Kalman-based MIMO Receivers using Gaussian Sum Approximations

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***Abstract*—This paper proposes a new multiple input multiple output receiver based on the Kalman filtering algorithm. The Kalman filtering algorithm is based on the Gaussian assumption of the input signal. However, the assumption is not appropriate for the digital communication system which has non-Gaussian input signal. The proposed receiver overcomes the problem by using multiple Kalman filters and its output is obtained using the weighted sum of the outputs of the Kalman filters by the Gaussian sum approximation method to make the data signal approximately Gaussian. Simulation results show that the bit error rate (BER) performance of the proposed receiver is better than the previous Kalman-based receivers and its BER performance is close to the maximum likelihood (ML) receiver with lower computational complexity than the ML receiver.**

I. Introduction

The Kalman filtering algorithm [1] is a efficient solution for many digital wireless communication algorithms such as the data equalization and channel estimation since it has good estimation and tracking ability. For the multiple input multiple output (MIMO) systems, which have been widely used for promising increased data rate and reliability of next generation wireless communication, i.e., WiMAX [2], Third Generation Partnership Project (3GPP) Long Term Evolution (LTE) [3] and LTE-Advanced [4], Kalman filtering algorithm is also a good solution to mitigate inter-symbol interference (ISI) and multi-stream interference (MSI) which is occured in the MIMO channels.

Kalman filtering has been widely used in equalization and detection for frequency selective channels in single input single output (SISO) and MIMO systems. For the SISO channels, Lawrence [5] proposed an adaptive Kalman equalizer for binary phase shift keying (BPSK) signals whose performance is superior to a much longer transversal equalizer for a completely known communication channel. For the MIMO channels, Kalman-probabilistic data association (PDA) equalization for the MIMO frequency selective fading channel was proposed by means of local multiuser detection (MUD) using soft-decision PDA detection and dynamic noise-interference tracking using the Kalman filtering [6]. Roy [7] proposed an iterative MIMO equalization method by modifying the structure of the conventional Kalman filter.

The important assumption of the Kalman filtering algorithm is the Gaussian assumption of the input signals. However, it is not appropriate for the digital wireless communication systems whose input signal is non-Gaussian. Since the estimation performance of the Kalman filtering algorithm is optimal for the Gaussian input signals, we cannot obtain the best Kalman filter performance when we applying the Kalman filtering algorithm to the digital wireless communication systems for the equalization or the signal detection. To obtain more performance gain, Marcos [8] proposed a new structure of an SISO equalizer based on Kalman filters called network of Kalman filters (NKF) by Gaussian sum approximations (GSA) in [9], [10], which approximates the non-Gaussian signals to a weighted sum of Gaussian distributions.

Although NKF [8] improves the performance of the conventional Kalman filters by using GSA, the approximation of the input signal in NKF has limitation since the NKF uses only the current symbol for the Gaussian approximation. From this reason, there is a considerable bit error rate (BER) performance gap between the NKF receiver and the maximum likelihood (ML) receiver which has the optimal BER performance. Therefore, we propose a new receiver using GSA, extended-GSA receiver for the MIMO channels. The extended-GSA receiver uses not only the current symbol to detect, but also the previous symbols to make the signal approximately Gaussian by GSA more accurately. The extended-GSA receiver shows similar BER performance compared to the ML receiver with much lower complexity than the ML receiver when the number of channel taps is large in MIMO frequency selective fading channels.

The paper is organized as follows. In Section II, we formulate the system model of the MIMO systems. In Section III, we describe the conventional Kalman receiver. Section IV describes a Kalman-based MIMO Receivers using GSA, NKF receiver and the proposed extended-GSA receiver with its computational complexity analysis and comparison with other MIMO receivers. Simulation results are presented in Section V. Section VI concludes this paper.

II. System Model

We consider a MIMO system with N_T transmit antennas, N_R receive antennas and an L tap inter-symbol interference (ISI) channel, as shown in Fig. 1. The transmitted signal at time k is the $N_T \times 1$ vector given by $\mathbf{s}(k) = [s_1(k), ..., s_{N_T}(k)]^T$. The $N_R \times 1$ received vector is given as

$$\mathbf{y}(k) = \frac{1}{\sqrt{n_T}} \sum_{l=0}^{L-1} \mathbf{h}^{(l)} \mathbf{s}(k-l) + \eta(k), \qquad (1)$$

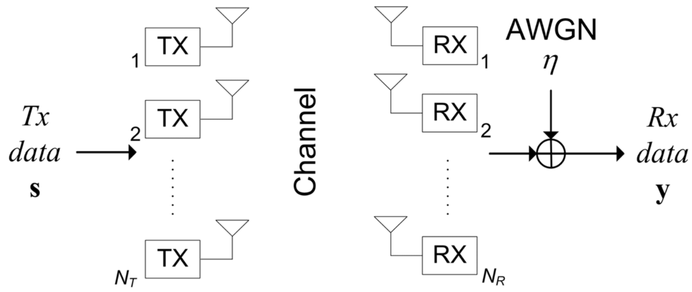

Fig. 1. A MIMO System.

where $\mathbf{h}^{(l)} = \mathbf{f}(l) \times \mathbf{H}^{(l)}$ for $0 \le l \le L-1$, $\mathbf{H}^{(l)}$ is the $N_R \times N_T$ matrix for the l^{th} ISI tap, whose entries are assumed to be independent identically distributed complex Gaussian random variables with zero mean, and $\mathbf{f}$ is the power delay profile of the channel, $\mathbf{f} = \left[\sigma_0^2, ..., \sigma_{L-1}^2\right]$ and $\sum_{l=0}^{L-1} \sigma_l^2 = 1$.

The channel coefficients are normalized, so that each of the sub-channels has unit energy, i.e., $\sum_{l=0}^{L-1} E \left|\mathrm{H}^{(l)}(i,j)\right|^2 = 1$, $1 \le i \le N_R$, and $1 \le j \le N_T$. $\eta(k)$ is the vector of additive white Gaussian noise (AWGN), whose components are assumed to be independent of each other and have a variance of $N_o/2$ dimension. The total power of the system is held constant and is normalized to unity [7], [11].

III. Conventional Kalman Receiver

Before introducing conventional Kalman receivers, we reformulate (1) as a state-space model to applying the Kalman filter algorithm.

$$\mathbf{x}(k) = \mathbf{F}\mathbf{x}(k-1) + \mathbf{w}(k) \qquad (2)$$

$$\mathbf{z}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v}(k), \qquad (3)$$

where (1) is the process equation and (2) is the observation equation. The $N_T(N+L-1) \times 1$ vector, $\mathbf{x}(k)$, is defined as

$$\mathbf{x}(k) = \left[\mathbf{s}^T(k), \mathbf{s}^T(k-1), ..., \mathbf{s}^T(k-N-L+2)\right]^T,$$

and the $NN_R \times 1$ vector $\mathbf{z}(k)$ is given as

$$\mathbf{z}(k) = \left[\mathbf{y}^T(k), \mathbf{y}^T(k-1), ..., \mathbf{y}^T(k-N+1)\right]^T,$$

where N is the number of accumulating received vectors from time k to time $k-N+1$. The $N_T(N+L-1) \times N_T(N+L-1)$ state transition matrix, $\mathbf{F}$, is defined as

$$\mathbf{F} = \begin{bmatrix} \mathbf{0}_{N_T \times N_T(N+L-2)} & \mathbf{0}_{N_T \times N_T} \\ \mathbf{I}_{N_T(N+L-2)} & \mathbf{0}_{N_T(N+L-2) \times N_T} \end{bmatrix}$$

and $\mathbf{w}(k)$ is a $N_T(N+L-1) \times 1$ vector which is given by $\mathbf{w}^T(k) = \begin{bmatrix} \mathbf{s}^T(k) & \mathbf{0} \end{bmatrix}$. $NN_R \times N_T(N+L-1)$ matrix, $\mathbf{H}$, is defined as

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}^{(0)} & \mathbf{h}^{(1)} & \cdots & \mathbf{h}^{(L-1)} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{h}^{(0)} & \cdots & \mathbf{h}^{(L-2)} & \mathbf{h}^{(L-1)} & \cdots & \mathbf{0} \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{h}^{(0)} & \cdots & \cdots & \mathbf{h}^{(L-1)} \end{bmatrix},$$

and $\mathbf{v}(k)$ is given by

$$\mathbf{v}(k) = \left[\eta^T(k), \eta^T(k-1), ..., \eta^T(k-N+1)\right]^T.$$

A. Kalman Receiver

Kalman receiver is a receiver which uses Kalman filter algorithm. It is based on the state-space model which has the process equation (2) and the observation equation (3). $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are the process noise with covariance matrix $\mathbf{Q}$ and the observation noise with covariance matrix $\mathbf{R}$, respectively. Moreover, the observation noise and the process noise which is the data symbols in this system are uncorrelated. In the conventional Kalman algorithm, it is assumed that each noise is the Gaussian process. The Kalman filter recursively obtains the estimate of $\mathbf{x}(k)$ by performing two steps as follows [7]:

Prediction step

$$\hat{\mathbf{x}}(k|k-1) = \mathbf{F}\hat{\mathbf{x}}(k-1|k-1),$$
$$\mathbf{P}(k|k-1) = \mathbf{F}\mathbf{P}(k-1|k-1)\mathbf{F}^H + \mathbf{Q},$$

Filtering step

$$\mathbf{K}_k = \mathbf{P}(k|k-1)\mathbf{H}^H[\mathbf{H}\mathbf{P}(k|k-1)\mathbf{H}^H + \mathbf{R}]^{-1},$$
$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + \mathbf{K}_k[\mathbf{z}(k) - \mathbf{H}\hat{\mathbf{x}}(k|k-1)],$$
$$\mathbf{P}(k|k) = [\mathbf{I} - \mathbf{K}_k\mathbf{H}]\mathbf{P}(k|k-1).$$

IV. Kalman-based Receivers for MIMO Systems using Gaussian Sum Approximation)

A. Network of Kalman Filters (NKF) Receiver

Since input of the process equation $\mathbf{w}$(k) is a data signal which is not a Gaussian process, the Gaussian assumption of the conventional Kalman filtering algorithm is not appropriate. The NKF receiver [8] can obtain performance improvement by applying Gaussian sum approximation in [9] to the density functions of the data signals. We introduce the NKF receiver for SISO channels in [8] appropriate for the MIMO channels.

The Gaussian sum representation p_A of a density function associated with a random *n*-dimensional vector $\mathbf{x}$ is defined as $p_A(\mathbf{x}) = \sum_{i=1}^{l} \alpha_i N[\mathbf{x} - \mathbf{a}_i, \mathbf{B}_i]$, where $N(\mathbf{a}, \mathbf{B}) = \exp\left(-\frac{1}{2}\mathbf{a}^T\mathbf{B}^{-1}\mathbf{a}\right)/(2\pi)^{\frac{n}{2}}|\mathbf{B}|^{\frac{1}{2}}$ and $\sum_{i=1}^{l} \alpha_i = 1$, $\alpha_i \ge 0$ for all i.

It can be shown in [10] that p_A converges uniformly to any density function of practical concern as the number of terms, l, increases and the covariance $\mathbf{B}_i$ approaches the zero matrix. The parameters α_i, $\mathbf{a}_i$ and $\mathbf{B}_i$ can be selected in various ways [9]. We consider a priori density function of $\mathbf{w}(k) = \begin{bmatrix} \mathbf{s}^T(k) & \mathbf{0} \end{bmatrix}^T$. There are q values that $\mathbf{s}(k)$ can take, $\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_q$, with the probabilities $p_1, p_2, ..., p_q$, respectively. For the MIMO system, q can be given as $q = M^{N_T}$ where M is the modulation order of the data signal. If the density function can be approximated by a weighted sum of Gaussian densities, whose mean values are $\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_q$, we can choose the density function

$$p(\mathbf{w}(k)) \approx \sum_{l=1}^{q} p_l N[\mathbf{w}(k) - \mathbf{w}_l, \mathbf{Q}_l], \qquad (4)$$

where $\mathbf{w}_l = \begin{bmatrix} \mathbf{s}_l^T & \mathbf{0} \end{bmatrix}^T$, $\mathbf{Q}_l = \varepsilon\mathbf{I}_{N_T(N+L-1)}$, and $\mathbf{I}_{N_T(N+L-1)}$ is the identity matrix of size $N_T(N+L-1)$. ε can be chosen small enough so that each Gaussian density function is located on a neighborhood of $\mathbf{w}_l$ with a probability mass equal to p_l. Now we consider the density functions $p(\mathbf{x}(k)|\mathbf{Z}^k)$ and $p(\mathbf{x}(k)|\mathbf{Z}^{k-1})$. The Gaussian sum density functions of $p(\mathbf{x}(k)|\mathbf{Z}^k)$ and $p(\mathbf{x}(k)|\mathbf{Z}^{k-1})$ are

$$p(\mathbf{x}(k)|\mathbf{Z}^k) = \sum_{i=1}^{\xi_k} \alpha_{i,k} N\left[\mathbf{x}(k) - \hat{\mathbf{x}}_i(k), \mathbf{P}_i(k)\right]$$

and

$$p(\mathbf{x}(k)|\mathbf{Z}^{k-1}) = \sum_{i=1}^{\xi_k} \alpha'_{i,k} N\left[\mathbf{x}(k) - \hat{\mathbf{x}}'_i(k), \mathbf{P}'_i(k)\right],$$

respectively, where $\hat{\mathbf{x}}_i(k)$ and $\hat{\mathbf{x}}'_i(k)$ are the $N_T(N+L-1)\times 1$ vectors, and $\mathbf{P}_i(k)$ and $\mathbf{P}'_i(k)$ are the $N_T(N+L-1)\times N_T(N+L-1)$ matrices, defined below.

A priori density function of $\mathbf{w}(k)$ is approximated by a weighted sum of Gaussian density functions, as in (4), and a priori density function of $\mathbf{v}(k)$ is assumed to be Gaussian distribution with the covariance $\mathbf{R}$.

With these assumptions, we can obtain new two steps, prediction and filtering steps as follows:

Prediction step

$$\begin{aligned}
\xi'_k &= q\xi_{k-1}, \\
\alpha'_{i,k} &= p_l \alpha_{j,k-1}, \\
\hat{\mathbf{x}}'_i(k) &= \mathbf{F}\hat{\mathbf{x}}(k-1) + \mathbf{w}_l, && (5) \\
\mathbf{P}'_i(k) &= \mathbf{F}\bar{\mathbf{P}}(k-1)\mathbf{F}^T + \mathbf{Q}_l, && (6)
\end{aligned}$$

Filtering step

$$\begin{aligned}
\xi_k &= \xi'_k, \\
\hat{\mathbf{x}}_i(k) &= \hat{\mathbf{x}}'_i(k) + \mathbf{K}_i(k)[\mathbf{z}(k) - \mathbf{H}\hat{\mathbf{x}}'_i(k)], && (7) \\
\mathbf{P}_i(k) &= (I - \mathbf{K}_i(k)\mathbf{H})\mathbf{P}'_i(k), && (8) \\
\mathbf{K}_i(k) &= \mathbf{P}'_i(k)\mathbf{H}^H[\mathbf{H}\mathbf{P}'_i(k)\mathbf{H}^H + \mathbf{R}]^{-1}, && (9)
\end{aligned}$$

$$\begin{aligned}
\alpha_{i,k} &= \frac{\alpha'_{i,k}\beta_{i,k}}{\sum_{i=1}^{\xi'_k} \alpha'_{i,k}\beta_{i,k}}, \\
\beta_{i,k} &= N[\mathbf{z}(k) - \mathbf{H}\hat{\mathbf{x}}'_i(k), \mathbf{H}\mathbf{P}'_i(k)\mathbf{H}^H + \mathbf{R}], && (10) \\
p(\mathbf{x}(k)|\mathbf{Z}^k) &= \sum_{i=1}^{\xi_k} \alpha_{i,k} N[\mathbf{x}(k) - \hat{\mathbf{x}}_i(k), \mathbf{P}_i(k)],
\end{aligned}$$

where

$$\begin{aligned}
\hat{\mathbf{x}}_i(k) &= \mathbf{x}_i(k|k), \\
\hat{\mathbf{x}}'_i(k) &= \mathbf{x}_i(k|k-1), \\
\mathbf{P}_i(k) &= \mathbf{P}_i(k|k), \\
\mathbf{P}'_i(k) &= \mathbf{P}_i(k|k-1).
\end{aligned}$$

Finally, the estimated process noise vector $\hat{\mathbf{x}}(k)$ and the error covariance matrix $\bar{\mathbf{P}}(k)$ can be obtained as follows:

$$\hat{\mathbf{x}}(k) = \sum_{i=1}^{\xi_k} \alpha_{i,k}\hat{\mathbf{x}}_i(k), \quad (11)$$

$$\bar{\mathbf{P}}(k) = \sum_{i=1}^{\xi_k} \alpha_{i,k}(\mathbf{P}_i(k) + (\hat{\mathbf{x}}_i(k) - \hat{\mathbf{x}}(k))((\hat{\mathbf{x}}_i(k) - \hat{\mathbf{x}}(k))^H). \quad (12)$$

B. Extended Gaussian Sum Approximation (Extended-GSA) Receiver

Although the NKF receiver in MIMO system achieves performance improvement in terms of BER, the approximation of the input signal in NKF has limitation since the NKF uses only the current symbol for the Gaussian approximation. Therefore, there is a considerable BER performance gap between the NKF receiver and the ML receiver which has the optimal BER performance. To improve the BER performance of the NKF receiver, we propose the extended-GSA receiver based on the Kalman filter by extending and modifying the conventional Kalman filter and the network of Kalman filters. In the extended-GSA receiver, we consider not only the current data symbol to detect, but also consider the previous data symbols to support the detection of the current data symbol. To this end, we modify and reformulate (5) and (6) as follows:

$$\hat{\mathbf{x}}'_i(k) = \mathbf{F}_P\hat{\mathbf{x}}(k-1) + \mathbf{w}_l^P \quad \text{for } l = 1, 2, ..., M^{N_T P} \quad (13)$$

and

$$\mathbf{P}'_i(k) = \mathbf{F}_P\bar{\mathbf{P}}(k-1)\mathbf{F}_P{}^T + \mathbf{Q}_l, \quad (14)$$

respectively, where

$$\mathbf{F}_p = \begin{bmatrix} \mathbf{0}_{N_T P\times N_T P} & \mathbf{0}_{N_T P\times N_T(N+L-P-1)} \\ \mathbf{0}_{N_T(N+L-P-1)\times N_T P} & \mathbf{I}_{N_T(N+L-P-1)} \end{bmatrix}\mathbf{F},$$

$\mathbf{w}_l^P = \begin{bmatrix} \mathbf{s}_{P,l}^T & \mathbf{0} \end{bmatrix}^T$, $\mathbf{s}_{P,l}$ is the possible combinations of a $1\times N_T P$ vector $\begin{bmatrix} \mathbf{s}(k) & \dots & \mathbf{s}(k-P+1) \end{bmatrix}$, P is the number of current and previous data symbols used in the extended-GSA receiver. The extended-GSA receiver with $P = p$ is called extended-GSA ($P = p$). Therefore, there are $M^{N_T P}$ parallel Kalman filters and each filter operates with own state vector, $\mathbf{w}_l^P, l = 1, 2, ..., M^{N_T P}$. By increasing P, we can extend the number of parallel Kalman filters and obtain better BER performances. The output of the extended-GSA receiver is obtained by combining the each filter's output based on the GSA criterion as given in (11) and (12).

C. Complexity Comparisons

To compare the computational complexity of various MIMO receiver schemes, we use the number of floating point operations (FLOPS), such as multiplication, addition, division and subtraction, to estimate a symbol vector. The computational complexity calculation of the proposed receiver is below. To calculate (13), $2L_X^2 + (2N_T - 2)L_X$ FLOPS are needed. The number of FLOPS of (14) is $3L_X^3 + L_X^2$. Equation (7), (8) and (9) need $4L_Z L_X$, $2L_X^3 + (2L_Z - 1)L_X^2$ and $6L_Z L_X^2 + (2L_Z^2 - 4L_Z)L_X + L_Z^2$ FLOPS, respectively. Equation (10) needs $4L_Z^2 - 2L_Z$ FLOPS. Equation (11) and (12) need $M^{pN_T}2L_X - L_X$ and $M^{pN_T}(2L_X^2 + 2L_X) - L_X^2$ FLOPS, respectively.

These equations are computed as number of Kalman filters in the proposed receiver, M^{pN_T}. However, once computed

TABLE I
COMPLEXITY COMPARISON OF VARIOUS MIMO RECEIVER SCHEMES
$(L_X = N_T(N + L - 1), L_Z = NN_R)$

MIMO receiver	Complexity (Number of FLOPS)
ZF	$L_X^3 + (4L_Z - 1)L_X^2 + (L_Z - 1)L_X$
MMSE	$L_X^3 + (4L_Z + 1)L_X^2 + (L_Z - 1)L_X$
Kalman	$5L_X^3 + 8L_Z L_X^2$ $+(L_Z^2 + L_Z)L_X + L_Z^3 + L_Z^2$
NKF	$M^{N_T}(6L_X^2 + (4L_Z + 2N_T + 2)L_X$ $+4L_Z^2 - L_Z + 2) + 5L_X^3 + 8L_Z L_X^2$ $+(2L_Z^2 - 2L_Z - 1)L_X + 2L_Z^3 + L_Z^2 - 1$
Extended-GSA $(P = p)$	$M^{pN_T}(6L_X^2 + (4L_Z + 2N_T + 2)L_X$ $+4L_Z^2 - L_Z + 2) + 5L_X^3 + 8L_Z L_X^2$ $+(2L_Z^2 - 2L_Z - 1)L_X + 2L_Z^3 + L_Z^2 - 1$
ML	$M^{N_T L}(2L_Z(N_T L + 1) - L_Z L - N)$

in the first filter, (6), (8) and (9) does not need to be computed again in other filters. The complexities of the zero-forcing (ZF), minimum mean squared error (MMSE), Kalman, proposed receiver and ML receiver by the Viterbi algorithm are shown in Table I.

V. Simulation Results

In order to compare the proposed MIMO receiver with the conventional MIMO receivers in terms of the BER performance and complexity, we consider 2×2 MIMO systems and a 3-tap quasi-static channel for a frequency selective fading channel. The power delay profile of the frequency selective channel is $\mathbf{f} = [0.16 \quad 0.68 \quad 0.16]$. An information symbol is BPSK modulated and spatially multiplexed across two transmit antennas.

Fig. 2 compares the BER curves of the proposed extended-GSA receiver and the Kalman MIMO receiver in frequency flat fading channels. Also, various MIMO linear and nonlinear receivers are also represented for the comparison. For the MIMO flat fading channel, since there is only current symbol to detect in the filter, the extended-GSA is exactly same as the NKF. The extended-GSA receiver always shows a better BER performance than the Kalman receivers because of the Gaussian approximation. Also, the extended-GSA receiver shows a better BER performance than the ZF, MMSE, Kalman, V-BLAST and shows a same BER performance as the ML receiver.

Fig. 3 compares the BER curves of the ZF, MMSE, Kalman, NKF, extended-GSA receivers with $N = 5$. Also, Fig. 3 shows the BER curve of the ML receiver with $N = 5$ for BER comparison. For the P value of the extended-GSA receivers, $P = \lceil (N + L - 1)/2 \rceil - 1 = 2$ and $P = \lceil (N + L - 1)/2 \rceil = 3$ is selected with moderate complexity. The BER performance of the extended-GSA receivers outperforms the ZF, MMSE, Kalman receiver. Also, the BER performance of the extended-GSA $(P = 2)$ receiver provides about 7dB gain compared to the NKF receiver. The BER performance of the extended-GSA $(P = 3)$ receiver has a 1.5dB SNR gain compared to the extended-GSA $(P = 2)$ receiver and close to the BER performance of the ML receiver.

To verify the performance improvement of the Kalman filtering algorithm using GSA, Fig. 4 shows the distributions of the output of the Kalman, NKF, extended-GSA $(P = 2)$, and extended-GSA $(P = 3)$ receivers with $N = 5$ when $E_b/N_o = 20dB$. Also, distribution of the ideal receiver, which has only value of $+1$ and -1, with additive Gaussian noise is shown. The output distribution of the extended-GSA equalizer

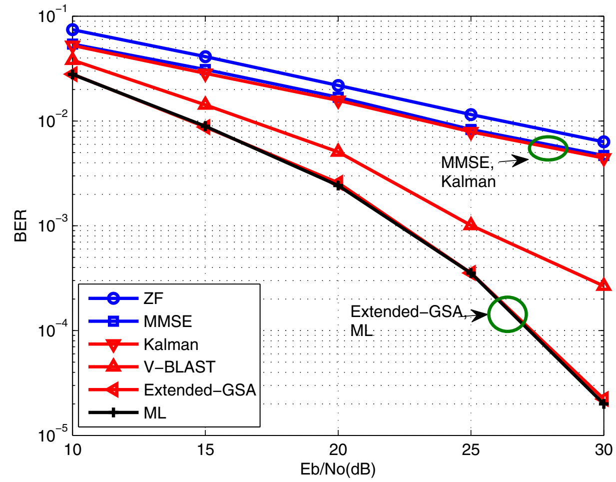

Fig. 2. BER performance of the extended-GSA receiver and various MIMO receivers in a frequency flat fading channel.

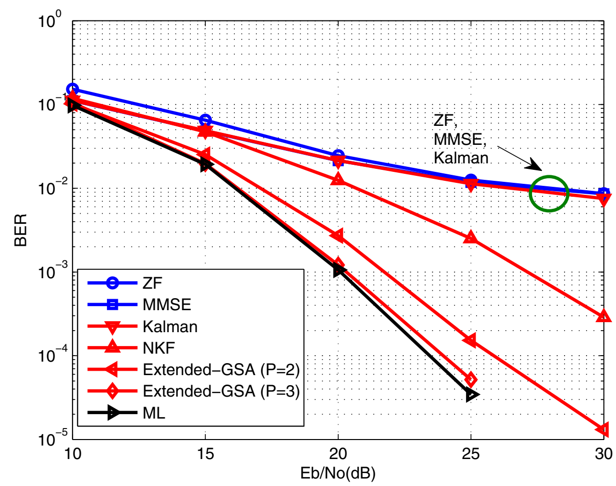

Fig. 3. BER performance of the extended-GSA receivers and various MIMO receivers with $N = 5$ in a frequency selective fading channel.

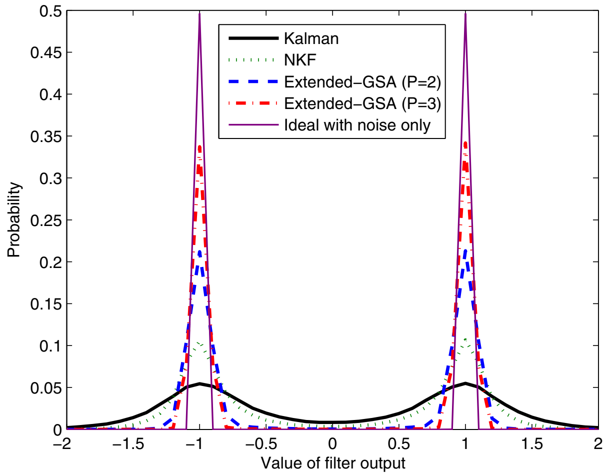

Fig. 4. Distributions of the output of the Kalman, NKF, and extended-GSA receivers with $N = 5$ at $E_b/N_o = 20dB$.

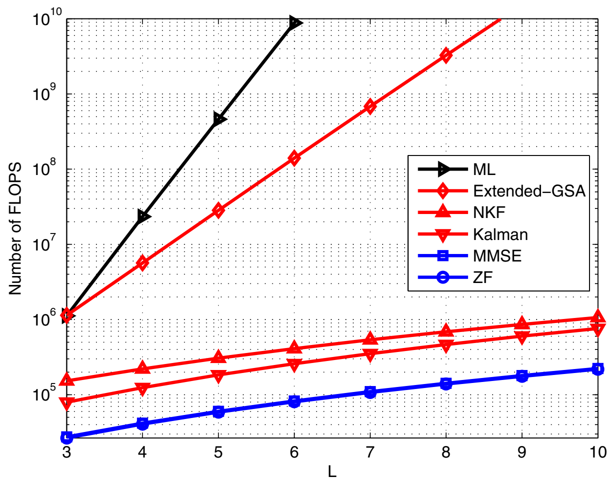

Fig. 5. Complexities of various MIMO receivers with various L.

is more concentrated around $+1$ and -1 compared to the Kalman and NKF receivers. Also, the extended-GSA ($P = 3$) receiver is more concentrated compared to the extended-GSA ($P = 2$) receiver and close to the ideal receiver case. It verifies that the extended-GSA ($P = p$) receiver can mitigate more effectively the interferences than the Kalman and NKF receiver as p increases.

Fig. 5 shows the complexities of various MIMO receivers while L is varying from 3 to 10, with $N_T = 4, N_R = 4$ and $N = 3$. The complexity of the extended-GSA receiver is calculated in the case of $P = \lceil (N + L - 1)/2 \rceil$, which used in the simulation of Fig. 3. It can be known from Fig. 3 and Fig. 5 that the computational complexity of proposed receiver is lower than that of the ML receiver as L increases whereas the BER performance of the proposed receiver is close to the optimal ML receiver.

VI. Conclusion

In this paper, a Kalman-based receiver for the MIMO channels by GSA, extended-GSA receiver, is proposed to overcome the limitation by the Gaussian assumption of the conventional Kalman filtering algorithm for the digital wireless communications. The extended-GSA receiver approximates the input signal to the Gaussian and improve the performance of the Kalman filtering algorithm with non-Gaussian inputs. The BER performance of the extended-GSA receiver is improved than the previous Kalman receiver and the NKF receiver. Also, the extended-GSA ($P = p$) receiver shows an improved BER performance as p increases and its performance is close to the ML receiver which has the optimal BER performance while the computational complexity of the extended-GSA receiver is lower than that of the ML receiver.

Acknowledgment

This work was supported in part by the National Research Foundation of Korea Grant funded by the Korean Government(MEST) (No. 2011-0005729).

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