Joint Channel Estimation and Data Detection Algorithms for MIMO-OFDM Systems

Kyeong Jin Kim [1]
Nokia Research Center
6000 Connection Dr. Irving, TX 75039
Kyeong.J.Kim@nokia.com

Jiang Yue
Department of Electrical Engineering
Southern Methodist University
Dallas, TX 75275
jyue@engr.smu.edu

Abstract — **We propose a new joint channel estimation and data detection algorithms for the MIMO-OFDM system. Considering a received signal introduced by propagation delay and a channel with multipath fading, we used the extended Kalman filter (EKF) for a delay/channel estimator. As a data detector we separately apply the QRD-M algorithm. By separating the data detector and the delay/channel estimator, we can efficiently detect and estimate the unknown parameters. Also, a new delay/channel estimator leads to a better data detection performance.**

1. Introduction

In this paper, we consider a multiple-input multiple-output (MIMO) system, equipped with multiple antennas at the transmitter and the receiver. The MIMO structure in the wireless communications system is a promising structure to increase data rates and performance of the system, and reduce the effects of flat fading. Orthogonal Frequency Division Multiplexing (OFDM) is used to mitigate the effects of frequency selective fading by forming multiple subcarriers, where each of subcarriers exhibits flat fading [1]. Thus, a MIMO-OFDM system can achieve high data rates over wireless channels. As a spatio-temporal processing algorithm, Bell Labs Layered Space-Time Architecture (BLAST) [2],[3] has been proposed. The BLAST algorithm combines beamforming technique and successive symbol cancellation, which sequentially removes the interference from the stronger data before detecting the weaker one.

Motivated by the approach proposed in [4], we extensively apply a data detection algorithm, called the QRD-M [4], to the MIMO-OFDM system. For an available channel estimate, we firstly apply the QR decomposition (QRD) [5] to the estimated channel matrix. Using the property of the QRD, the maximum likelihood (ML) cost function for a data detection leads to an ideal tree searching algorithm constructed with the defined states and the branch metrics. However, the number of branch metrics grows exponentially with the number of transmit antennas and the cardinality of the subcarrier modulation. Combining an M-algorithm with the QRD, called the QRD-M algorithm, we can reduce the prohibitive complexity with small values of M. This approach is somewhat similar to [3], where the QRD is combined with the hard or soft interference cancellation algorithm. However, the detection algorithm here incorporates the M-algorithm. Compared with other interference canceler based alternatives, such as [2],[3], the QRD-M algorithm is more attractive because it provides its user with the flexible performances with a different value of M. It is conceivable, therefore, that replacing the interference canceler by the M-algorithm should greatly enhance the performances.

In a generalized case, the received signal for the MIMO-OFDM system over a path between transmitter and receiver may be a nonlinear function of the channel and the propagation delay. The extended Kalman filter (EKF) is employed in the sequel for implicit joint estimation of the nonlinear delay and channel coefficients in a manner similar to [6].

Using the previous channel/delay estimates, we separately apply the QRD-M algorithm as a data detector. By separating the data detector from the delay/channel estimator we can jointly detect and estimate them, and we can develop a feasible joint algorithm.

In our simulations, we show the effects on the BER performance over time-varying multipath channel under different scenarios. In Section 2, signal and channel models for the MIMO-OFDM system are described. The extended Kalman filter developed in Section 3. Simulation results are provided in Section 4, and conclusions are summarized in Section 5.

2. Signal and Channel Models for MIMO-OFDM Systems

In this paper, we consider a baseband model for a received MIMO OFDM signal over time-varying multipath fading channel. The MIMO OFDM system is equipped with multiple antennas at the transmitter and the receiver. Throughout this paper, K denotes the number of subcarriers, N_t the number of transmit antennas, N_r the number of receive antennas, $(\mathbf{A})_l$ the l-th column vector of the matrix $\mathbf{A}$, $(\mathbf{A})_{l,m}$ the (l,m) element of the matrix $\mathbf{A}$, and $(\mathbf{y})_l$ the l-th element of the vector $\mathbf{y}$. Also, p is the transmit antenna index, q is the receiver antenna index, and k is the subcarrier index with $1 \le p \le N_t$, $1 \le q \le N_r$, and $0 \le k \le K-1$. At a time n, a sequence of information $d_k^p(n)$ is input to the p-th modulator (a K-point IFFT) which modulates $d_k^p(n)$ onto

[1] Author to whom all correspondence should be addressed.

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K subcarriers. The information symbol sequence, $d_k^p(n)$, is chosen from a complex-valued finite alphabet. The symbols $d_k^q(n)$ are assumed independent in indices k, p and n. The independence assumption is valid for either an uncoded system, or in a coded system with sufficient interleaving. Note that *we use the same signal constellation for all subcarriers and* antennas. The outputs of the p-th modulator in the interval, $nT_d^g \le t \le (n+1)T_d^g$, with the guard time interval, T_g, is

$$s^p(t) = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} d_k^p(n) e^{j2\pi k(t-T_g-nT_d^g)/T_d} p(t-T_g-nT_d^g). \quad (1)$$

In (1), $T_d^g = (K+N_g)T_s$ is the OFDM symbol interval with the guard time interval, T_s is the sampling time, N_g is the number of samples for T_g, $1/T_d$ is the OFDM subcarrier spacing, with $T_d = KT_s$, and $p(t)$ is the pulse with support on $[0, T_d)$. The channel between the p-th transmit antenna and the q-th receive antenna, $f_l^{p,q}(n)$, is modeled by a tapped delay line (TDL) with taps, $f_l^{p,q}(n) \in \mathcal{C}$, spaced T_s sec apart [[7],Chap.7]. Thus, the received signal at the q-th receive antennas is

$$r^q(t) = \sum_{p=1}^{N_t} \sum_{l=0}^{N_f-1} f_l^{p,q}(n) s^p(t - lT_s - T^{p,q}(n)) + n^q(t), \quad (2)$$

where N_f is the number of multipaths and $T^{p,q}(n) \in \mathcal{R}$ is *the propagation delay between the p-th transmit antenna and* the q-th receive antenna. Note that $T^{p,q}(n)$ is represented as $T^{p,q}(n) = T_0(n) + d^{p,q}/C$, where $T_0(n)$ is an unknown overall symbol timing, $d^{p,q}$ is the distance between antennas p, q, and C is the speed of light. The multipath spread with delay spread is assumed to be $T^{p,q}(n) + N_f T_s \ll T_g$. The complex gains $\{f_l^{p,q}(n)\}$ include an actual channel response and a *bandwidth-efficient transmission pulse shape*. Also, $\{f_l^{p,q}(n)\}$ are assumed to be constant over one OFDM symbol duration but varies from symbol to symbol [8]. The additive noise $n^q(t)$ is circular white Gaussian with spectral density N_0. The receiver is assumed to be matched to the transmitted pulse. Eliminating the guard interval, the received baseband signal sampled at instance $((m+N_g)T_s + nT_d^g)$ is given by

$$\begin{aligned} r^q(mT_s) &\triangleq r^q((m+N_g)T_s + nT_d^g) \\ &= \frac{1}{\sqrt{K}} \sum_{p=1}^{N_t} \sum_{l=0}^{N_f-1} f_l^{p,q}(n) \sum_{k=0}^{K-1} d_k^p(n) e^{(\cdot)} + n^q(mT_s), \quad (3) \end{aligned}$$

where $e^{(\cdot)} = e^{j2\pi k(mT_s - lT_s - T^{p,q}(n))/T_d}$. Note that $f_l^{p,q}(n)$ is convolved with the transmitter filter, transmission channel, and the receiver filter. The sampled received baseband OFDM signal vector for the n-th symbol interval can be written as

$$\mathbf{r}^q(n) = \frac{1}{\sqrt{K}} \sum_{p=1}^{N_t} \sum_{l=0}^{N_f-1} f_l^{p,q}(n) \sum_{k=0}^{K-1} d_k^p(n) \mathbf{s}_k e^{(\cdot\cdot)} + \mathbf{n}^q(n), \quad (4)$$

where

$$\begin{aligned} e^{(\cdot\cdot)} &= e^{-j2\pi k(lT_s + T^{p,q}(n))/T_d}, \\ \mathbf{r}^q(n) &\triangleq [r^q(N_g T_s + nT_d^g), \ldots, r^q((K-1+N_g)T_s + nT_d^g)]^T, \\ \mathbf{n}^q(n) &\sim \mathcal{N}(\mathbf{n}^q(n); 0, 2N_0 T_s \mathbf{I}_{K\times K}). \quad (5) \end{aligned}$$

In (5), $\mathcal{N}(\mathbf{x}; \bar{\mathbf{x}}, \mathbf{R})$ represents a circular Gaussian density with mean vector $\bar{\mathbf{x}}$ and covariance matrix $\mathbf{R}$, and $\mathbf{s}_k$ is defined by

$$\mathbf{s}_k = 1/\sqrt{K}[1, e^{j2\pi kT_s/T_d}, \ldots, e^{j2\pi k(K-1)T_s/T_d}]^T. \quad (6)$$

The received signal vector in (4) can be alternatively expressed as

$$\mathbf{r}^q(n) = \sum_{p=1}^{N_t} \mathbf{S}\mathbf{F}^{p,q}(n)\mathbf{d}^p(n) + \mathbf{n}^q(n), \quad (7)$$

where

$$\begin{aligned} \mathbf{S} &\triangleq [\mathbf{s}_0, \mathbf{s}_1, \ldots, \mathbf{s}_{K-1}] \in \mathcal{C}^{K\times K}, \\ \mathbf{c}_k^{p,q}(n) &\triangleq \tilde{\mathbf{c}}_k e^{-j2\pi kT^{p,q}(n)/T_d} \in \mathcal{C}^{1\times N_f}, \\ \tilde{\mathbf{c}}_k &\triangleq [1, e^{-j2\pi kT_s/T_d}, \ldots, e^{-j2\pi k(N_f-1)T_s/T_d}] \in \mathcal{C}^{1\times N_f}, \\ \mathbf{f}^{p,q}(n) &\triangleq \left[f_0^{p,q}(n), f_1^{p,q}(n), \ldots, f_{N_f-1}^{p,q}(n)\right]^T \in \mathcal{C}^{N_f}, \\ \mathbf{F}^{p,q}(n) &\triangleq \mathrm{diag}\{F_0^{p,q}(n), F_1^{p,q}(n), \ldots, F_{K-1}^{p,q}(n)\}, \\ F_k^{p,q}(n) &\triangleq \tilde{\mathbf{c}}_k e^{-j2\pi kT^{p,q}(n)/T_d} \mathbf{f}^{p,q}(n), \\ \mathbf{d}^p(n) &\triangleq \left[d_0^p(n), d_1^p(n), \ldots, d_{K-1}^p(n)\right]^T. \quad (8) \end{aligned}$$

Note that $\mathbf{r}^q(n)$ is a sufficient statistic, $\mathbf{S}$ is the DFT matrix satisfying $\mathbf{S}^H\mathbf{S} = \mathbf{I}_{K\times K}$, and $\tilde{\mathbf{c}}_k$ is the truncated FFT vector. The demodulator output (a K-point FFT) is now given by

$$\begin{aligned} \mathbf{y}^q(n) &= \sum_{p=1}^{N_t} \mathbf{S}^H \mathbf{r}^q(n), \\ &= \sum_{p=1}^{N_t} \mathbf{F}^{p,q}(n)\mathbf{d}^p(n) + \mathbf{z}^q(n), \quad (9) \end{aligned}$$

where $\mathbf{z}^q(n) \triangleq \mathbf{S}^H\mathbf{n}^q(n) \sim \mathcal{N}(\mathbf{z}^q(n); 0, 2N_0T_s\mathbf{I}_{K\times K})$. The overall goal of this paper is to find an effective strategy to detect $\mathbf{d}^p(n)$ and estimate $\theta(n) = \{f_l^{p,q}(n)\}$ from the received samples. Since the computational complexity with (9) is prohibitively high, we first develop a new data detection algorithm suitable for each subcarrier. Using the definition of the matrix $\mathbf{F}^{p,q}$, defined in (8), we get the following equations for *the k-th subcarrier*

$$\begin{aligned} y_k^q(n) &\triangleq (\mathbf{y}^q(n))_k = \sum_{p=1}^{N_t} F_k^{p,q}(n) d_k^p(n) + z_k^q(n), \\ \mathbf{y}_k(n) &\triangleq [y_k^1(n), y_k^2(n), \ldots, y_k^{N_r}(n)]^T, \\ &\triangleq \mathbf{F}_k(n)\mathbf{d}_k(n) + \mathbf{z}_k(n), \end{aligned}$$

$$
\begin{aligned}
\mathbf{F}_k(n) &\triangleq \begin{bmatrix} F_k^{1,1}(n) & F_k^{2,1}(n) & \dots & F_k^{N_t,1}(n) \\ F_k^{1,2}(n) & F_k^{2,2}(n) & \dots & F_k^{N_t,2}(n) \\ \vdots & \vdots & \dots & \vdots \\ F_k^{1,N_r}(n) & F_k^{2,N_r}(n) & \dots & F_k^{N_t,N_r}(n) \end{bmatrix}, \\
\mathbf{d}_k(n) &\triangleq [d_k^1(n), d_k^2(n), \dots, d_k^{N_t}(n)]^T, \\
\mathbf{z}_k(n) &\sim \mathcal{N}(\mathbf{z}_k(n); \mathbf{0}, 2N_0T_s\mathbf{I}). \qquad (10)
\end{aligned}
$$

In the definition (10), $\mathbf{F}_k(n) \in \mathcal{C}^{N_r \times N_t}$ represents frequency responses of all $N_t \times N_r$ channels at FFT frequency k, with linear phase shifts in k due to the delay $T^{p,q}(n)$. With an available channel estimate computed from the previous OFDM symbol, the ML data detection for the k-th subcarrier is

$$\hat{\mathbf{d}}_k(n)_{\mathrm{ML}} = \arg \min_{\mathbf{d}_k(n) \in |S|^{N_t}} ||\mathbf{y}_k(n) - \hat{\mathbf{F}}_k(n)\mathbf{d}_k(n)||^2, \quad (11)$$

where $\hat{\mathbf{F}}_k(n)$ is an estimate of the effective MIMO channel frequency response matrix and $|S|$ is the cardinality of the subcarrier modulation. With the given channel model, we can solve the complete problem with K independent solution of (11). This follows from (8), where $\mathbf{F}^{p,q}(n)$ is diagonal. To reduce the complexity associated with (11), we combine the suboptimal detection algorithm, called the QRD-M algorithm [4].

3. Joint Data Detection and Channel/Delay Estimation Algorithm

The maximum Doppler spread considered for the applications here is 100 Hz., with a maximum OFDM symbol rate of $1/T_d = 1$ MHz. Hence, it is reasonable to model the channel coefficient vectors $\mathbf{f}^{p,q}(n)$ as slowly varying autoregressive processes. A decision-directed extended Kalman filter channel estimator is proposed here based on the following representation of the received signal at antenna q.

$$y_k^q(n) = (\mathbf{y}^q(n))_k = \sum_{p=1}^{N_t} (\alpha^{p,q}(n))^k \tilde{\mathbf{c}}_k \mathbf{f}^{p,q}(n) d_k^p(n) + z_k^q(n), \quad (12)$$

where $\alpha^{p,q}(n) = \exp(-j2\pi T^{p,q}(n)/T_d)$, and $\tilde{\mathbf{c}}_k$ is the truncated FFT vector defined in (8). The estimation strategy is to track the unstructured phase term $\alpha^{p,q}(n) \in \mathcal{C}$, rather than the actual delay $T^{p,q}(n) \in \mathcal{R}$. This approach allows the $\alpha^{p,q}(n)$ and $\mathbf{f}^{p,q}(n)$ variables to be combined into a single complex-valued state vector, which can then be tracked using a complex-valued EKF. The unknown data $d_k^p(n)$ are replaced by decisions from the M-algorithm $\hat{d}_k^p(n)$. At time n, the M-algorithm uses predicted channel values $\hat{\mathbf{f}}^{p,q}(n|n-1), \hat{\alpha}^{p,q}(n|n-1)$ from the EKF to compute $\hat{d}_k^p(n)$.

The channel estimation problem is separable in the N_r receive antennas, since the $\mathbf{f}^{p,q}(n)$ are assumed to evolve independently, and the noises at the antennas $z_k^q(n)$ are independent white processes. However, all K subcarrier measurements $y_k^q(n)$, $k = 0, 1, \dots, K-1$ depend on the same set of channel variables $\mathbf{f}^{p,q}(n), \alpha^{p,q}(n)$, and hence K separate EKFs are applied to the composite measurement vectors $\mathbf{y}^q(n) \in \mathcal{C}^K$. These vectors are then approximated using M-algorithm decisions by

$$
\begin{aligned}
\mathbf{y}^q(n) &= \mathbf{H}(\hat{\mathbf{d}}^p(n), \alpha^q(n))\mathbf{f}^q(n) + \mathbf{z}^q(n) \qquad (13) \\
&= \mathbf{h}(\mathbf{x}^q(n)) + \mathbf{z}^q(n),
\end{aligned}
$$

where $\alpha^q(n) \triangleq [\alpha^{1,q}(n), \alpha^{2,q}, \dots, \alpha^{N_t,q}(n)]^T$, $\hat{\mathbf{d}}^p(n) \triangleq [\hat{d}_0^p(n), \dots, \hat{d}_{K-1}^p(n)]^T$, and the state vector $\mathbf{x}^q(n) \in \mathcal{C}^{N_t(N_f+1)}$ is defined by

$$\mathbf{x}^q(n) = [\alpha^{1,q}(n), \dots, \alpha^{N_t,q}(n), \mathbf{f}^{1,q}(n)^T, \dots, \mathbf{f}^{N_t,q}(n)^T]^T,$$

and the nonlinear measurement function $\mathbf{h}()$ is defined via (13). Furthermore, the composite channel vector and measurement function are defined by

$$
\begin{aligned}
\mathbf{f}^q(n) &= [\mathbf{f}^{1,q}(n)^T, \mathbf{f}^{2,q}(n)^T, \dots, \mathbf{f}^{N_t,q}(n)^T]^T \qquad (14) \\
\mathbf{H}(\hat{d}^p(n), \alpha^q) &= \left[\hat{\mathbf{D}}^1(n)\mathbf{A}^{1,q}(n)\mathbf{C}, \dots, \hat{\mathbf{D}}^{N_t}(n)\mathbf{A}^{N_t,q}(n)\mathbf{C}\right],
\end{aligned}
$$

where $\mathbf{C} \in \mathcal{C}^{K \times N_f}$ is the truncated FFT matrix defined by $\mathbf{C} = [\tilde{\mathbf{c}}_0^T, \tilde{\mathbf{c}}_1^T, \dots, \tilde{\mathbf{c}}_{K-1}^T]^T$. The measurement function has a nonlinear dependence on the data decisions and phases, given by the $K \times K$ diagonal matrices

$$
\begin{aligned}
\hat{\mathbf{D}}^p(n) &= \mathrm{diag}\{\hat{d}_0^p(n), \hat{d}_1^p(n), \dots, \hat{d}_{K-1}^p(n)\} \qquad (15) \\
\mathbf{A}^{p,q}(n) &= \mathrm{diag}\{1, \alpha^{p,q}(n), (\alpha^{p,q}(n))^2, \dots, (\alpha^{p,q}(n))^{K-1}\}.
\end{aligned}
$$

To derive the EKF, an autoregressive model for the channel coefficients is assumed [4],[6]. The multipath coefficients and phase terms are assumed to be independent AR processes following

$$
\begin{aligned}
\mathbf{f}^{p,q}(n) &= \mathsf{F}_f \mathbf{f}^{p,q}(n-1) + \mathbf{w}_f^{p,q}(n) \qquad (16) \\
\alpha^{p,q}(n) &= \mathsf{f}_\alpha \alpha^{p,q}(n-1) + w_\alpha^{p,q}(n),
\end{aligned}
$$

where $\mathsf{F}_f \in \mathcal{C}^{N_f \times N_f}$ is typically diagonal with nonzero elements computed according to a nominal Doppler spread. The noises $\mathbf{w}_f^{p,q}(n)$ and $w_\alpha^{p,q}(n)$ are independent circular Gaussian with variances $\mathcal{Q}_f$ and q_α, respectively. In terms of the state vector, the AR model is then

$$\mathbf{x}^q(n) = \mathsf{F}_x \mathbf{x}^q(n-1) + \mathbf{w}_x^q(n), \quad (17)$$

where the one-step transition matrix $\mathsf{F}_x \in \mathcal{C}^{N_t(N_f+1) \times N_t(N_f+1)}$ is

$$\mathsf{F}_x = \text{ block diag}\{f_\alpha, \dots, f_\alpha, \mathsf{F}_f, \dots, \mathsf{F}_f\}. \quad (18)$$

The process noise $\mathbf{w}_x^q(n)$ has covariance matrix $\mathcal{Q}_x \in \mathcal{C}^{N_t(N_f+1) \times N_t(N_f+1)}$ given by

$$\mathcal{Q}_x = \text{ block diag}\{q_\alpha, \dots, q_\alpha, \mathcal{Q}_f, \dots, \mathcal{Q}_f\}. \quad (19)$$

The EKF derivation is readily completed once the Jacobian matrix is derived. Specifically, the Jacobian for the q-th EKF, $\mathbf{J}^q(n) \in \mathcal{C}^{K \times N_t(N_f+1)}$ is given by

$$
\begin{aligned}
\mathbf{J}^q(n) &= \partial \mathbf{h}(\mathbf{x}^q(n)) / \partial \mathbf{x}^q(n)|_{\mathbf{x}^q(n) = \hat{\mathbf{x}}^q(n|n-1)} \qquad (20) \\
&= \left[\hat{\mathbf{D}}^1(n)\hat{\mathbf{A}}_d^{1,q}(n)\mathbf{C}\hat{\mathbf{f}}^{1,q}(n|n-1), \dots, \right. \\
&\quad \hat{\mathbf{D}}^{N_t}(n)\hat{\mathbf{A}}_d^{N_t,q}(n)\mathbf{C}\hat{\mathbf{f}}^{N_t,q}(n|n-1), \\
&\quad \left. \hat{\mathbf{D}}^1(n)\hat{\mathbf{A}}^{1,q}(n)\mathbf{C}, \dots, \hat{\mathbf{D}}^{N_t}(n)\hat{\mathbf{A}}^{N_t,q}(n)\mathbf{C}\right],
\end{aligned}
$$

Given $\{\hat{\mathbf{f}}^q(n\|n-1), \hat{\alpha}^q(n\|n-1)\}$
Use detection algorithm to make decisions $\{\hat{d}_k^p(n)\}$
For $q = 1, 2, \ldots, N_r$
Given $\hat{\mathbf{f}}^q(n\|n-1), \hat{\alpha}^q(n\|n-1)$
Compute Jacobian matrix $\mathbf{J}^q(n)$
Compute measurement updates
$\mathbf{P}^q(n\|n)^{-1} = \mathbf{P}^q(n\|n-1)^{-1} + \frac{1}{2N_0T_s}\mathbf{J}^q(n)^H\mathbf{J}^q(n)$
$\hat{\mathbf{x}}^q(n\|n) = \hat{\mathbf{x}}^q(n\|n-1) +$
$\mathbf{P}^q(n\|n)\mathbf{J}^q(n)^H\frac{1}{2N_0T_s}[\mathbf{y}^q(n) - \mathbf{h}(\hat{\mathbf{x}}^q(n\|n))]$
Compute one-step predictions
$\mathbf{P}^q(n+1\|n) = \mathsf{F}_x\mathbf{P}^q(n\|n)\mathsf{F}_x^H + Q_x$
$\hat{\mathbf{x}}^q(n+1\|n) = \mathsf{F}_x\hat{\mathbf{x}}^q(n\|n)$
Next antenna q

Table 1: QRD-M EKF Channel Estimation Algorithm

where

$$\hat{\mathbf{A}}^{p,q}(n) = \operatorname{diag}\{1, \hat{\alpha}^{p,q}(n|n-1), \ldots, \hat{\alpha}^{p,q}(n|n-1)^{K-1}\},$$
$$\hat{\mathbf{A}}_d^{p,q}(n) = \operatorname{diag}\{0, 1, 2\hat{\alpha}^{p,q}(n|n-1), \ldots, (K-1)\hat{\alpha}^{p,q}(n|n-1)^{K-2}\}.$$

The complete QRD-M EKF algorithm is given in Table 1.

4. Simulation Results

In simulations, we assume the following :

- $N_t = 4, N_r = 4, K = 64$.
- Use the 16-QAM for all subcarriers and antennas.
- Packet size is 1 OFDM symbol.

We also considered different scenarios.

[scenario 1 (exact knowledge of a fading channel information)]
For 5-tap fading channel $\{0.749, 0.502, 0.3365, 0.2256, 0.1512\}$, $N_f = 5$, Figure 1 shows the bit error rate (BER) performance. When $M = 1$, the BER performance of the QRD-M algorithm is slightly worse than that of the BLAST algorithm. However, as the value of M increases, we can significantly improve the BER performance. Since the packet error rate (PER) is expressed exponentially with respect to the BER, its performance improvement is much more significant compared with the BLAST algorithm as shown in Figure 2. It is worthwhile to note that we can reduce the computations significantly to achieve the performance associated with the maximum likelihood sequence detector (MLSD). We can expect from the simulation that when $M = 16$, BER and PER performances may reach to those of the MLSD with a reduced complexity. While the actual number of branches for the MLSD is 65,536, we need only 256 branches with the M-algorithm.

[scenario 2 (estimation of the channel with an exact knowledge of delays)]
For a slowly time varying channel, $\mathbf{F}_f = 0.9999\mathbf{I}_{Nf\times Nf}, f_\alpha = 0.9999, N_f = 2, \{0.8307, 0.5567\}$, Figure 3 shows the BER performance for the joint detection and the channel estimation based on the ordinary Kalman filter. As in the scenario 1, we can improve the performance with a larger value of M for the QRD-M algorithm. With a more reliable data decisions made by the M-algorithm, we can, in general, improve the channel estimator performance. Figure 4 shows the channel tracking capability of the joint algorithm under $\mathbf{F}_f = \mathbf{I}_{Nf\times Nf}, f_\alpha = 1.0, N_f = 2, \{0.8307, 0.5567\}$.

[scenario 3 (estimation of delays with an exact knowledge of channels)]
For $\mathbf{F}_f = 0.9999\mathbf{I}_{Nf\times Nf}$, $f_\alpha = 0.9999$, $N_f = 2$, $\{0.8307, 0.5567\}$, Figure 5 shows the BER performance for the joint detection and the delay estimation based on the EKF. However, compared with our expectations, the delay estimation is not good with the EKF. This may come from the severe nonlinearity. A small estimation error may cause substantial loss of performance. For this reason, to jointly estimate the delay and channel, we need to consider more powerful nonlinear estimation techniques as [9],[10].

5. Conclusions

We propose a new detection algorithm for the MIMO-OFDM system, equipped with a general number of antennas in the transmitter and the receiver, that uses the QRD-M to detect data, with the EKF algorithm for a channel and delay estimation. The performances is evaluated with simulations and shows that replacing a kind of interference canceler by the QRD-M algorithm should greatly enhance the performances with a reduced computational complexity. However, the simulation results lead us that we need to consider more powerful nonlinear estimator.

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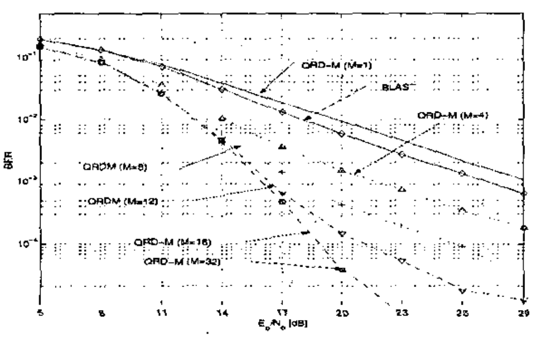

Figure 1: BER performance for the QRD-M EKF algorithm with an exact knowledge of channel and delays.

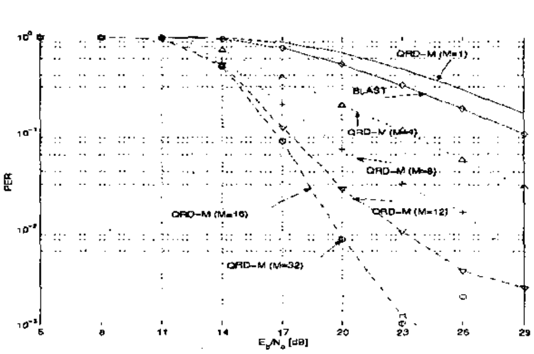

Figure 2: PER performance for the QRD-M EKF algorithm with an exact knowledge of channel and delays.

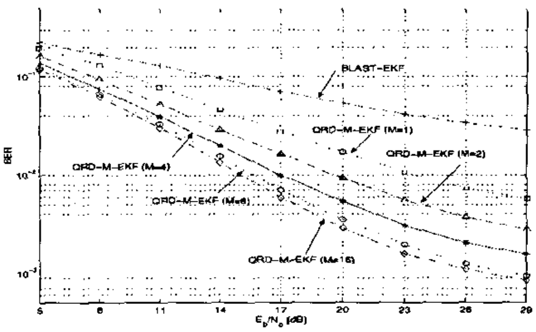

Figure 3: BER performance for the QRD-M EKF algorithm with an exact knowledge of delays.

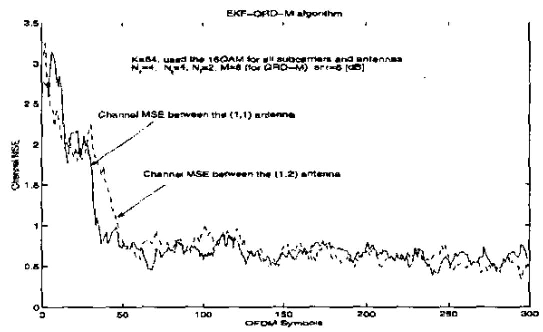

Figure 4: Channel estimate with the QRD-M EKF algorithm with an exact knowledge of delays.

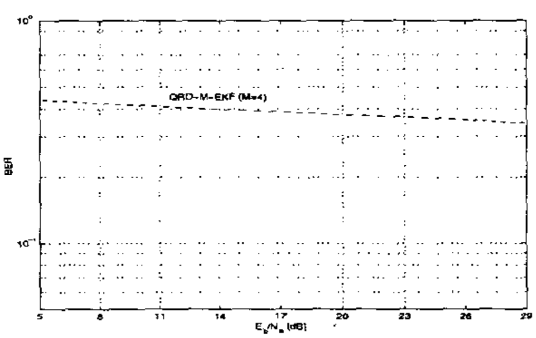

Figure 5: BER performance for the QRD-M EKF algorithm with an exact knowledge of channel.