ORDERED SUCCESSIVE INTERFERENCE CANCELLATION
MIMO DECISION FEEDBACK EQUALIZATION BASED ON
CONSTANT MODULUS PROPERTY

YUN WANG , JINKUAN WANG AND ZHIBIN XIE

Abstract. The ordered successive interference cancellation MIMO decision feedback equalization based on constant modulus property is obtained by canceling decided symbols from the received symbols successively with the decision feed-forward equalizer (DFE) solution as a well known expression encountered in improved log-normal error function based on CMA (ILNCMA-OSIC-DFE) adaptive algorithms. The decision feedback equalizer replaces a convolution of the decision feed-forward equalizer with the channel. The ILNCMA-OSIC-DFE algorithm avoids the interference of the decided symbols and improves the detection performance. In the environment where lots of wireless communications are scattered over, simulation testing and the results shown that the detection performance of proposed algorithm is dramatically improved in comparison with the traditional ordered decision feedback equalization based on recursive least square algorithm (RLS-O-DFE).

Key Words. log-normal error function based on CMA, ordered successive interference cancellation, decision feedback

1. Introduction

Multi-input-multi-output (MIMO) digital communication systems are receiving an increasing attention due to their potential of increasing the overall system throughput [1]-[2]. In such systems, MIMO decision feedback equalization (DFE) is often used to mitigate inter-symbol-interference (ISI), which results from channel multi-path propagation. In many of such systems, the transmitted symbol consists of a known training sequence followed by unknown data. An efficient equalization technique in this scenario is to first estimate the channel impulse responses between each transmitter and each receiver using the training sequence, and then use this estimate to compute the optimal decision feedback equalizer tap coefficients corresponding to the estimated channel. The computed tap coefficients are then uploaded to the equalizer taps. For time-varying channels, the detection ordering and nulling vectors need to be updated for each time, plus the channel parameters should be tracked. These update and tracking operations in the time domain require excessive computations. To overcome this drawback, a simplified policy for updating and tracking is proposed in [3], where the V-BLAST (Vertical Bell Laboratories Layered Space-Time coding) detection is updated block-wise, and the channel tracking is interpolation-based, thereby creating a tradeoff between complexity and performance. As an alternative approach to detecting MIMO systems in time-varying channels, the adaptive techniques in [4]-[7] may be employed. By
successively detecting the transmitted symbols at each time, the adaptive decor-relating detector in [4] can suppress the co-channel interference caused by spatial multiplexing, but it requires channel estimation to determine the order of detection. The adaptive decision feedback equalizer in [5] and [6] are useful for reducing intersymbol interference in MIMO systems over frequency-selective channels. However, they are not suitable for reducing the co-channel interference; in the DFE, the transmitted symbols at each time are simultaneously detected without considering the order of detection. The adaptive method in [7] is a blind technique, whereas the receivers in [4]-[6] are data aided. A data-aided ordered based on the recursive least squares ordered decision feed-back equalizer (RLS-O-DFE) architecture is proposed in [8]. For each time, the tap weight vectors are updated using an RLS based-time and order-update algorithm and detection ordering determined according to a least squares error (LSE) criterion. But the proposed algorithm doesn’t cancel interference from detected symbols successively and the detection performance deteriorated. A variable step size blind equalization algorithm based on log-normal error function is proposed in [9]. The algorithm has faster convergent rate and smaller the mean square error (MSE) than the constant modulus algorithm (CMA). But most cost is on the computing of error function and the complexity is increased.

In this letter, an improved log-normal error function based on CMA algorithm ordered successive interference cancellation decision feedback equalization (ILNCMA-OSIC-DFE) is proposed. The algorithm improved the variable step size blind equalization algorithm based on log-normal error function firstly and added decision conditions. So the convergent rate is accelerated and the computational complexity is reduced. Then it cancels the detected symbols as interference from received symbols and overcomes the drawback of the RLS-O-DFE algorithm, such as instability and high bit error ratio (BER), while the computational complexities are increased a little. Performance analysis and simulation results show the effectiveness of the proposed algorithm.

2. System model

We consider here the following data mode

\[ y(t) = \mathbf{H}(t)\mathbf{x}(t) + \mathbf{n}(t) \]

Where \( \mathbf{x}(t) = [x_1(t), \ldots , x_{N_t}(t)]^H \), \( y(t) = [y_1(t), \ldots , y_{N_r}(t)]^H \) are, respectively, the sent, the received symbols. \( \mathbf{n}(t) = [n_1(t), \ldots , n_{N_r}(t)]^H \) are the noise symbols. \( N_t \) and \( N_r \) denote the number of transmitted and received antennas. \( (\cdot)^H \) denotes vector complex conjugate transposition. The symbols \( \mathbf{x}(t) \) and \( \mathbf{n}(t) \) are mutually uncorrelated, zero-mean random processes with variances \( E\left\{||\mathbf{x}(t)||^2\right\} = 1 \) and \( E\left\{||\mathbf{n}(t)||^2\right\} = N_0 \). The element of \( \mathbf{H}(t) \) represents channel gains between transmit and receive antennas at the discrete time \( t \).

For brevity of notation the discrete time index \( t \) is abandoned in the subsequent consideration so (1) becomes

\[ y = \mathbf{H}\mathbf{x} + \mathbf{n} \]

For commodity, we denote by \( \mathbf{h}_i \) the \( i \)-th column of the matrix \( \mathbf{H} \).
3. Ordered successive interference cancellation MIMO decision feedback equalization based on constant modulus property

In the V-BLAST systems with time-varying frequency-selective channels, to be specific, the following notations are introduced: \( \{ w_{f,i}(t) \} \) denote the \( N_r \)-dimensional feed forward weight vectors; \( \{ w_{b,i}(t) \} \) denote the \( i \)-1-dimensional feedback weight vectors; \( \hat{x}_i(t) \) and \( \hat{x}_i(t) \) denote the \( i \)-th detected symbol and decided symbol respectively. Then the output of the equalizers \( \tilde{y}(t) \) can be represented as

\[
\tilde{y}(t) = w_{f,i}(t)y(t) + w_{b,i}(t)\hat{x}(t-1)
\]

Where, \( \hat{x}(t-1) = [\hat{x}_1(t), \hat{x}_2(t), ..., \hat{x}_{i-1}(t)] \) and \( w_{b,i}(t) = 0 \) when \( i = 1 \). \((\cdot)^T\) denotes vector complex transposition. For notational convenience, define \( w_{t,i}(t) \) as the equalizer vector of the \( i \)-th unordered detection at time \( t \), then

\[
w_{t,i}(t) = \begin{cases} w_{f,i}(t), & i = 1 \\ [w_{f,i}(t), w_{b,i}(t)]^T, & i = 2, ..., N_t \end{cases}
\]

and

\[
y_{t,i}(t) = \begin{cases} y(t), & i = 1 \\ [y(t), \tilde{x}(t)]^T, & i = 2, ..., N_t \end{cases}
\]

Then, (3) is rewritten as

\[
\hat{x}_i(t) = w_{t,i}(t)y_{t,i}(t)
\]

When the channel is fixed, the optimal detection order under the minimum mean square error (MMSE) criterion can be written as

\[
k_i = \arg \min_j \varepsilon_{i,j}(t) = \arg \min_j \sum_{l=1}^{t} \lambda^{i-l}\| \hat{x}_j(l) - \hat{y}_{t,j}(l) \|^2
\]

where

\[
w_{t,j}(t) = \Phi_{j}^{-1}(t)z_{i,j}(t)
\]

where \( \lambda \) is the forgetting factor that satisfies \( 0 < \lambda \leq 1 \). \( \varepsilon_{i,j}(t) \) denotes the least squares estimation. Then

\[
\varepsilon_{i,j}(t) = \sum_{l=1}^{t} \lambda^{i-l}\| \hat{x}_j(l) - \hat{y}_{t,j}(l) \|^2 = \alpha_j(t) - \hat{y}_{t,j}(l)
\]

Where \( \alpha_j(t) \) denotes the autocorrelation matrix of the transmitted symbols.

\[
\Phi_j(t) = \sum_{l=1}^{t} \lambda^{i-l}\| \hat{x}_j(l) \|^2
\]

\( \Phi_j(t) \) denotes the autocorrelation matrix of the received symbols with time-varying channels at time \( t \).

\[
\Phi_j(t) = \sum_{l=1}^{t} \lambda^{i-l}\| y_{t,j}(l) \|^2 + \Phi_j(0)
\]

\( z_{i,j}(t) \) denotes the cross-correlation matrix of the received and transmitted symbols with time-varying channels

\[
z_{i,j}(t) = \sum_{l=1}^{t} \lambda^{i-l}\| y_{t,j}(l) \|
\]
Where $(\cdot)^\ast$ denotes vector complex conjugate. Using the constant modulus property of the transmitted signals we can regard the transmitted signals as $x(t) = y(t)/|y(t)|$. Then the transmitted signals can be calculated by $y(t)$ without training sequence, so (7) and (10) becomes

\begin{equation}
 k_i = \arg \min_j \varepsilon_{i,j}(t) = \arg \min_j \sum_{l=1}^t \lambda^{t-l} |y_{t,j}(l)|/|y_{t,j}(l)| - w_{t,j}^H(t)y_{t,j}(l)|^2 \tag{13}
\end{equation}

and

\begin{equation}
 \alpha_j(t) = \sum_{l=1}^t \lambda^{t-l} |y_{t,j}(l)|/|y_{t,j}(l)|^2 \tag{14}
\end{equation}

In the least square constant modulus algorithm, we define the error function as

\begin{equation}
 e_{k_i}(t) = 2\hat{x}_{k_i}(t)\text{sgn}(|\hat{x}_{k_i}(t)|^2 - 1) \tag{15}
\end{equation}

Where $\text{sgn}(\cdot)$ denotes sign function. The cost function can be defined as

\begin{equation}
 J = E\{|w_{t,k_i}^H(t)y_{t,k_i}(t)| - 1|^2\} \tag{16}
\end{equation}

Then the iterative process of the weight vector is

\begin{equation}
 w_{t,k_i}(t) = w_{t,k_i-1}(t) + \chi y_{t,k_i-1}(t)e_{k_i-1}^*(t) \tag{17}
\end{equation}

Where $\chi$ is iteration step-size parameter.

The error curve shown by (15) is asymmetry\cite{9} and it is the main cause leading to large MSE and slow convergence of the LSCMA. So, we redefine error function as log-normal error function

\begin{equation}
 e_{k_i}(t) = \frac{1}{\sqrt{2\pi}\sigma_{\theta_{k_i}}(t)} \exp\left\{\frac{-(\ln|\theta_{k_i}(t)| - \mu)^2}{2\sigma^2}\right\} \tag{18}
\end{equation}

where

\begin{equation}
 \theta_{k_i}(t) = |\hat{x}_{k_i}(t)|^2 - 1 \tag{19}
\end{equation}

$\ln(\cdot)$ is log function based $e$ and $\exp(\cdot)$ denotes exponential function based $e$. $\mu$, $\sigma$ are the mean value and standard error of the log-normal error function. The relation curve of the log-normal error function $e_{k_i}(t)$ and equalization output $\theta_{k_i}(t) = |\hat{x}_{k_i}(t)|^2 - 1$ is showed in figure 1.

We can conclude from figure 1 that:

1. The range of $e_{k_i}(t)$ decreases and the error curve becomes flat increasingly while increasing $\mu$ and $\sigma$. For fast convergence rate, we should select small $\mu$ and $\sigma$, but it will incur large MSE.

2. $e_{k_i}(t)$ is odd symmetry. The symmetric point is $(1,0)$ for the log normal error function $e_{k_i}(t)$. All the points that deviate the symmetric point $(1,0)$ same distances are compensated same by the symmetry and the equalization results show good performance.

By combining all above factors, we should select the error function with moderate range and fast convergence rate. We may find from figure 1 that the convergence rate of $e_{k_i}(t)$ accelerates while $\theta_{k_i}(t) = |\hat{x}_{k_i}(t)|^2 - 1$ is in the inclusion region of error functions’ stationary point. Let $d(e_{k_i}(t))/d(\theta_{k_i}(t)) = 0$, we can get the stationary
Because \( \sqrt{2\pi}\sigma^3 \theta_{ki}^2(t) \neq 0 \) and \( \exp\{-(\ln|\theta_{ki}(t)|-\mu)^2/2\sigma^2\} > 0 \), the equation \( \mu - \ln|\theta_{ki}(t)| - \sigma^2 = 0 \) holds. So we can conclude from (20) that

\[
\theta_{ki}(t) = \pm e^{\mu - \sigma^2}
\]

Then substitute (19) in (21) yields

\[
|\hat{x}_{ki}(t)|^2 = 1 \pm e^{\mu - \sigma^2}
\]

While \( |\hat{x}_{ki}(t)|^2 \) satisfies the following equation

\[
1 - e^{\mu - \sigma^2} \leq |\hat{x}_{ki}(t)|^2 \leq 1 + e^{\mu - \sigma^2}
\]

the MSE \( e_{ki}(t) \) decreases from the extreme point and the convergence rate accelerates obviously. While \( \mu = 0 \) and \( \sigma = 1 \), we get the critical point of the range of accelerating MSE’s convergence rate.

\[
0.6403 \leq |\hat{x}_{ki}(t)|^2 \leq 1.3597
\]

While estimating the equalization vector, we may judge by the module value of the decision signals. If the module value of the received signal is in the range \( [1 - e^{\mu - \sigma^2}, 1 + e^{\mu - \sigma^2}] \) it iterates. Otherwise, it doesn’t iterate and judges by the module value of next decision signals.
Then, substitute (18) and (19) in (17) yields the ordered updating equalization channel

\[ w_{t,k_i}(t) = w_{t,k_i-1}(t) \]

(25)\[ \chi_{y_{t,k_i-1}}(t) \left[ \frac{1}{\sqrt{2\pi\sigma^2(\hat{x}_{k_i-1}(t))^2 - 1}} \exp \left\{ - \frac{(\ln \|\hat{x}_{k_i-1}(t)\| - 1 - \mu)^2}{2\sigma^2} \right\} \right]^* \]

For the \( k_i \)-th sub-stream, considering canceling decided symbols \( \hat{x}_{k_i-1}(t) \) from the received signals. Then

\[ \hat{y}^T(t) = y^T(t) - \sum_{i=1}^{i} w_{t,i}^{-H}(t)\hat{x}_{k_i}(t) \]

Using the matrix inversion lemma, the iteration expression of \( w_{t,i}^{-1}(t) \) in terms of \( w_{t-1,i}(t) \) can be concluded.

\[ w_{t,k_i}^{-1}(t) = \left\{ \begin{bmatrix} w_{t,k_i-1}(t) & 0 \\ 0 & 0 \end{bmatrix} + \chi_{y_{t,k_i-1}}(t) \begin{bmatrix} e_{k_i}(t) \\ 1 \end{bmatrix} \right\}^{-1} \]

(27)\[ = \left[ w_{t,k_i-1}(t) \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \chi_{y_{t,k_i-1}}(t) \begin{bmatrix} e_{k_i}(t) \\ 1 \end{bmatrix} \right]^{-1} - 1 + \chi_{y_{t,k_i-1}}(t) \begin{bmatrix} e_{k_i}(t) \\ 1 \end{bmatrix} \right]^{-1} \]

Then substitute (26) in (4) and (5) yields new expression of the received symbols and ordered updating equalization.

\[ \tilde{w}_{t,k_i}(t) = \begin{cases} w_{f,k_i}(t), & i = 1 \\ w_{2,t,k_i}^{-1}(t) + \alpha_{k_i,j}(t), & i = 2, ..., N_t \end{cases} \]

(28)\[ \tilde{y}_{t,k_i}(t) = \begin{cases} y(t), & i = 1 \\ [y^T(t) - \hat{x}_{k_i-1}(t), \hat{x}_{k_i-1}(t)]^T, & i = 2, ..., N_t \end{cases} \]

Where \( \alpha_{k_i}(t) = [w_{1,t}^{-H}(t), w_{2,t}^{-H}(t), ..., w_{k_i}(t)] \) denotes the interference canceling equalization vector. For the \( k_i \)-th sub-stream the autocorrelation matrix of the received symbols can be expressed as

\[ \Phi_{k_i}(t) = \sum_{i=1}^{t} \lambda^{t-i} \tilde{y}_{t,i}(t)\tilde{y}_{t,i}^H(t) \]

(30)\[ = \sum_{i=1}^{t} \lambda^{t-i} [y^T(t) - \hat{x}_{k_i-1}(t), \hat{x}_{k_i-1}(t)]^T [y^T(t) - \hat{x}_{k_i-1}(t), \hat{x}_{k_i-1}(t)] \]

\[ = \begin{bmatrix} \Phi_{k_i}(t) - 2z_{k_i}(t) + \alpha_{k_i}(t) \\ z_{k_i}(t) - \alpha_{k_i}(t) \end{bmatrix} \]

\[ \begin{bmatrix} z_{k_i}(t) & -\alpha_{k_i}(t) \end{bmatrix} \]
4. Performance analysis

For the analysis, the following assumptions are made.
1. The transmitted signals \( x(t) \) and received signals \( y(t) \) are jointly Gaussian.
2. There is detecting error

\[
e_{o,k_{i+1}}(t) = x_{k_{i+1}}(t) - w_{o,k_{i+1}}^{H}(t)y(t)
\]

Where \( w_{o,k_{i+1}}(t) \) is the regression parameter vector. The characterization of \( e_{o,k_{i+1}}(t) \) as white noise means that its successive samples are uncorrelated, as shown by

\[
E\{e_{o,k_{i+1}}(t)e_{o,k_{i+1}}^{*}(t-n)\} = \begin{cases} J_{\text{min}}, & n = 0 \\ 0, & n \neq 0 \end{cases}
\]

Where \( J_{\text{min}} \) is the least mean square.
3. Received symbols \( y(t) \) are drawn from a stochastic process, which is ergodic in its autocorrelation function. Then, we can substitute time averages for ensemble averages and we may express the ensemble average correlation matrix of the received symbols \( y(t) \) as

\[
R_{k_{i+1}}(t) \approx \frac{1}{t} \Phi_{k_{i+1}}(t)
\]

Accordingly, the ensemble average correlation matrix of the received symbols \( \tilde{y}(t) \) can be expressed as

\[
\tilde{R}_{k_{i+1}}(t) \approx \frac{1}{t} \tilde{\Phi}_{k_{i+1}}(t)
\]

4. The fluctuations in the weight-error vector \( \xi(t) \) are slow compared with those of the received symbols \( \tilde{y}(t) \).

\[
\xi_{k_{i+1}}(t) = w_{o,k_{i+1}}(t) - \tilde{w}_{t,k_{i+1}}(t)
\]


For the \( k_{i+1} \)-th sub-stream, it can be concluded from (8), (11) and (12)

\[
\tilde{w}_{t,k_{i+1}}(t) = w_{o,k_{i+1}}(t) - \Phi_{k_{i+1}}^{-1}(t)\Phi_{k_{i+1}}(0)w_{o,k_{i+1}}(t)
\]

\[
+ \Phi_{k_{i+1}}^{-1}(t) \sum_{l=1}^{t} \tilde{y}_{k_{i+1}}(l)e_{0,i+1}^{*}(l)
\]

\[
= w_{o,k_{i+1}}(t) - \Phi_{k_{i+1}}^{-1}(t)\Phi_{k_{i+1}}(0)w_{o,k_{i+1}}(t)
\]

\[
+ \Phi_{k_{i+1}}^{-1}(t) \sum_{l=1}^{t} y_{k_{i+1}}(l)e_{0,i+1}^{*}(l) - \Phi_{k_{i+1}}^{-1}(t) \sum_{l=1}^{t} \Psi_{k_{i+1}}(t)e_{0,i+1}^{*}(l)
\]

Where \( \Psi_{k_{i}}(t) = [-\tilde{\Sigma}_{k_{i}}, -\tilde{\Sigma}_{k_{i}}^{T}]^{T} \). Taking the expectation of both sides of (36)

\[
E\{\tilde{w}_{t,i+1}(t)\} = w_{o,i+1}(t) - \frac{1}{t} \tilde{R}_{k_{i+1}}^{-1}(t)w_{o,i+1}(t)
\]

Equation (37) has the same mathematical expression with that of CMA[11]. Let the step-size parameter \( \chi \) be chosen to satisfy the condition

\[
0 < \chi < \frac{2}{\lambda_{\text{max}}}
\]

Equation (38) states that the ILNCMA-OSIC-DFE algorithm is convergent in the mean value. Here \( \lambda_{\text{max}} \) is the largest eigenvalue of the correlation matrix \( R_{k_{i+1}} \).
Define a priori estimation error the norm to the parameter vector from frame to frame.

In the computer simulation, the following parameters are assumed: the channels are independent Rayleigh flat fading, and each channel between a transmit and receive antenna pair is varied based on the Jakes model. Following in the previous development, the performance is measured in term of BER for a frame of 1000 bits from 8PSK constellations averaged over 100 frames. Channel realizations are i.i.d. from frame to frame.

4.2. Mean-Square deviation of the ILNCMA-OSIC-DFE algorithm. For the \( k_{i+1} \)-th sub-stream, the weight-error correlation matrix is concluded from (35)

\[
\mathbf{L}_{k_{i+1}}(t) = E\{e_{o,k_{i+1}}(t)\xi_{k_{i+1}}(t)^H\}
\]

(39)

Substituting (36) into (39), we get

\[
\mathbf{L}_{k_{i+1}}(t) = E\{\mathbf{\Phi}_{k_{i+1}}^{-1}(t) \sum_{k=1}^{t} \sum_{l=1}^{t} \mathbf{y}_{k_{i+1}}(k)\mathbf{y}_{k_{i+1}}(l)^H \mathbf{\Phi}_{k_{i+1}}^{-1}(t)\phi_{o,k_{i+1}}(k)\phi_{o,k_{i+1}}(l)\}
\]

(40)

The mean-square deviation is defined\([11]\) by

\[
D_{k_{i+1}}(t) = \frac{1}{t - (N_t + i)} \sigma_{o,k_{i+1}}^2 \text{tr}[\mathbf{R}_{k_{i+1}}(t)\mathbf{R}_{k_{i+1}}^{-2}(t)]
\]

(41)

Where, \( \text{tr}[-] \) denotes the trace operator. The \( \lambda_{i+1} \) are the eigenvalues of the ensemble-average correlation matrix \( \mathbf{R}_{k_{i+1}}(t) \). The \( \lambda_{i+1} \) are the eigenvalues of the ensemble-average correlation matrix \( \mathbf{R}_{k_{i+1}}(t) \). The mean-square deviation \( D_{k_{i+1}}(t) \) decays almost linearly with the number of iterations \( t \) and \( \mathbf{w}_{t_{i+1}}(t) \) converges in the norm to the parameter vector \( \mathbf{w}_{o,i+1}(t) \) of the multiple linear regression model almost linearly with time.

4.3. Ensemble-average learning curve of the ILNCMA-OSIC-DFE algorithm. Define a priori estimation error

\[
e_{o,k_{i+1}}(t) = e_{o,k_{i+1}}(t) + [\mathbf{w}_{o,k_{i+1}}(t - 1) - \bar{\mathbf{w}}_{t,k_{i+1}}(t - 1)]^H \mathbf{y}_{t,k_{i+1}}(t)
\]

(42)

Adopting the analysis in [11], we can show the following. We therefore base a computation of the ensemble-average learning curve of the ILNCMA-OSIC-DFE algorithm on the priori estimation error \( e_{o,k_{i+1}}(t) \), as follows:

\[
J_{k_{i+1}}(t) = E[\|e_{o,k_{i+1}}(t)\|^2]
\]

(43)

Here, we may now express the correlation matrix of the weight-error vector \( \xi_{k_{i+1}}(t) \) by a corresponding series as follows:

\[
E[\xi_{k_{i+1}}(t)\xi_{k_{i+1}}^H(t)] = \mathbf{K}_{k_{i+1}}(t)\mathbf{I}
\]

5. Simulations

In the computer simulation, the following parameters are assumed: the channels are independent Rayleigh flat fading, and each channel between a transmit and receive antenna pair is varied based on the Jakes model. Following in the previous development, the performance is measured in term of BER for a frame of 1000 bits from 8PSK constellations averaged over 100 frames. Channel realizations are i.i.d. from frame to frame.
Example 1: square error convergence comparison of the RLS-O-DFE and ILNCMA-OSIC-DFE algorithms.

For the analysis, the following assumptions are made: Number of iterations is 20, the length of the equalization is 4, the SNR of the channel is 15dB and the forgetting factor $\lambda = 0.999$. Figure 2 gives the curve figure of square error convergence produced by the two algorithms. It can be seen from Figure 2 that the square error produced by the ILNCMA-OSIC-DFE algorithm is much smaller than that of the RLS-O-DFE algorithm.

Example 2: considering under correlated channels, ZF and MMSE criteria are used at the receiver side respectively. While the decoding algorithms are ILNCMA-OSIC-DFE, RLS-O-DFE algorithms and V-BLAST algorithm with known channel, we compare detecting performance. The BER curves are verified in Figure 3 and Figure 4 while ZF and MMSE criteria are used respectively in $N_t = 4, N_r = 4$ and $N_t = 6, N_r = 8$ MIMO antenna systems.

It can be concluded from Figure 3 and Figure 4 that the detection performance of ILNCMA-OSIC-DFE algorithm is superior to that of the RLS-O-DFE algorithm.

Example 3: Simulation of the learning curve produced by ILNCMA-OSIC-DFE algorithm.

The learning curve corresponding to $e_{pri,k_{i+1}}(t)$ is shown in Figure 5. The theoretical MSE reached a steady-state after about 14 iterations and is close to that of the experimental MSE from ILNCMA-OSIC-DFE Algorithm.

Example 4: The comparison between the equalization output of the ILNCMA and the CMA. The iteration number is 80 and 160. The equalization output constellations of the ILNCMA and the CMA are shown in Figure 6.

It can be concluded from Figure 6 that the equalization output constellation of the ILNCMA is clearer than that of CMA. When the iteration times is 80, the result of ILNCMA is quite agree with 160 iteration times of CMA. It showed that the ILNCMA can accelerate the convergence efficiently.
6. Summary and conclusions

We have presented a new adaptive algorithm for computing MIMO minimum mean-square-error decision feedback equalizer taps. The algorithm improved the variable step size blind equalization algorithm based on log-normal error function firstly and added a decision condition. Then it is obtained by identifying the feed-forward equalizer solution as a well-known variable encountered in fast recursive least squares adaptive algorithms, for which fast recursions are immediately applicable. The feedback equalizer is computed via update the weight vectors through time-update and order-update operations and adaptively determine the detection ordering according to an LSE criterion with canceling interference produced by detected symbols successively. With time-varying channels, the ILNCMA-OSIC-DFE algorithm has good performance than a RLS-O-DFE processor based on increasing
the timing complexity a little. We further observed good numerical stability of the ILNCMA-OSIC-DFE algorithm in finite precision.

Acknowledgments

This work is supported by research fund for the doctoral program of higher education under Grant no.20050145019.

References


**Yun Wang** was born in Tianjin, China, in 1979. He received M.S. degree in computer software and theory at Northeastern University in China in 2005. Since March 2005, he has been working for her PhD degree at the Northeastern University. His research interest is adaptive MIMO Decision Feedback Equalization.

E-mail: yun_wang@126.com

**Jinkuan Wang** received the PhD degree from the University of Electro-Communications, Japan, in 1993. He is currently a professor in the School of Information Science and Engineering at Northeastern University, China, since 1998. His main interests are in the area of intelligent control and adaptive array.

E-mail: wjk@mail.neuq.edu.cn

**Zhibin Xie** was born in Baotou, Inner Mongolia, China, in 1981. He received M.S. degree in pattern recognition and intelligent system at Northeastern University in China in 2006. Since March 2006, he has been working for her PhD degree at the Northeastern University. His research interest is intelligent control and signal processing.

E-mail: xiezb@126.com

School of Information Science and Engineering, Northeastern University, Shenyang, 110004, China

URL: [http://www.neuq.edu.cn/sasp/index.htm](http://www.neuq.edu.cn/sasp/index.htm)