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TIME-SELECTIVE MIMO CHANNEL ESTIMATION BASED ON IMPLICIT TRAINING

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ABSTRACT

A novel scheme to perform multiple input multiple output(MIMO) channel estimation in time-selective fading environments is suggested.In order to improve transmission efficiency,training sequences are arithmetically added to the information symbols. We regard the output of information symbols ,additive white noises and dc-offsets at the receiver as fiction measurement noise, whose mean and variance are both unknown.A time-varying measurement noise recursive estimator and Kalman filters cooperate to track the time-varying MIMO channel impulse response(CIR). Finally,it is compared with some existing methods,and all these indicate that the proposal exhibits better performance.

***Index Terms*—**MIMO,channel estimation,implicit training, Kalman filtering,dc-offset.

1. INTRODUCTION

Wireless MIMO systems have drawn much attention because of their large capacity and high information rate. Accurate channel state information(CSI) is a prerequisite for most MIMO physical layer technologies.Although large numbers of investigations on MIMO channel estimation are devoloped,all of them can be classified into three types: training-based,blind,semi-blind.For training-based schemes, when they work in time-selective environments,training sequences have to send frequently and periodically to track the time-varying channel.This results in huge waste of resource. Semi-blind methods use not only training sequences but also non-training based data.This allows one to shorten the training period. Blind approaches[1][2] obtain CIR based only on noisy data via statistical and other properties of the information sequences in order to save bandwidth. However, most of existing blind schemes are generally computationally intensive and sometimes unreliable.

Several papers have recently been devoted to implicit training based channel estimation.It is an attractive choice because no bandwidth is lost in sending training sequences at the cost of some transmission power.It could be considered blind scheme in a broad sense.But it remarkably simplifies computational complexity and improves reliability of channel estimation. [3][4][5] adopted first order statistics scheme based on implicit training, however it can't be used in fast fading environments. A new method was put forward in [6] and was extended to MIMO system in [7],but the performance is not so good.

If MIMO system works in a direct conversion receiver mode, i.e. zero intermediate frequency(IF) technology, an unknown dc-offset will appear. [5] offered a solution but it is very complicated. In this paper, We regard the unknown dc-offset as the mean of the fiction measurement noise,which is estimated as a byproduct via Kalman filters.

Since R.E Kalman derived the Kalman filtering(KF) in [8] at the first time,it has been widely used because it is suitable for both stationary and nonstationary signal processing. Moreover, if the signal and noise are jointly Gaussian,it is an optimal estimator[9].In[10][11],KF was applied in space-time coding MIMO systems over time-selective channels. Nevertheless, as we know,if the a priori system model is low precision or time-varying,performance of Kalman filtering will degenerate, even lead to divergence. In order to improve the performance of KF,Sage and Husa proposed a kind of adaptive KF in [12],but it isn't able to estimate time-varying noise.A modified adaptive KF was derived in[13]. A forgetting factor to emphasize the effect of new data and forget old data gradually was adopted in[14],which can be applied into time-varying systems. We extend the works mentioned above and propose a joint recursive measurement noise estimation and KF algorithm in this paper.

The rest of this paper is organized as follows.Section 2 presents MIMO system model.Section 3 derives joint noise estimation and KF algorithm.Section 4 offers computer simulation results. Finally,in section 5,we draw conclusions.

2. SYSTEM MODEL

We consider the general case of MIMO system with N transmit antennas and M receive antennas.The discrete-time baseband,complex envelope equivalent communica- tions link show in figure 1,where

$x_i(n)$ information symbol of ith input;
$t_i(n)$ training sequence of i th input;
$S_i(n) = x_i(n) + t_i(n);$

h_{ij} CIR between the jth input and the ith output;
d_j DC-offset at the jth output;
$v_j(n)$ zero mean AWGN at the jth output;
$y_j(n)$ jth channel output.

We make the general assumption that $x_i(n)$ is zero mean and

$$E[x_i(n)x_j^*(n+k)] = \begin{cases} \sigma_x^2\delta(k), i = j \\ 0, \quad i \neq j \end{cases}$$

Where $\delta(\bullet)$ is Dirac-delta function, $(\bullet)^*$ denotes conjugate of $(\bullet)$ and $E(\bullet)$ denotes expected value.From figure 1

$$\begin{aligned} y_j(n) &= \sum_{i=1}^{N} h_{ij}[x_i(n)+t_i(n)]+d_j+v_j(n) \\ &= \mathbf{h}_j^T\mathbf{S}(n)+w_j(n), j=1,2,\cdots,M. \end{aligned} \tag{1}$$

Where

$w_j(n) = d_j + v_j(n)$;

$\mathbf{S}(n) = \begin{bmatrix} S_1(n) & S_2(n) & \cdots & S_N(n) \end{bmatrix}^T$;

$\mathbf{h}_j = \begin{bmatrix} h_{1j} & h_{2j} & \cdots & h_{Nj} \end{bmatrix}^T$.

Then we can express (1) in matrix notation by grouping the received data from all M channel outputs as follows:

$$\mathbf{y}(n) = \overline{\mathbf{H}}^T\mathbf{S}(n) + \mathbf{w}(n) \tag{2}$$

Where

$\mathbf{y}(n) = \begin{bmatrix} y_1(n) & y_2(n) & \cdots & y_M(n) \end{bmatrix}^T$;

$\mathbf{w}(n) = \begin{bmatrix} w_1(n) & w_2(n); & \cdots & w_M(n) \end{bmatrix}^T$

$\overline{\mathbf{H}} = \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \cdots & \mathbf{h}_M \end{bmatrix}$.

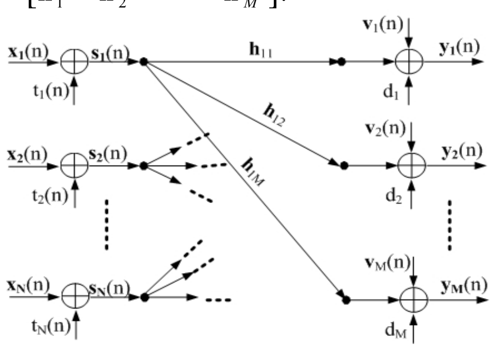

Figure 1. Discrete-time MIMO channel model.

3. JOINT MEASUREMENT NOISE ESTIMATION AND KF ALGORITHM SPECIFICATION

3.1. MIMO channel estimation based on KF

Literature [15] has denoted that wireless channel can be expressed in p-order autoregressive (AR(p)) model,i.e.,

$$h_{ij}(n) = \sum_{m=1}^{p-1} a_{ij}^m h_{ij}(n-m) + \mu_{ij}(n-1) \tag{3}$$

Where $\mu_{ij}(n)$ is a zero mean white-noise scalar which denotes process noise.Using the result in (3),we can get

$$\mathbf{H}(n) = \mathbf{A}\mathbf{H}(n-1) + \boldsymbol{\mu}(n-1) \tag{4}$$

Where

$\mathbf{H}(n) = \begin{bmatrix} \mathbf{H}_1^T(n) & \mathbf{H}_2^T(n) & \cdots & \mathbf{H}_M^T(n) \end{bmatrix}^T$;

$\mathbf{H}_j(n) = \begin{bmatrix} h_{1j}(n) & \cdots & h_{1j}(n-p+1) & \cdots & h_{Nj}(n) & \cdots & h_{Nj}(n-p+1) \end{bmatrix}^T$;

$\mathbf{A} = diag(\mathbf{A}_{11}, \cdots, \mathbf{A}_{N1}, \cdots, \mathbf{A}_{1M}, \cdots, \mathbf{A}_{NM})$;

$$\mathbf{A}_{ij} = \begin{pmatrix} a_{ij}^1 & a_{ij}^2 & \cdots & & a_{ij}^p \\ 1 & 0 & \cdots & & 0 \\ 0 & 1 & \cdots & & 0 \\ \vdots & \ddots & \ddots & & \vdots \\ 0 & \cdots & 0 & 1 & 0 \end{pmatrix};$$

$(\mathbf{u}_{ij}(n-1))_{p\times 1} = \begin{bmatrix} u_{ij}(n-1) & 0 & \cdots & 0 \end{bmatrix}$;

$diag(\bullet)$ diagonal matrix;
$(\bullet)_{q_1\times q_2}$ q1×q2 matrix.

Then we can equivalently express (2) as follows:

$$\mathbf{y}(n) = \overline{\mathbf{S}}(n)\mathbf{H}(n) + \mathbf{w}(n) \tag{5}$$

Where

$(\overline{\mathbf{S}}(n))_{M\times(pNM)} = diag(\mathbf{S}'(n), \mathbf{S}'(n), \cdots, \mathbf{S}'(n))$;

$(\mathbf{S}'(n))_{1\times pN} = [S_1(n) \ 0 \ \cdots \ 0 \ \cdots \ S_N(n) \ 0 \ \cdots \ 0]$.

If let $\overline{\mathbf{x}}(n), \overline{\mathbf{t}}(n)$ be defined in a similar way to $\overline{\mathbf{S}}(n)$,it is possible to write (5) as

$$\begin{aligned} \mathbf{y}(n) &= [\overline{\mathbf{t}}(n) + \overline{\mathbf{x}}(n)]\mathbf{H}(n) + \mathbf{w}(n) \\ &= \overline{\mathbf{t}}(n)\mathbf{H}(n) + \overline{\mathbf{x}}(n)\mathbf{H}(n) + \mathbf{w}(n) \\ &= \overline{\mathbf{t}}(n)\mathbf{H}(n) + \boldsymbol{\eta}(n) \end{aligned} \tag{6}$$

Where $\boldsymbol{\eta}(n) = \overline{\mathbf{x}}(n)\mathbf{H}(n) + \mathbf{w}(n)$,we call it fiction measurement noise. And we can easily obtain the mean of $\boldsymbol{\eta}(n)$

$$\begin{aligned} \mathbf{m}(n) &= E[\boldsymbol{\eta}(n)] = E[\overline{\mathbf{x}}(n)\mathbf{H}(n) + \mathbf{w}(n)] \\ &= E[\overline{\mathbf{x}}(n)]\mathbf{H}(n) + \mathbf{d} = \mathbf{d}. \end{aligned} \tag{7}$$

Where $\mathbf{d} = \begin{bmatrix} d_1 & d_2 & \cdots & d_M \end{bmatrix}^T$. Now, define autocovariance matrix as

$$\mathbf{C}(n,n-k) = E\{[\boldsymbol{\eta}(n) - E(\boldsymbol{\eta}(n))]\,[\boldsymbol{\eta}(n-k) - E(\boldsymbol{\eta}(n-k))]^H\}, k = 0, \pm 1, \pm 2, \cdots \tag{8}$$

Where $(\bullet)^H$ denotes conjugate and transpose.From assumption aforementioned, when k≠0,we get $\mathbf{C}(n,n-k)=0$. Because $\mathbf{H}(n)$ is time-varying,as a result, $\mathbf{C}(n,n)$ is time-varying too. Consequently, $\boldsymbol{\eta}(n)$ is a white noise vector with unknown constant mean and time-varying autocovariance. (4) and (6) therefore present the process equation and the measurement equation of KF.

3.2. Measurement noise recursive estimator

As we know,KF requires precise knowledge on statistics of process and measurement noises.Thus the unknown $\mathbf{d}$ and time-varying $\mathbf{C}(n,n)$ need be estimated "online". From (6), we get following white noise smoother

$$\boldsymbol{\eta}(i|n) = \mathbf{y}(i) - \overline{\mathbf{t}}(i)\mathbf{H}(i|n), 0 \le i \le n \tag{9}$$

When assume that $\boldsymbol{\eta}(n)$ is stationary and ergodic, $\mathbf{C}(n,n) = \mathbf{C}$, is a constant.We are able to obtain maximum a posteriori (MAP) time-invariant noise estimator as

$$\hat{\mathbf{d}}(n) = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{\eta}(i|n);$$

$$\hat{\mathbf{C}}(n,n) = \frac{1}{n}\sum_{i=1}^{n}[\boldsymbol{\eta}(i|n) - \mathbf{d}]\,[\boldsymbol{\eta}(i|n) - \mathbf{d}]^H;$$

to simplify the computation,we substitute $\boldsymbol{\eta}(i|i)$ for $\boldsymbol{\eta}(i|n)$, then get following sub-optimal noise estimator

$$\hat{\mathbf{d}}(n) = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{\eta}(i|i); \tag{10}$$

$$\hat{\mathbf{C}}(n,n)=\frac{1}{n}\sum_{i=1}^{n}[\boldsymbol{\eta}(i|i)-\mathbf{d}]\,[\boldsymbol{\eta}(i|i)-\mathbf{d}]^H; \tag{11}$$

from (9),we get

$$\boldsymbol{\eta}(i|i)=\mathbf{y}(i)-\bar{\mathbf{t}}(i)\mathbf{H}(i|i) \tag{12}$$

When $\mathbf{C}$ and $\mathbf{d}$ are known,the optimal Kalman filter is

$$\mathbf{H}(i|i)=\mathbf{H}(i|i-1)+\mathbf{G}(i)\boldsymbol{\alpha}(i) \tag{13}$$

where $\mathbf{H}(n|m)$ denotes the estimated channel at time n based on the state at time m. $\mathbf{G}(n)$ is Kalman gain and $\boldsymbol{\alpha}(n)$ is innovations vector at time n.Substituting (13) into (12) gives

$$\boldsymbol{\eta}(i|i)=\mathbf{d}+[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]\boldsymbol{\alpha}(i) \tag{14}$$

Thus (13) can be written as

$$\hat{\mathbf{C}}(n,n)=\frac{1}{n}\sum_{i=1}^{n}[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]\boldsymbol{\alpha}(i)\boldsymbol{\alpha}^H(i)[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H \tag{15}$$

Where we have used the fact that $\boldsymbol{\alpha}(i)=\mathbf{y}(i)-\bar{\mathbf{t}}(i)\mathbf{H}(i|i-1)$.

Obviously,from (10) ,$E[\hat{\mathbf{d}}(n)]=\mathbf{d}$, so $\hat{\mathbf{d}}(n)$ is unbiased. However

$$E[\hat{\mathbf{C}}(n,n)]=\frac{1}{n}\sum_{i=1}^{n}[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]E[\boldsymbol{\alpha}(i)\boldsymbol{\alpha}^H(i)][\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H \tag{16}$$

Denote by $\mathbf{K}(n|n),\mathbf{K}(n|n-1)$ the correlation matrix of the error in $\mathbf{H}(n\,|\,n)$ and $\mathbf{H}(n\,|\,n-1)$,we can get

$E[\boldsymbol{\alpha}(i)\boldsymbol{\alpha}^H(i)]=\bar{\mathbf{t}}(i)\mathbf{K}(i|i-1)\bar{\mathbf{t}}^H(i)+\mathbf{C}$,

so it is possible to rewrite (16) as

$$\begin{aligned}E[\hat{\mathbf{C}}(n,n)]&=\frac{1}{n}\sum_{i=1}^{n}[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]\,[\bar{\mathbf{t}}(i)\mathbf{K}(i|i-1)\bar{\mathbf{t}}^H(i)+\mathbf{C}]\,[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H\\&=\frac{1}{n}\sum_{i=1}^{n}\mathbf{C}\,[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H\\&=\mathbf{C}-\frac{1}{n}\sum_{i=1}^{n}\mathbf{C}\bar{\mathbf{t}}(i)\mathbf{G}(i)^H\\&=\mathbf{C}-\frac{1}{n}\sum_{i=1}^{n}\bar{\mathbf{t}}(i)\mathbf{K}(i|i-1)[\mathbf{I}-\bar{\mathbf{t}}^H(i)\mathbf{G}(i)^H]\bar{\mathbf{t}}^H(i)\\&=\mathbf{C}-\frac{1}{n}\sum_{i=1}^{n}\bar{\mathbf{t}}(i)\{[\mathbf{I}-\mathbf{G}(i)\bar{\mathbf{t}}(i)]\mathbf{K}(i|i-1)\}^H\bar{\mathbf{t}}^H(i)\\&=\mathbf{C}-\frac{1}{n}\sum_{i=1}^{n}\bar{\mathbf{t}}(i)\mathbf{K}(i|i)\bar{\mathbf{t}}^H(i)\end{aligned} \tag{17}$$

Where we have used the facts that

$\mathbf{G}(i)=\mathbf{K}(i|i-1)\bar{\mathbf{t}}^H(i)[\bar{\mathbf{t}}(i)\mathbf{K}(i|i-1)\bar{\mathbf{t}}^H(i)+\mathbf{C}]^{-1}$;

$\mathbf{K}(i|i)=[\mathbf{I}-\mathbf{G}(i)\bar{\mathbf{t}}(i)]\mathbf{K}(i|i-1)$;

$\mathbf{K}^H(i|i-1)=\mathbf{K}(i|i-1)$; $\mathbf{K}^H(i|i)=\mathbf{K}(i|i)$.

Therefore $\hat{\mathbf{C}}(n,n)$ is a biased estimation of $\mathbf{C}(n,n)$ .From (17), we can get following unbiased estimation for $\mathbf{C}(n,n)$

$$\hat{\mathbf{C}}(n,n)=\frac{1}{n}\sum_{i=1}^{n}\{[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]\boldsymbol{\alpha}(i)\boldsymbol{\alpha}^H(i)[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H+\bar{\mathbf{t}}(i)\mathbf{K}(i|i)\bar{\mathbf{t}}^H(i)\}\,. \tag{18}$$

For the sake of the time-varying $\mathbf{C}(n,n)$ estimation,we bring in a forgetting factor λ to emphasize the effect of new data and forget old data gradually.Thus we may use the following exponential weighting estimator

$$\hat{\mathbf{C}}(n,n)=\sum_{i=1}^{n}\frac{1-\lambda}{1-\lambda^n}\lambda^{n-i}\{[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]\boldsymbol{\alpha}(i)\boldsymbol{\alpha}^H(i)[\mathbf{I}-\bar{\mathbf{t}}(i)\mathbf{G}(i)]^H+\bar{\mathbf{t}}(i)\mathbf{K}(i|i)\bar{\mathbf{t}}^H(i)\} \tag{19}$$

Next,let derive the recursive form of measurement noise estimator. From (10)

$$\hat{\mathbf{d}}(n)=\frac{n-1}{n}\hat{\mathbf{d}}(n-1)+\frac{1}{n}[\mathbf{y}(n)-\bar{\mathbf{t}}(n)\mathbf{H}(n)]. \tag{20}$$

And from (19), we get

$$\hat{\mathbf{C}}(n,n)=\frac{\lambda(1-\lambda^{n-1})}{1-\lambda^n}\hat{\mathbf{C}}(n-1,n-1)+\frac{1-\lambda}{1-\lambda^n}\{[\mathbf{I}-\bar{\mathbf{t}}(n)\mathbf{G}(n)]\boldsymbol{\alpha}(n)\boldsymbol{\alpha}^H(n)[\mathbf{I}-\bar{\mathbf{t}}(n)\mathbf{G}(n)]^H+\bar{\mathbf{t}}(n)\mathbf{K}(n|n)\bar{\mathbf{t}}^H(n)\} \tag{21}$$

(20) and (21) therefore stand for the measurement noise recursive estimator.

3.3. Joint measurement noise estimation and KF recursions

In table 1,we present a summary of joint measurement noise estimation and Kalman filtering.

TABLE 1 JOINT MEASUREMENT NOISE ESTIMATION AND KF RECURSIONS

Initial conditions: $\mathbf{K}(1\,|\,0)$, $\mathbf{H}(1\,|\,0)$, $\mathbf{d}(0)$, $\mathbf{C}(0,0)$, λ.
Computation: $n=1,2,3,\cdots$ $\mathbf{G}(n)=\mathbf{K}(n\,|\,n-1)\bar{\mathbf{t}}^H(n)[\bar{\mathbf{t}}(n)\mathbf{K}(n\,|\,n-1)\bar{\mathbf{t}}^H(n)+\mathbf{C}(n-1,n-1)]^{-1}$; $\boldsymbol{\alpha}(n)=\mathbf{y}(n)-\bar{\mathbf{t}}(n)\mathbf{H}(n\,|\,n-1)\mathbf{K}(n\,|\,n-1)-\mathbf{d}(n-1)$; $\mathbf{H}(n\,|\,n)=\mathbf{H}(n\,|\,n-1)+\mathbf{G}(n)\boldsymbol{\alpha}(n)$; $\mathbf{d}(n)=\frac{n-1}{n}\mathbf{d}(n-1)+\frac{1}{n}[\mathbf{y}(n)-\bar{\mathbf{t}}(n)\mathbf{H}(n\,|\,n)]$; $\mathbf{H}(n+1\,|\,n)=\mathbf{A}\mathbf{H}(n\,|\,n)$; $\mathbf{K}(n\,|\,n)=\mathbf{K}(n\,|\,n-1)-\mathbf{G}(n)\bar{\mathbf{t}}(n)\mathbf{K}(n\,|\,n-1)$; $\mathbf{C}(n,n)=\frac{\lambda(1-\lambda^{n-1})}{1-\lambda^n}\mathbf{C}(n-1,n-1)+$ $\frac{1-\lambda}{1-\lambda^n}\{[\mathbf{I}-\bar{\mathbf{t}}(n)\mathbf{G}(n)]\boldsymbol{\alpha}(n)\boldsymbol{\alpha}^H(n)[\mathbf{I}-\bar{\mathbf{t}}(n)\mathbf{G}(n)]^H+\bar{\mathbf{t}}(n)\mathbf{K}(n|n)\bar{\mathbf{t}}^H(n)\}$; $\mathbf{K}(n+1\,|\,n)=\mathbf{A}\mathbf{K}(n\,|\,n)\mathbf{A}^H+\mathbf{Q}$.

4. SIMULATION RESULTS

In all simulations presented in this section,we transmit QPSK information symbols through (2,2) Rayleigh fading channels.The carrier frequency is 2.0G Hz, information rate is 2.0M bps and terminal speed is 100km/h.

4.1. Performance of channel estimation

At first, let observe what happens when the information symbols are extracted based on the channel estimation proposed in this paper as follows

$$\hat{\mathbf{x}}(i)=[\hat{\bar{\mathbf{H}}}^T(i)]^{+}\mathbf{y}(i)-\mathbf{t}(i)\quad . \tag{22}$$

Where $(\bullet)^+$ denotes Moore-Penrose inverse. signal-to-noise ratio(SNR) is 20dB.Figure 2 is the plot of 2048 output symbols of the unequalized channel.Obviously, a high error rate is expected.Using the proposed channel estimation and (22) to equalize,the output is shown in figure 3.

4.2. Comparisons with competing methods

We compare the proposed algorithm with LS and the method suggested in [7].The comparisons are measured by normalized mean-square error (NMSE), Figure 4 shows that the proposal outperforms the method suggested in [7].And for low SNR, it is superior to LS met-hod;For high SNR,it is competitive with LS method.

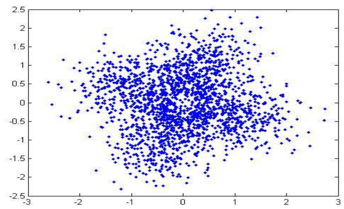

Figure 2. The output of the unequalized channel,SNR=20dB.

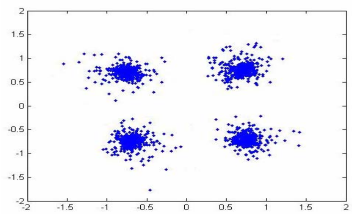

Figure 3. The output of the equalized channel,SNR=20dB.

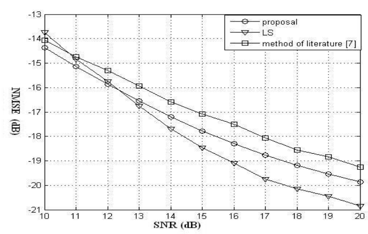

Figure 4. Comparisons with competing methods.

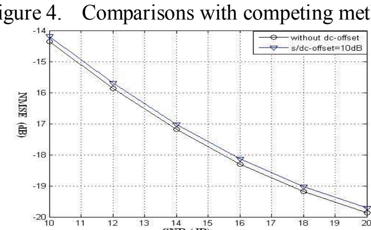

Figure 5. Performance under dc-offset.

4.3. Performance under dc-offset

We compare the scenario under dc-offset with the ben-chmark(the scenario without dc-offset).The signal power to dc-offset power is taken to 10dB.Figure 5 shows that the performance of the proposal under dc-offset is quite good.

5.CONCLUSIONS

We have presented a new algorithm for time-varying MIMO channel estimation based on implicit training. While the proposal uses some transmit power for training sequence, it saves bandwidth at the same time. Joint measurement noise estimation and Kalman filtering recursions is derived. The dc-offset is solved in a simple way. It can be concluded that the proposal offers good performance from simulation results.

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