Blind Adaptive Channel Estimation using Multichannel Linear Prediction

Juphil Cho†, Kyung Seung AHN†† and JeeWon Hwang†††

ABSTRACT

Blind channel estimation of communication channels is a problem of important current theoretical 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. This paper proposes the blind adaptive channel estimation using multichannel linear prediction method. Computer simulations are presented to compare the proposed algorithm with the existing ones.

다채널 선형예측을 이용한 블라인드 적응 채널 추정

조주필† · 안경승†† · 황지원†††

요 약

블라인드 채널 추정은 매우 중요한 문제이다. 기존의 방법들은 대부분 고차통계를 이용한 방법들이었으나 최근에 안테나 어레이를 통과한 수신신호나 수신신호를 오버샘플링한 신호의 2차통계를 이용한 방법들에 관한 많은 연구가 진행되고 있다. 본 논문에서는 다채널 선형예측 방법을 이용한 블라인드 적응 채널 추정 방법을 제안하고 컴퓨터 모의실험을 통하여 제안한 방법과 기존의 방법의 성능을 비교 분석한다. 본 논문에서 제안한 방법은 기존의 방법들보다 우수한 성능을 보였으며 채널의 정확한 차수를 모르는 경우에도 우수한 성능을 보임을 확인하였다.

Key words: channel estimation, linear prediction

1. Introduction

In recent years, the interest in blind channel estimation problem has received considerable attention. The basic blind channel estimation problem involves the channel model where only the observation signal is available for processing in the estimation channel. Earlier blind channel estimation approaches mostly depend on higher order statistics (HOS), because the second order statistics (SOS) does not contain phase information for stationary signal [1,2]. Using HOS-based methods, it has been shown that the performance index as the optimization criterion is nonlinear with respect to estimation parameters and these methods require a large amount of data samples. Therefore, these methods have the disadvantage that their computational complexity may be large. See, for example, [1] 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

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† 준회원, ETRI 무선전송방식연구팀
†† 전북대학교 전자공학과 대학원
††† 국립익산대학 컴퓨터과학과

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 [1,3]. Up to date, the implementation of SOS based methods has 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.

In this paper, the blind channel estimation is proposed by exploiting multichannel linear prediction error method. It can be implemented adaptively using RLS- or LMS-like algorithm. Most notations are standard: vectors and matrices are boldface small and capital letters, respectively; the matrix transpose, and the Hermitian are denoted by $(\cdot)^T$, and $(\cdot)^H$, respectively; $E[\cdot]$ is the statistical expectation. This paper is organized as follows. In section 2, we review the blind channel estimation problem. A blind channel estimation method based on multichannel linear prediction and adaptive implementation is proposed in section 3. Simulation results are performed in section 4. Section 5 concludes our results.

2. Problem Formulation

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 $v(t)$ is additive noise. The fractionally-spaced discrete-time model can be obtained either by time oversampling or by the sensor array at the receiver [1,2]. The oversampled single-input single-output (SISO) model results single-input multi-output (SIMO) model as in Fig. 1. The corresponding SIMO model is described as following

$$x_i(n) = \sum_{k=0}^{L-1} h_i(k)s(n-k) + v_i(n) = a_i(n) + v_i(n),\ i = 1,\cdots,P \tag{2}$$

where P is the number of subchannel, and L is the maximum order of the each subchannel.

Let

$$\begin{aligned}\mathbf{x}(n) &= [x_1(n),\cdots,x_P(n)]^T\\ \mathbf{h}(n) &= [h_1(n),\cdots,h_P(n)]^T\\ \mathbf{v}(n) &= [v_1(n),\cdots,v_P(n)]^T\end{aligned} \tag{3}$$

We represent $xi(n)$ in a vector form as

$$\begin{aligned}\mathbf{x}(n) &= \sum_{k=1}^{L-1} s(k)\mathbf{h}(n-k) + \mathbf{v}(n)\\ &= \mathbf{a}(n) + \mathbf{v}(n)\end{aligned} \tag{4}$$

Stacking N received vector samples into an $NP \times 1$ vector, we can write a matrix equation as

$$\mathbf{x}_N(n) = \mathbf{H}\mathbf{s}(n) + \mathbf{v}_N(n) \tag{5}$$

where $\mathbf{H}$ is an $NP\times(N+L-1)$ block Toeplitz matrix, $\mathbf{s}(n)$ is $(N+L)\times 1$, $\mathbf{x}_N(n)$, and $\mathbf{v}_N(n)$ are $NP \times 1$ vectors,

$$\begin{aligned}\mathbf{s}(n) &= [s(n),\cdots,s(n-L-N+2)]^T\\ \mathbf{x}_N(n) &= [\mathbf{x}^T(n),\cdots,\mathbf{x}^T(n-N+1)]^T\\ \mathbf{v}_N(n) &= [\mathbf{v}^T(n),\cdots,\mathbf{v}^T(n-N+1)]^T\end{aligned} \tag{6}$$

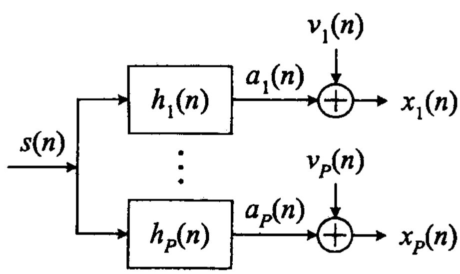

Fig. 1 Equivalent SIMO model with P subchannels

and

$$\mathbf{H}=\begin{bmatrix} \mathbf{h}(0) & \cdots & \mathbf{h}(L-1) & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{h}(0) & \cdots & \mathbf{h}(L-1) \end{bmatrix} \qquad (7)$$

We assume the following throughout in this paper about the channel and source conditions [2].

- Assumption 1: Subchannels do not share common zeros, i.e., they are coprime.
- Assumtions 2: The noise $\upsilon(n)$ is zero mean, white with known covariance, no cochannel correlation, and uncorrelated with source signal.

Assumption 1 provides the necessary and sufficient condition to the unique solution for the blind channel estimation problem. This condition has been regarded as the major difficulty of blind algorithms using the SOS. The assumption that L is known may be practical. To address this problem, there are three approaches [2].

Many recent blind channel estimation methods exploit subspace structure of the received signal. They are attractive because of the closed-form estimation. On the other hand, they may not be robust against modeling error. Also, they are often more computationally expensive. It is well known that all blind identification methods suffer from a possible scale ambiguity. Therefore, some constraint must be imposed while minimizing some cost function as described in [9] and [10]. In [9], the algorithm has been developed based on linear constraint. In [10], it has been shown that the cost function is a quadratic form and has the unique solution. To achieve blind channel estimation, a cost function as mean square error (MSE) of subchannel output signal. The main problem of the subspace method is that the channel order L cannot be over estimated. Furthermore, for finite samples, this algorithm may be biased [2].

3. Proposed Algorithms

As described earlier, subspace method may not robust against modeling order overestimation. Linear prediction-based method does not require the exact channel order L, thus it is robust against overestimation of the channel order. In this section, a new approach is proposed that is based on multichannel linear prediction.

3.1 Multichannel Linear Prediction

Consider the noise-free case. For convenience, we can rewrite (5) as

$$\mathbf{x}_N(n)=\mathbf{H}\mathbf{s}(n)=[\mathbf{H}_1\ \ \mathbf{H}_2\ \ \mathbf{H}_3]\begin{bmatrix}\mathbf{s}_1(n)\\ \mathbf{s}_2(n)\\ \mathbf{s}_3(n)\end{bmatrix} \qquad (8)$$

where $\mathbf{H}_1$ is of dimension $NP\times d$, the $NP\times 1$ vector $\mathbf{H}_2$ is the $(d+1)$th column of $\mathbf{H}$, and the last part of $\mathbf{H}$ is denoted by $\mathbf{H}_3$ with dimension $NP\times(N+P-d-1)$ [4]. An $NP\times 1$ multichannel linear prediction error vector can be obtained as [4]

$$\mathbf{f}_1(n)=[\mathbf{I}\ \ -\mathbf{P}_1(n)]\begin{bmatrix}\mathbf{x}_N(n)\\ \mathbf{x}_M(n-d)\end{bmatrix}=\mathbf{H}_1\mathbf{s}_1(n) \qquad (9)$$

where $\mathbf{P}_1(n)$ is an $NP\times MP$ matrix. $\mathbf{x}_N(n)$ id defined in (6), and $\mathbf{x}_M(n-d)$ is defined as

$$\mathbf{x}_M(n-d)=\begin{bmatrix}\mathbf{x}(n-d)\\ \vdots\\ \mathbf{x}(n-d-M+1)\end{bmatrix} \qquad (10)$$

The optimal $\mathbf{P}_1$ is obtained by minimizing as following cost function

$$J_1=\mathrm{tr}[E[\mathbf{f}_1(n)\mathbf{f}_1^H(n)]] \qquad (11)$$

Letting the partial derivative of (11) with respect to $\mathbf{P}_1$ equals to zero and we get as

$$\mathbf{P}_1=[E[\mathbf{x}_M(n-d)\mathbf{x}_M^H(n-d)]]^+E[\mathbf{x}_N(n)\mathbf{x}_M(n-d)] \qquad (12)$$

Consider another multichannel linear prediction problem

$$\mathbf{f}_2(n)=[\mathbf{I}\ \ -\mathbf{P}_2(n)]\begin{bmatrix}\mathbf{x}_N(n)\\ \mathbf{x}_M(n-d-1)\end{bmatrix}=[\mathbf{H}_1\ \ \mathbf{H}_2]\begin{bmatrix}\mathbf{s}_1(n)\\ \mathbf{s}_2(n)\end{bmatrix} \qquad (13)$$

The proof is again provided in [4]. Compared with (11) and (12), we can know that the optimal P_2 is obtained as following

$$\mathbf{P}_2 = [E[\mathbf{x}_M(n-d-1)\mathbf{x}_M^H(n-d-1)]]^+ E[\mathbf{x}_N(n)\mathbf{x}_M(n-d-1)] \tag{14}$$

In order to consider H_2, we can compute

$$\mathbf{f}(n) = \mathbf{f}_2(n) - \mathbf{f}_1(n) = \mathbf{H}_2\mathbf{s}_2(n) \tag{15}$$

Then, we know that

$$E[\mathbf{f}(n)\mathbf{f}^H(n)] = \sigma_s^2\mathbf{H}_2\mathbf{H}_2^H = \sigma_s^2\mathbf{H}(d)\mathbf{H}^H(d) \tag{16}$$

The rank of matrix $E[\mathbf{f}(n)\mathbf{f}^H(n)]$ is one. Therefore, H(d) is the singular vector corresponding to the largest singular value of matrix $E[\mathbf{f}(n)\mathbf{f}^H(n)]$. If the d equals channel length, then we can obtain channel coefficient since H_2 is just the channel coefficients vector.

3.2 Adaptive Algorithms

We propose the adaptive algorithms for updating the multichannel linear prediction error filter coefficients. Two multichannel linear prediction problems are required in estimating the channel coefficients. We are required to compute the multichannel prediction matrices in (12) and (14) and to estimate the multichannel prediction errors in (9), (13), and (15). For fast convergence, we can use the RLS algorithm to update the multichannel linear prediction as following

- Compute multichannel linear prediction error vector:

$$\begin{aligned}\mathbf{f}_1(n) &= \mathbf{x}_N(n) - \mathbf{P}_1(n-1)\mathbf{x}_M(n-d)\\ \mathbf{f}_2(n) &= \mathbf{x}_N(n) - \mathbf{P}_2(n-1)\mathbf{x}_M(n-d-1)\end{aligned} \tag{17}$$

- Compute Kalman gain:

$$\begin{aligned}\mathbf{K}_1(n) &= \frac{\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}{\lambda + \mathbf{x}_M^H(n-d)\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}\\ \mathbf{K}_2(n) &= \frac{\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)}{\lambda + \mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)}\end{aligned} \tag{18}$$

- Update inverse of the correlation matrix:

$$\begin{aligned}\mathbf{Q}_1(n) &= \lambda^{-1}\mathbf{Q}_1(n-1) - \lambda^{-1}\mathbf{K}_1(n)\mathbf{x}_M^H(n-d)\mathbf{Q}_1(n)\\ \mathbf{Q}_2(n) &= \lambda^{-1}\mathbf{Q}_2(n-1) - \lambda^{-1}\mathbf{K}_2(n)\mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n)\end{aligned} \tag{19}$$

- Update multichannel linear prediction coefficient matrix:

$$\begin{aligned}\mathbf{P}_1(n) &= \mathbf{P}_1(n-1) + \mathbf{f}_1(n)\mathbf{K}_1^H(n)\\ \mathbf{P}_2(n) &= \mathbf{P}_2(n-1) + \mathbf{f}_2(n)\mathbf{K}_2^H(n)\end{aligned} \tag{20}$$

- Compute another prediction error vector:

$$\mathbf{f}(n) = \mathbf{f}_1(n) - \mathbf{f}_2(n) \tag{21}$$

The term λ ($0 < \lambda \leq 1$) is intended to reduce the effect of past values on the statistics when the filter operates in non-stationary environment. It affects the convergence speed and the tracking accuracy of the algorithm [6]. From the covariance matrix of in (16), its estimation of adaptive manner is given by

$$\mathbf{F}(n) = \lambda\mathbf{F}(n-1) + \mathbf{f}(n)\mathbf{f}^H(n) \tag{22}$$

The multichannel linear prediction problems can be computed by an LMS algorithm. The first one can be updated by

$$\begin{aligned}\mathbf{f}_1(n) &= \mathbf{x}_N(n) - \mathbf{P}_1(n-1)\mathbf{x}_M(n-d)\\ \mathbf{f}_2(n) &= \mathbf{x}_N(n) - \mathbf{P}_2(n-1)\mathbf{x}_M(n-d-1)\end{aligned} \tag{23}$$

The second one is updated by

$$\begin{aligned}\mathbf{P}_1(n) &= \mathbf{P}_1(n-1) + \mu_1\mathbf{f}_1(n)\mathbf{x}_M^H(n-d)\\ \mathbf{P}_2(n) &= \mathbf{P}_2(n-1) + \mu_2\mathbf{f}_2(n)\mathbf{x}_M^H(n-d-1)\end{aligned} \tag{24}$$

3.3 Crosscorrelation Vector Estimation

A simple iterative algorithm known as the power method can be used to find the largest eigenvector and its associated eigenvector [7,8]. Let **F** be a matrix with eigenvalues ordered as $\lambda_1 > \lambda_2 \geq L \geq \lambda_{NP}$, with corresponding eigenvectors e_1, e_2L, e_{NP}. Let **e**(0) be a normalized vector that is assumed to be not orthogonal to $\mathbf{e}_1$. The vector **e**(0) can be written in terms of the eigenvector as

$$\mathbf{e}(0) = a_1\mathbf{e}_1 + a_2\mathbf{e}_2 + \cdots + a_{NP}\mathbf{e}_{NP} \tag{25}$$

for some set of coefficient a_i, where $a_1 \neq 0$. We define the power method recursion by

$$\mathbf{e}(n+1) = \frac{\mathbf{Fe}(n)}{\|\mathbf{Fe}(n)\|} \tag{26}$$

Then

$$\mathbf{e}(1) = \frac{\mathbf{Fe}(0)}{\|\mathbf{Fe}(0)\|} = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\frac{\lambda_2}{\lambda_1}\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\frac{\lambda_{NP}}{\lambda_1}\mathbf{e}_{NP}\right)}{\|\mathbf{Fe}(0)\|}$$
$$\mathbf{e}(2) = \frac{\mathbf{Fe}(1)}{\|\mathbf{Fe}(1)\|} = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\left(\frac{\lambda_2}{\lambda_1}\right)^2\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\left(\frac{\lambda_{NP}}{\lambda_1}\right)^2\mathbf{e}_{NP}\right)}{\|\mathbf{Fe}(1)\|}$$
$$\vdots$$
$$\mathbf{e}(n) = \frac{\mathbf{Fe}(n-1)}{\|\mathbf{Fe}(n-1)\|} = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\left(\frac{\lambda_2}{\lambda_1}\right)^n\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\left(\frac{\lambda_{NP}}{\lambda_1}\right)^n\mathbf{e}_{NP}\right)}{\|\mathbf{Fe}(n-1)\|} \tag{27}$$

Because of the ordering of the eigenvalues, as $n \to \infty$

$$\mathbf{e}(n) \to a_1\mathbf{e}_1 \tag{28}$$

which is the eigenvector of $\mathbf{F}$ corresponding to the largest eigenvalue. The eigenvalue itself is found by a Rayleigh quotient.

$$\frac{\mathbf{e}^H(n)\mathbf{Fe}(n)}{\|\mathbf{e}(n)\|} \to \lambda_1 \tag{29}$$

Therefore, we can estimate the channel coefficients vector as following

$$\hat{\mathbf{H}}(d) = \sqrt{\lambda_1}\mathbf{e}(n) \tag{30}$$

4. Simulation Results

Computer simulations are conducted to evaluate the performance of the proposed algorithm in comparison with existing algorithms. For all simulations, two channel SIMO model is assumed. The input signal is 16-QAM and additive noises are i.i.d. zero mean circular Gaussian. We use the SNR defined as $E[\|\mathbf{a}(n)\|^2]/E[\|\mathbf{v}(n)\|^2]$. For simplicity of comparison, we assume that the channel order L is known. The performance index is achieved by examining the root mean square error (RMSE).

$$\mathrm{RMSE} = \frac{1}{\|\mathbf{h}\|^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\|\mathbf{h}_i - \mathbf{h}\|^2} \tag{31}$$

where N is number of Monte Carlo trials, $\mathbf{h}$ is the optimal channel coefficients, and $\mathbf{h}_i$ is the estimate of the channels from the ith trial. For simulations, we use the real-measured channel which is a length-16 version of an empirically measured ($T/2$)-spaced digital microwave radio channel P=2 with 230 taps, which we truncate to obtain a channel with L=7. The Microwave channel *chan1.mat* is founded at http://spib.rice.edu/spib/microwave.html. The shortened version is derived by linear decimation of the FFT of the full-length ($T/2$)-spaced impulse response and taking the IFFT of the decimated version (see [5] for more details on this channel). The total number of 50 independent trials is performed.

Fig. 2 shows the RMSE of the channel estimates

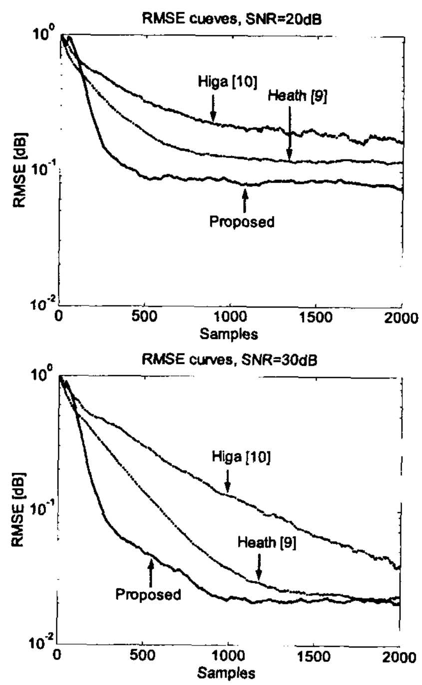

Fig. 2 RMSE comparison of the proposed and existing algorithms

from existing algorithms and the proposed algorithm under SNR=20dB and SNR=30dB, respectively. From these figures, we can see that the proposed algorithm performs better than the others. Fig. 3 shows the 50 estimates of the channel under SNR=20dB and SNR=30dB, respectively. In these figures, solid line denotes the original channel, dotted line denotes the averaged estimatesstandard deviation, and the square symbol represents the mean value of the 50 estimates. Fig. 4 presents the RMSE performance after 2000 samples for the several order of estimator for the proposed algorithm. From Fig. 4, we can conclude that the exact order is not needed in the proposed algorithm.

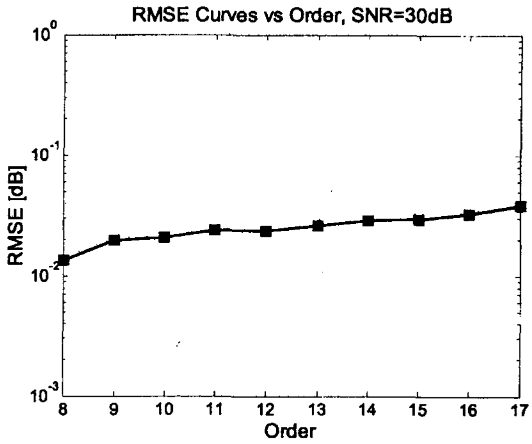

Fig. 4 RMSE value versus order.

5. Conclusion

This paper presents the new method for blind channel estimation based on multichannel linear prediction. 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 estimation and the development of the MIMO equalization problem.

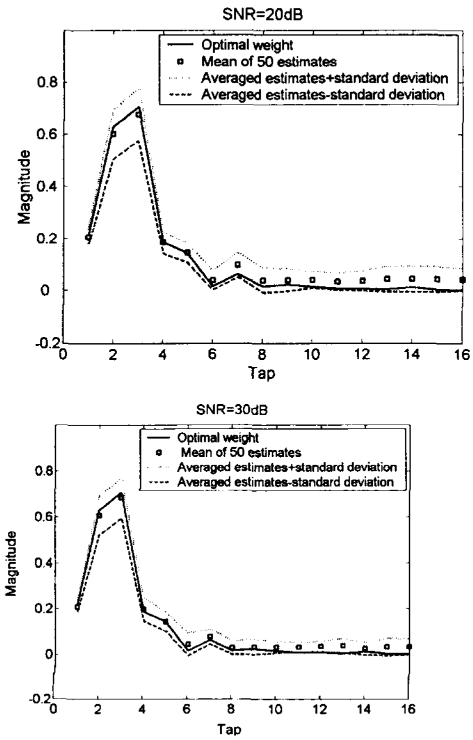

Fig. 3 Magnitude of the estimated channel under SNR=20dB and SNR=30dB at 50 trials.

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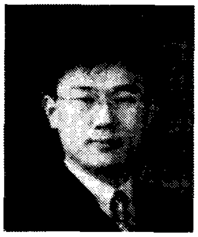

Juphil Cho

was born in Jeonju, Korea, in 1970. He received the B.S. degree in information and telecommunication engineering from Jeonbuk National University, Korea, in 1992, and M.S. and Ph.D. degrees in electronic engineering from Jeonbuk National University, in 1994 and 2001, respectively. Since 2000, he has been with Electronics and Telecommunication Research Institute (ETRI). Currently, he is a senior member of engineering staff at Radio Transmission Methodology Research team, Mobile Telecommunication Research Laboratory. His current research interests are AM for 4G mobile communication, OFDM system, and signal processing technology in communication.

Kyung Seung AHN

received the B.S., and M.S. degrees in the Department of Electronic Engineering from Chonbuk National University in 1996 and 1998, respectively. He is now working toward to Ph.D. degree in Department of Electronic Engineering from Chonbuk National University. His current interests, which include signal processing and communication theory, are currently focused on the field of blind channel identification and equalization for communication applications.

JeeWon Hwang

He is presently an Associate Professor of Department of computer science at Iksan Natl Col. He received B.S., M.S., and Ph. D. at Chonbuk Natl Univ. His research interests include are adaptive signal processing, nonlinear signal processing.

교신저자

조 주 필 대전광역시 유성구 가정동 161번지 ETRI 무선 전송방식연구팀