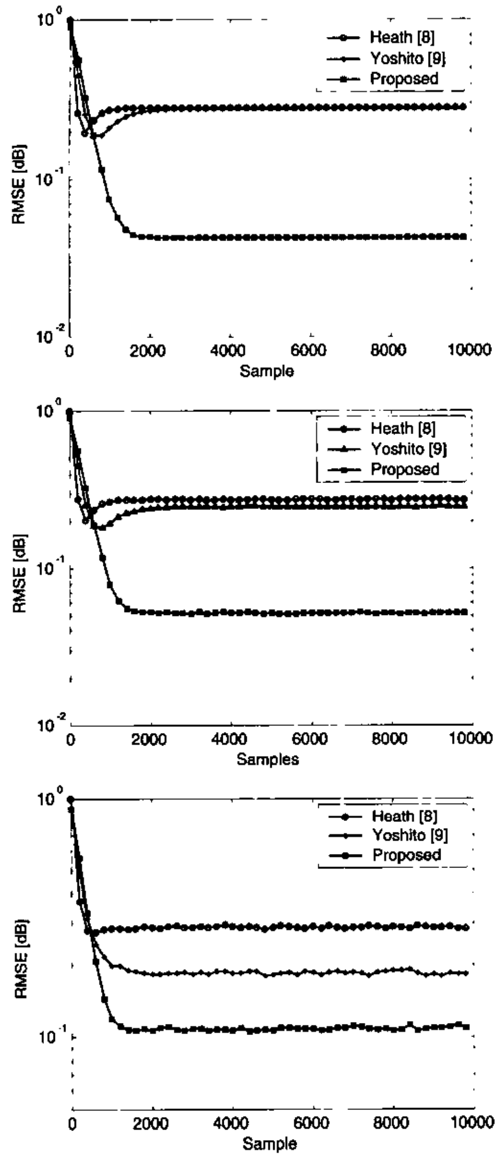

Fig. 4 RMSE comparison of the proposed and existing algorithms for channel 2, under SNR=30dB, 20dB, and 10dB.

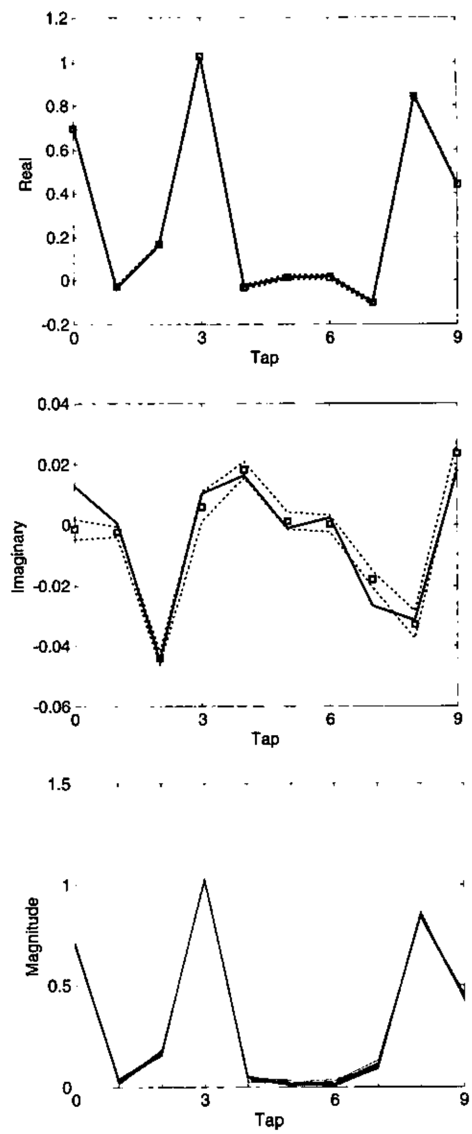

Fig. 5 The estimated and the magnitude of the channel 1 under SNR=20dB, (a) real part estimation, (b) imaginary part estimation, and (c) magnitude of the estimation at 50 trials.

Fig. 3 and Fig. 4 show the RMSE of the channel estimates from existing algorithms and the proposed algorithm for channel 1 and channel 2, respectively. From this figures, we can see that the proposed algorithm always performs better than others because we use the unit norm constraint for weight update. But previous algorithms are assuming that linear constraint which is needed gain control. The proposed algorithm converges very fast to a good channel estimate. Moreover, it is very robust to noise even with an SNR=10dB. By inspection, we can observe that RMSE values of the proposed method are decreased more or less 8-14dB, 6-10dB, and 1-2dB under SNR=30dB, 20dB, and 10dB, respectively, on both channel 1 and channel 2. From Fig. 5 to Fig. 8, figures show the 50 estimates of the channel and the magnitude for

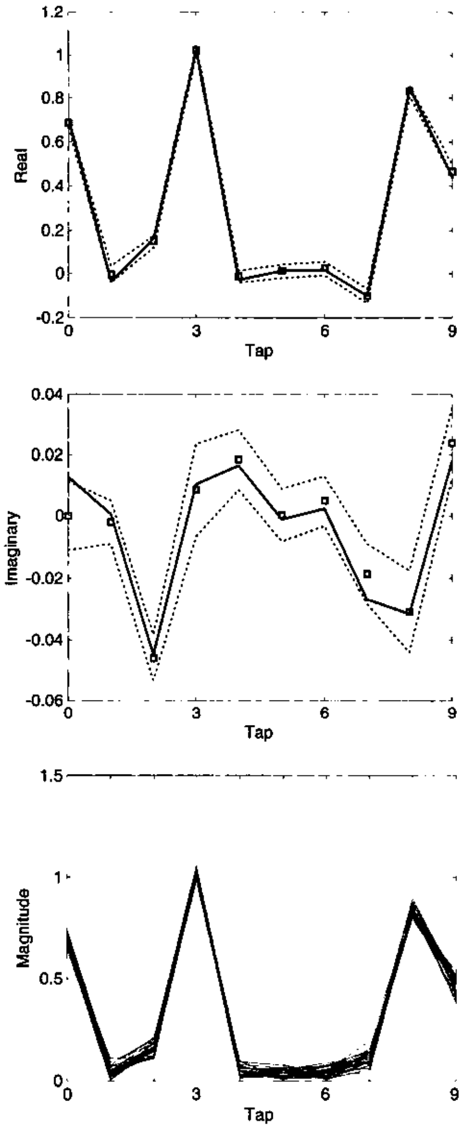

Fig. 6 The estimated and the magnitude of the channel 1 under SNR=10dB, (a) real part estimation, (b) imaginary part estimation, and (c) magnitude of the estimation at 50 trials.

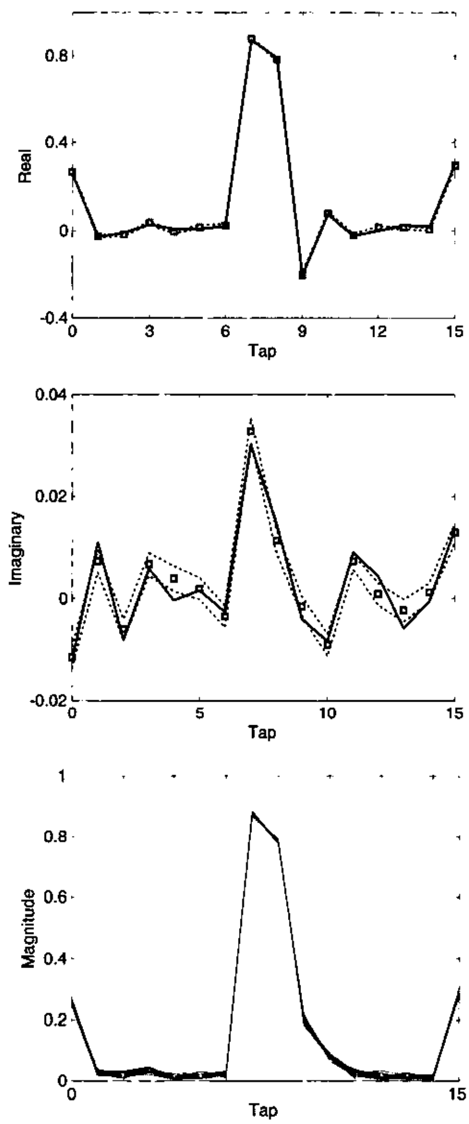

Fig. 7 The estimated and the magnitude of the channel 2 under SNR=20dB, (a) real part estimation, (b) imaginary part estimation, and (c) magnitude of the estimation at 50 trials.

channel 1 and channel 2 under SNR=20dB and 10dB. In all figures, solid line denotes the original channel, dotted line denotes the averaged estimates±standard deviation, and the square symbol represents the mean value of the 50 estimates. Clearly, we can observe the significant improvement of the proposed algorithm over existing algorithms for both random and real-measured channel.

V. CONCLUSION

In this paper, a new and simple approach to adaptive blind channel identification has been presented. The method is based on adaptive eigenvalue decomposition. The eigenvector corresponding to the minimum eigenvalue of the covariance matrix of the received signals contains

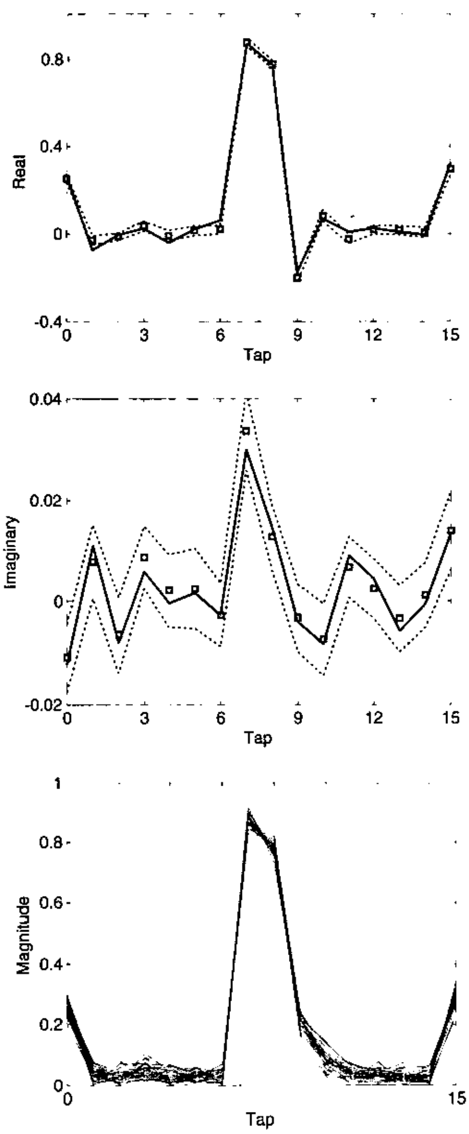

Fig. 8 The estimated and the magnitude of the channel 2 under SNR=10dB, (a) real part estimation, (b) imaginary part estimation, and (c) magnitude of the estimation at 50 trials.

the channel impulse response. And we use a simple constrained LMS algorithm to estimate iteratively the eigenvector corresponding to the minimum eigenvalue. Simulation results have demonstrated the performance improvement of the proposed algorithm. In comparison with other algorithms, the proposed one seems to be more efficient in a low SNR channel and much more accurate. Our future works include the extension to blind multi-input multi-output (MIMO) channel identification and the development of the constrained RLS algorithm for fast convergence.

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