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A Semi-blind Method for MIMO Channel Identification*

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***Abstract* -A semi-blind algorithm to perform channel identification for multiple input multiple output(MIMO) systems in frequency and time-selective fading environments is proposed. It contains two steps:training and tracking.In training phase, improved Kalman filtering,namely robust Kalman filtering (RKF), is exploited to identify channel impulse response(CIR). After that,in tracking stage,the RKF and minimum mean-square error feedback decision equalizer (MMSE-DFE) cooperate to track the time-varying channel.The RKF recursions is presented and a closed-form solution for baud rate MIMO MMSE-DFE under perfect knowledge of CIR and correct past decisions conditions is derived. In addition, it regards unknown dc-offset due to zero intermediate frequency(IF) at the receiver as the mean of measurement noise, which is estimated as a byproduct through robust Kalman filters. Finally, it is compared with well-known ones, such as least mean-square(LMS),recursive least square (RLS),Kalman filtering (KF).All these show that the proposal exhibits better performance.**

Index Terms - MIMO;channel identification; DFE; robust Kalman filtering;dc-offset.

I. INTRODUCTION

Wireless MIMO systems offer significant improvements in channel capacity and information rate. Inaccurate channel state information(CSI) affects not only the receiver performance, but also results in sub-optimal transmission. Although large numbers of investigations on MIMO channel identification 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 varying channel.This results in huge waste of resource.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,the blind schemes are generally computationally intensive and sometimes unreliable.Semi-blind methods use not only training sequences but also non-training based data.This allows one to shorten the training period.The method is presented in this paper belongs to the class of semi-blind.It contains two steps:training and tracking. In training phase, RKF is exploited to identify channel impulse response. After that,in tracking stage,the RKF and MMSE-DFE cooperate to track the time-varying channels. Here we assume both channel identification and past decisions are correct,and derive a baud rate MMSE-DFE based on the work in [13].

Since R.E.Kalman derived the Kalman filtering in[3] at the first time,it has been widely used because it is suitable for both stationary and nonstationary environments.furthermore,if the signal and noise are jointly Gaussian,it is an optimal estimator[4].In[5][6], KF is 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 divergency.In order to improve the performance of KF,Sage and Husa propose a kind of adaptive KF in [7].But it isn’t able to estimate time-varying noise.For implement in systems with time-varying process noise and measurement noise, a modified adaptive KF is derived in[8],Dynamic matrix and forgetting factor to emphasize the effect of new data and forget old data gradually are adopted in[9].In [10],Z.L. Deng compensated unknown time-varying fiction noise for autoregressive move average(ARMA) model error of the system: hence,the word “robust”,and obtain good performance. In this paper,we extend the works mentioned above and applied it to identify MIMO CIR.

Several papers have recently been devoted to iterative channel identification[11][12].It is an attractive choice because it improves channel identification through iterations.We adopt this method and discuss it detailedly in section Ⅴ.

When this method were to work in a direct conversion receiver, i.e. zero IF, an unknown dc-offset will appear[14].In this paper, We regard the unknown dc-offset as the mean of measurement noise and solve it via time-varying noise recursive estimator.

The rest of this paper is organized as follows.Section Ⅱ presents MIMO system model.Section Ⅲ discusses RKF. Section Ⅳ derives MMSE-DFE.Section Ⅴ depicts the proposed algorithm in detail.Section Ⅵ offers computer simulation results. Finally,in section Ⅶ,we draw conclusions.

II. 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 communications link show in fig.1,where

$\mathbf{x}_i(n)$ information symbols vector of i th input;
$\mathbf{h}_{ij}$ CIR between the i th input and the j th output;

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d_j dc-offset at the j th output;

$v_j(n)$ zero mean AWGN at the j th output;

$\mathbf{y}_j(n)$ jth channel output vector.

From Fig.1,we can write

$$y_j(n) = \sum_{i=1}^{N}\sum_{k=0}^{L-1} h_{ij}^k x_i(n-k) + d_j + v_j(n)$$
$$= \mathbf{h}_j^T \mathbf{x}(n) + w_j(n),\ j = 1, 2, \cdots, M. \qquad (1)$$

Where

L the channels model order(or their upper bound);

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

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

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

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

$$\mathbf{y}(n) = \mathbf{H}^T \mathbf{x}(n) + \mathbf{w}(n) \qquad (2)$$

Where

$\mathbf{y}(n) = [y_1(n) \quad y_2(n) \quad \cdots \quad y_M(n)]^T$;

$\mathbf{w}(n) = [w_1(n) \quad w_2(n) \quad \cdots \quad w_M(n)]^T$;

$\mathbf{H} = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \cdots \quad \mathbf{h}_M]$.

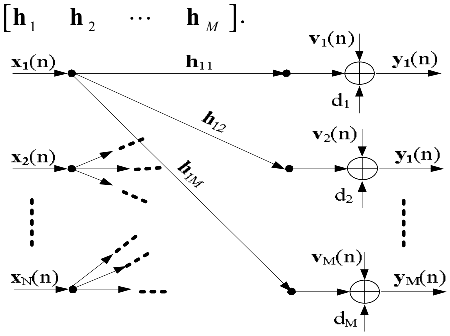

Fig. 1 Discrete-time MIMO channel model.

III. MIMO CHANNEL IDENTIFICATION BASED ON KF

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

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

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

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

Where

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

$(\mathbf{H}_j(n)) = \begin{bmatrix} \mathbf{h}_{1j}^T(n) & \mathbf{h}_{2j}^T(n) & \cdots & \mathbf{h}_{Nj}^T(n) \end{bmatrix}^T$;

$(\mathbf{H}_{ij}(n))_{(Lp)\times 1} = \begin{bmatrix} h_{ij}^0(n) & \cdots & h_{ij}^0(n-p+1) & \cdots & h_{ij}^{L-1}(n) & \cdots & h_{ij}^{L-1}(n-p+1) \end{bmatrix}^T$;

$\mathbf{A} = diag(\mathbf{A}_1 \quad \mathbf{A}_2 \quad \cdots \quad \mathbf{A}_M)$;

$\mathbf{A}_j = diag(\mathbf{A}_{1j}^0, \cdots, \mathbf{A}_{1j}^{L-1}, \cdots, \mathbf{A}_{Nj}^0, \cdots, \mathbf{A}_{Nj}^{L-1})$

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

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

$\mathbf{u}_j(n) = \begin{bmatrix} \mathbf{u}_{1j}^T(n) & \mathbf{u}_{2j}^T(n) & \cdots & \mathbf{u}_{Nj}^T(n) \end{bmatrix}^T$;

$(\mathbf{u}_{ij}(n))_{pL} = \begin{bmatrix} u_{ij}^0(n) & 0 & \cdots & 0 & \cdots & u_{ij}^{L-1}(n) & 0 & \cdots & 0 \end{bmatrix}^T$;

$diag(\bullet)$ diagonal matrix;

$(\bullet)_{m\times n}$ m×n matrix.

Then we can equivalently express (2) as follows:

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

Where

$(S(n))_{M\times(MNPL)} = diag(\overline{\mathbf{x}}(n) \quad \overline{\mathbf{x}}(n) \quad \cdots \quad \overline{\mathbf{x}}(n))$;

$\overline{\mathbf{x}}(n) = \begin{bmatrix} \overline{\mathbf{x}}_1^T(n) & \overline{\mathbf{x}}_2^T(n) & \cdots & \overline{\mathbf{x}}_N^T(n) \end{bmatrix}$;

$(\overline{\mathbf{x}}_i(n))_{(pL)\times 1} = \begin{bmatrix} x_i(n) & 0 & \cdots & 0 & \cdots & x_i(n-L+1) & 0 & \cdots & 0 \end{bmatrix}^T$.

(4) and (5) therefore present the process equation and the measurement equation of KF.

As we know,KF requires precise knowledge on AR model of the system.However,it is unknown in many practical implements.Therefore,we assume that there is unknown model error$\Delta\mathbf{A}$ in process equation, (4) can be expressed in

$$\mathbf{H}(n) = (\mathbf{A} + \Delta\mathbf{A})\mathbf{H}(n-1) + \boldsymbol{\mu}(n-1)$$
$$= \mathbf{A}\mathbf{H}(n-1) + \boldsymbol{\eta}(n-1) \qquad (6)$$

Where $\boldsymbol{\eta}(n-1) = \Delta\mathbf{A}\mathbf{H}(n-1) + \boldsymbol{\mu}(n-1)$. In generally, $\Delta\mathbf{A} \ll \mathbf{A}$, therefore,we approximately consider that $\boldsymbol{\eta}(n)$ is complex valued Gussian noise,whose mean and variance are unknown.Thus the filter performance is compensated by a fiction noise $\boldsymbol{\eta}(n)$ .Moreover, we assume the variance of $V_j(n)$ is unknown too.Denote by $\mathbf{H}(n|m)$ the identified channel at time n based on the state at time m. Extend the works in [6],[7]and [8],we obtain following time-varying noise recursive estimator:

$$\mathbf{q}(n) = \mathbf{q}(n-1) + \beta(n)[\mathbf{H}(n|n) - \mathbf{H}(n|n-1)] \qquad (7)$$

$$\mathbf{d}(n) = [1-\beta(n)]\mathbf{d}(n-1) + \beta(n)[\mathbf{y}(n) - \mathbf{S}(n)\mathbf{H}(n|n-1)] \qquad (8)$$

$$\mathbf{Q}_1(n) = \mathbf{Q}_1(n-1) + \beta(n)[\mathbf{G}(n)\boldsymbol{\alpha}(n)\boldsymbol{\alpha}^H(n)\mathbf{G}^H(n) + \mathbf{K}(n) - \mathbf{K}(n,n-1)] \qquad (9)$$

$$\mathbf{Q}_2(n) = [1-\beta(n)]\mathbf{Q}_2(n-1) + \beta(n)[\boldsymbol{\alpha}(n)\boldsymbol{\alpha}^H(n) - \mathbf{S}(n)\mathbf{K}(n|n-1)\mathbf{S}^H(n)] \qquad (10)$$

Where

$\beta(n) = \dfrac{1-\theta}{1-\theta^n}$;

θ forgetting factor, generally, $0.95 \le \theta \le 0.995$;

$\mathbf{q}(n)$ espected value of $\boldsymbol{\eta}(n)$;

$\mathbf{Q}_1(n)$ autocovariance matrix of $\boldsymbol{\eta}(n)$;

$\mathbf{Q}_2(n)$ autocovariance of $\boldsymbol{\mu}(n)$;

$\boldsymbol{\alpha}(n)$ innovations process;

$\mathbf{G}(n)$ Kalman gain;

$\mathbf{K}(n)$ filtered state-error correlation matrix;

$\mathbf{K}(n|n-1)$ predicted state-error correlation matrix;

Eqs.(7)-(10) and KF recursions therefore formulate the solution to using RKF to identify MIMO channels.

IV. MIMO BAUD RATE MMSE-DFE

A typical MIMO DFE block diagram is shown in Fig.2.it contains a set of feedforward filters(FFF) and a set of feedback filters (FBF) . The FFF operate on the receive signal , and the FBF operate on past decisions.For notational convenience,we describe N_f,the nonzero taps in $\mathbf{f}$,equals to L.The extension to $N_f \neq L$ is straightforward.Furthermore, we assume that the past decisions is correct and the MIMO system CIR is known,then

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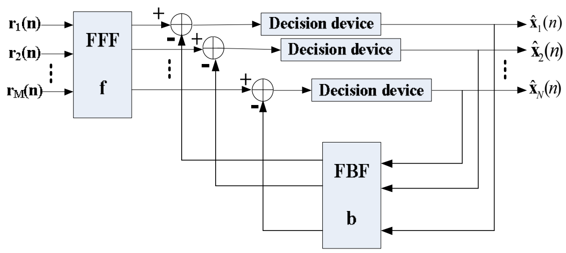

Fig.2 MIMO MMSE-DFE block diagram.

we can get

$$\hat{x}_i(n) = \sum_{j=1}^{M}\sum_{k=0}^{L-1} f_{ij}^k r_j(n+k) - \sum_{m=1}^{N}\sum_{k=1}^{L-1} b_{im}^k x_m(n-k) = \mathbf{f}_i^T \mathbf{r}(n) - \mathbf{b}_i^T \mathbf{x}'(n-1) \tag{11}$$

Where

$$r_j(n) = y_j(n) - d_j(n);$$
$$\mathbf{r}(n) = \left[\mathbf{r}_1^T(n) \quad \mathbf{r}_2^T(n) \quad \cdots \quad \mathbf{r}_M^T(n)\right]^T;$$
$$\mathbf{r}_j(n) = \left[r_j(n) \quad r_j(n+1) \quad \cdots \quad r_j(n+L-1)\right]^T;$$
$$\mathbf{f}_i(n) = \left[\mathbf{f}_{i1}^T \quad \mathbf{f}_{i2}^T \quad \cdots \quad \mathbf{f}_{iM}^T\right]^T;$$
$$\mathbf{f}_{ij}(n) = \left[f_{ij}^0 \quad f_{ij}^1 \quad \cdots \quad f_{ij}^{L-1}\right]^T;$$
$$\mathbf{b}_i = \left[\mathbf{b}_{i1}^T \quad \mathbf{b}_{i2}^T \quad \cdots \quad \mathbf{b}_{iN}^T\right]^T;$$
$$\mathbf{b}_{ij} = \left[b_{ij}^1 \quad b_{ij}^2 \quad \cdots \quad b_{ij}^{L-1}\right];$$
$$\mathbf{x}'(n-1) = \left[\mathbf{x}_1'^T(n-1) \quad \mathbf{x}_2'^T(n-1) \quad \cdots \quad \mathbf{x}_N'^T(n-1)\right];$$
$$\mathbf{x}_i'(n-1) = \left[x_i(n-1) \quad x_i(n-2) \quad \cdots \quad x_i(n-L+1)\right]^T;$$

Then it can be shown that the MMSE-DFE error at time n is given by:

$$\begin{aligned} e_i(n) &= x_i(n) - \hat{x}_i(n) \\ &= x_i(n) - \mathbf{f}_i^T \mathbf{r}(n) + \mathbf{b}_i^T \mathbf{x}'(n-1) \\ &= \mathbf{B}_i^T \mathbf{x}(n) - \mathbf{f}_i^T \mathbf{r}(n) \end{aligned} \tag{12}$$

Where

$$\mathbf{B}_i = \left[\mathbf{B}_{i1}^T \quad \mathbf{B}_{i2}^T \quad \cdots \quad \mathbf{B}_{iN}^T\right]^T;$$
$$\mathbf{B}_{ij} = \begin{cases} \left[1 \quad \mathbf{b}_{ij}^T\right]^T, & i = j \\ \left[0 \quad \mathbf{b}_{ij}^T\right]^T, & else \end{cases}.$$

Using the *orthogonality principle*, which denotes $E\left[e_i(n)\mathbf{r}^*(n)\right] = \mathbf{0}$,where E(•) presents the expected value of (•). Substituting (19) into (20),we get

$$\mathbf{f}_i^{opt} = \mathbf{R}_r^{-1}\mathbf{P}\mathbf{B}_i^{opt}$$

Where $\mathbf{P} = E\left[\mathbf{r}^*(n)\mathbf{x}^T(n)\right]$, $\mathbf{R}_r = E\left[\mathbf{r}^*(n)\mathbf{r}^T(n)\right]$.

Grouping all $\mathbf{f}_i^{opt}, i = 1, 2, \cdots N$,we get

$$\mathbf{F}^{opt} = \mathbf{R}_r^{-1}\mathbf{P}\mathbf{B}^{opt} \tag{13}$$

Where

$$\mathbf{F}^{opt} = \left[\mathbf{f}_1^{opt} \quad \mathbf{f}_2^{opt} \quad \cdots \quad \mathbf{f}_N^{opt}\right];$$
$$\mathbf{B}^{opt} = \left[\mathbf{B}_1^{opt} \quad \mathbf{B}_2^{opt} \quad \cdots \quad \mathbf{B}_N^{opt}\right].$$

Next,let derive the optimal $\mathbf{B}$ .when $f_i = f_i^{opt}$, the mean-square error (MSE)

$$\begin{aligned} \xi_i &= E[e_i(n)e_i^*(n)] = \mathbf{B}_i^T[\mathbf{R}_x^* - \mathbf{P}^T(\mathbf{R}_r^{-1})^*\mathbf{P}^*]\mathbf{B}_i^* \\ &= \mathbf{B}_i^T\mathbf{R}\mathbf{B}_i^* \end{aligned}$$

Where $\mathbf{R}_x = E[\mathbf{x}^*(n)\mathbf{x}^T(n)]$, $\mathbf{R} = [\mathbf{R}_x^* - \mathbf{P}^T(\mathbf{R}_r^{-1})^*\mathbf{P}^*]$.

To obtain the optimal tap-weight of FBF equivalently solve the constrained optimization as follows:

$$\min_{\mathbf{B}_i}(\xi_i) = \min_{\mathbf{B}_i}(\mathbf{B}_i^T\mathbf{R}\mathbf{B}_i^*)$$

subject to the constraint $\mathbf{\Phi}\mathbf{B}_i^* = \mathbf{C}_i$, Where

$$(\mathbf{\Phi})_{N\times(N\times L)} = \begin{pmatrix} \varphi_{1,1} & \cdots & \varphi_{1,(N\times L)} \\ \vdots & \ddots & \vdots \\ \varphi_{N,1} & \cdots & \varphi_{N,(N\times L)} \end{pmatrix};$$

$$\varphi_{kj} = \begin{cases} 1, & j = (k-1)L+1, k = 1, 2, \cdots, N \\ 0, & else \end{cases};$$

$$(\mathbf{C}_i)_{N\times 1} = \left[C_i^1 \quad C_i^2 \quad \cdots \quad C_i^N\right]^T;$$

$$C_i^k = \begin{cases} 1, & k = (i-1)L+1 \\ 0, & else \end{cases}.$$

applying the *method of Lagrange multipliers*, the adjoint equation for this optimization problem is

$$\frac{\partial}{\partial \mathbf{B}_i^*}[\mathbf{B}_i^T\mathbf{R}\mathbf{B}_i^*] + \frac{\partial}{\partial \mathbf{B}_i^*}[\boldsymbol{\rho}^T(\mathbf{C}_i - \mathbf{\Phi}\bullet\mathbf{B}_i^H)] = 0$$

where $(\boldsymbol{\rho})_{N\times 1}$ is a real-valued lagrange multiplier-vector.we easily get $\mathbf{B}_i^{opt} = \mathbf{R}^{-1}\mathbf{\Phi}^T[\mathbf{\Phi}(\mathbf{R}^{-1})^*\mathbf{\Phi}^T]^{-1}\mathbf{C}_i$ .Grouping all $\mathbf{B}_i^{opt}$,we get

$$\mathbf{B}^{opt} = \mathbf{R}^{-1}\mathbf{\Phi}^T[\mathbf{\Phi}(\mathbf{R}^{-1})^*\mathbf{\Phi}^T]^{-1}\mathbf{C} \tag{14}$$

where $\mathbf{C} = [\mathbf{C}_1 \quad \mathbf{C}_2 \quad \cdots \quad \mathbf{C}_N]$. Thus (13) and (14) denote the optimal linear equalizer.

V. ALGORITHM SPECIFICATION

At first,in training session,using the RBF adaptive algorithm,we obtain $\hat{\mathbf{H}}$ and $\hat{d}_j$, After which,it switches to tracking mode.In this stage,the robust Kalman filters and the DFE cooperate to perform identification and equalization.The second stage is discussed detailedly as follows.

At the beginning of tracking,we assume that the estimators have converged at ture MIMO channels.A coarse prediction of $\hat{\mathbf{H}}$ Can be obtained directly from(6).Next,get $\hat{d}_j$ from (8). Substituting $\hat{\mathbf{H}}$ and $\hat{d}_j$ into(13) and(14),via equalization and decision,we get $\hat{\mathbf{x}}_i(n)$ .Then we exploit RKF to obtain refined channel estimates.The iterative algorithm aforementioned implies that the decisions vector and estimator rely on each other. Assume that tracking phase begin at time n,our MIMO tracking and equalization algorithm is summarized in following steps:

Initialization) Obtain $\mathbf{H}(n-1|n-1)$ from training mode;
S 1) Obtain $\mathbf{H}(n|n-1)$ using (6);
S 2) Using (13),(14) to equalize ,After decide,we obtain $\hat{\mathbf{x}}(n)$;
S 3) Perform RBF to obtain $\mathbf{H}(n|n)$;

S 4) Retrieve decisions vector $\hat{\mathbf{x}}(n)$ based on $\mathbf{H}(n|n)$,in order to improve the performance,we can iterate *S3* and *S4* more than one times.

S 5) Repeat *S1-S4* to obtain $\mathbf{H}(k|k)$, $d_j(k)$ and $\hat{\mathbf{x}}(k)$, k=n+1, n+2,⋯.

In order to prevent algorithm divergence,training and tracking are alternatively performed.With known training sequences,channel identification is improved and persistent divergence is avoided.

VI. SIMULATION RESULTS

In all simulations presented in this section,we transmitted QPSK information symbols through (2,2) Rayleigh fading channels,whose model order L=3. The carrier frequency was 1.9G Hz and terminal speed was 70 km/h. There were 5000 symbols used for training and tracking .Training symbols to signal symbols was taken to 10%.

A. Performance of channel identification

signal to noise ratio(SNR) was 10dB.Because all channels are mutually independent ,we demonstrated the performance of channel identification by h_{11}^0.We plot 300 points of h_{11}^0 in tracking stage.Fig.3 confirms that the proposal does an excellent job in channel identification.

B. Comparisons with competing methods

We compared the proposed RKF-DFE(AR(2)) with KF-DFE (AR(2)),LMS-DFE(step-size=0.01)and RLS-DFE (λ = 0.96). The comparisons were measured in tracking stage by

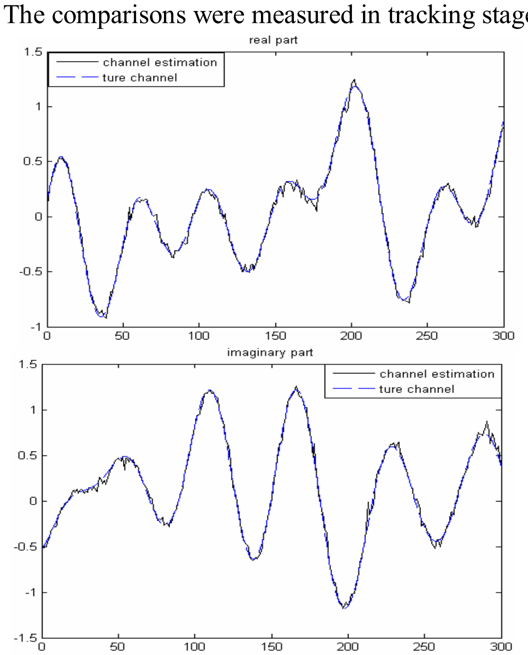

Fig.3 Tracking real part and imaginary part of h_{11}^0.

normalized mean-square error(NMSE) , which was defined as follows:

$$NMSE = \frac{\sum_n \| \hat{\mathbf{H}}(n) - \mathbf{H}(n) \|^2}{\sum_n \| \mathbf{H}(n) \|^2} \tag{15}$$

Fig.4 indicates that RKF outperforms the others. Nevertheless, with the increase of signal to noise ratio(SNR),performance of all schemes became closer and closer. This resulted from decrease of noise influence.

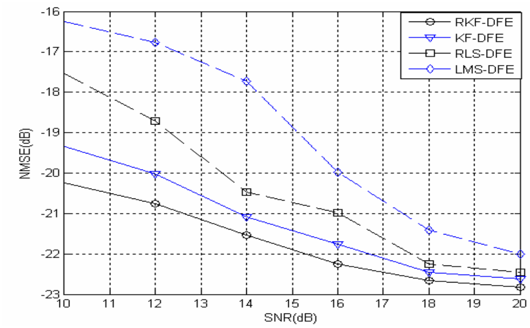

Fig.4 Comparisons with competing methods.

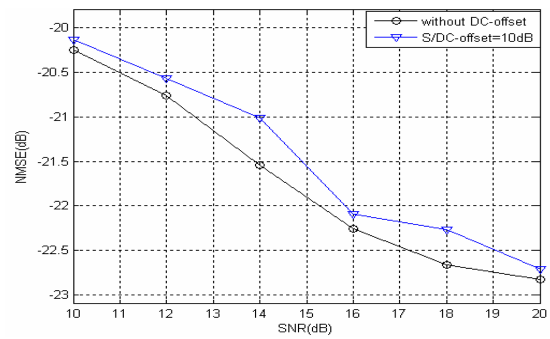

Fig.5 Performance under dc-offset.

C. Performance under dc-offset

We compared the scenario under dc-offset with the benchmark (the scenario without dc-offset). The signal power to dc-offset power was taken to 10dB.Fig.5 shows that the performance of the proposal under dc-offset is quite good.

VII. CONCLUSIONS

We presented an improved algorithm for joint channel identification and equalization over MIMO doubly-selective fading channels. The RKF and MMSE-DFE cooperated to track the channel. The dc-offset was taken into account. Robust performance has been achieved at the cost of computational complexity. How to simplify the computation is the most important topic for further research.

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