A Spatial Diversity Reception of Binary Signal Transmission over Rayleigh Fading Channels with Correlated Impulse Noise

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***Abstract*—A Class-A density is well known to model interference, which is impulsive by nature. This model is expressed as a weighted infinite linear combination of Gaussian densities with different variances. The extension of this model for multiple receiving antennas is currently limited to two antennas. An algebraic extension leads to a multivariate Class-A density, which can be used for an arbitrary number of antennas. In this paper, we consider the design of optimum diversity combining for Rayleigh fading channels in the presence of Class-A interference. Since recent studies show a significant level of noise correlation in some wireless systems, we begin with a correlated multivariate Class-A model. Then, we show that the optimum combiner can be approximated by a maximum ratio combiner (MRC) preceded by noise decorrelators, which has a much lower complexity compared with the optimum one. When the interference is uncorrelated, we prove that the conventional MRC approximates the optimum combining.**

I. Introduction

Non-Gaussian, impulsive interference arises in a variety of important practical wireless situations such as radio frequency interference (RFI) in indoor and outdoor channels [1], [2], wireless data transceivers deployed in computers [3], and co-channel interference [4]. The source of interference can be either natural or man-made such as atmospheric noise, power lines, ignition, and closely located wireless systems. Middleton's Class-A model (MCA) [2] represents a widely-accepted statistical-physical model for impulsive interference superimposed onto additive white Gaussian noise (AWGN). This model has two basic parameters that can be adapted to fitting a wide variety of impulse noise phenomena occurring in practice. Middleton's models for impulse noise are derived and confirmed by a large number of comparisons of the analytical model with measurements for single antenna systems in different impulse noise environments. The extension of this model is obtained based on statistical-physical principles for two closely-spaced antennas under the assumption of narrowband and far-field interference [5]. Extending the Middleton model to multiple antenna systems is complicated, which restricts any analysis to two receive antennas. To overcome this restriction, the uncorrelated multivariate MCA model is proposed in [6], [7].

Spatial diversity is usually used to combat the detrimental effects of fading in wireless communication channels. In fading channels, the AWGN assumption in diversity branches leads to maximum ratio combining (MRC). In [7], The performance analysis of an MRC and some other diversity combining techniques is evaluated in the presence of uncorrelated multivariate MCA model. This model is applied to multiple-input multiple-output (MIMO) systems to derive the optimum decoder for space-time coding schemes [6]. In [8], we considered the design of an optimum detector in fading channels with impulse noise for a single receive antenna. We showed that the conventional detector is still optimum for MCA noise. So far, there has been no investigation how the optimum combiner for binary signals with correlated multivariate MCA noise should look like. Moreover, there are no clear justifications why the conventional MRC performs like the optimum detector in uncorrelated multivariate MCA noise.

The basic objectives of this paper can be summarized by two contributions. The primarily contribution is to extend the bivariate MCA density to a multivariate MCA density for correlated complex-valued noise observations. The second contribution is to derive a simplified form of an optimum detector and subsequently justify the performance of the optimum combiner in different impulse noise environments.

This paper is organized as follows. Section II briefly describes the system model and a MCA model for correlated interference. In Section III, we introduce the optimum diversity combiner in an impulse noise channel. In Section IV, we derive a simplified maximum likelihood (ML) combiner for correlated and uncorrelated multivariate MCA model. Finally, simulation results and concluding remarks are presented in sections V and VI, respectively.

II. System Model

We consider a wireless communication channel of a binary signal transmission corrupted by MCA interference. For simplicity, we restrict our analysis to binary signals (BPSK). However, the generalization to an arbitrary M-ary signal set is straightforward. We assume that there are L diversity

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channels, carrying the same transmitted signal. The fading processes along the L diversity channels are assumed to be mutually statistically independent with slow frequency-nonselective Rayleigh fading envelops. We further assume that the transmitted signal $\pm s(t)$ uses a rectangular pulse over $0 \le t \le T_b$. Therefore, the equivalent low-pass received signal in one signaling interval is

$$r_l(t) = \pm\sqrt{\frac{E_b}{N_0}} h_l s(t) + z_l(t)\,, \;\; l = 1, \cdots, L\,, \tag{1}$$

where E_b is the transmitted energy per bit, N_0 is the noise variance, h_l is a complex Gaussian channel gain with zero mean and variance normalized to 1 and $z_l(t)$ denotes the complex-valued MCA process corrupting the signal in the l^{th} channel. The interference process as seen by the l^{th} receiver includes two noise components: a Gaussian component $n_l(t)$, which describes the thermal background noise generated at the receiver and an impulse component $i_l(t)$ due to the interference from various man-made or natural sources. Hence, the received noise at the l^{th} receiver is given by

$$z_l(t) = n_l(t) + i_l(t)\,, \tag{2}$$

where $n_l(t)$ and $i_l(t)$ are assumed to be statistically independent. Similar to [2], the interference waveforms comprising $i_l(t)$ have the same form. However, their envelopes, duration, frequencies, and phases are randomly distributed. The locations of interfering sources and their emission times are randomly distributed in space and time according to a homogeneous Poisson point process with a rate λ. At the receiver, after matched-filtering and sampling (see Fig. 1), the l^{th} element of the received signal vector $\mathbf{r} = [r_1 \cdots r_L]^T$ can be expressed as

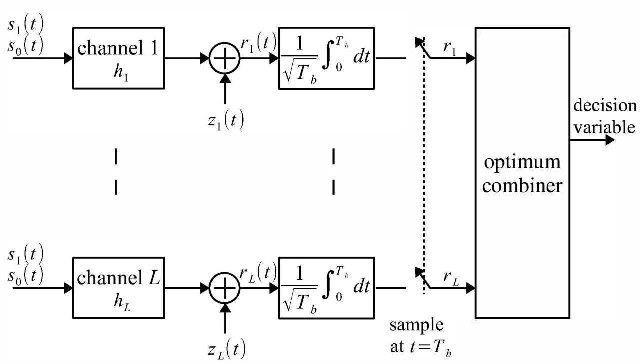

Fig. 1. Model of binary digital communication with spatial diversity

$$r_l = h_l s_{1,0} + z_l\,, \;\; l = 1, \cdots, L\,, \tag{3}$$

where $s_{1,0} \in \pm\sqrt{\frac{E_b}{N_0}}$ corresponds to the transmitted antipodal signal and z_l represent the samples of the complex noise process, $\frac{1}{\sqrt{T_b}}\int_0^{T_b} z_l(t)dt$, at the l^{th} receive antenna. The complex random variable z_l can be modeled by a MCA density as [7]

$$p(z_l) = \sum_{m=0}^{\infty} \alpha_m g(z_l; 0, \sigma^2_{m,l})\,, \tag{4}$$

where

$$\alpha_m = \frac{e^{-A}A^m}{m!}\,, \tag{5}$$

$$g(z;\mu,\sigma^2) = \frac{1}{\pi\sigma^2} e^{-\frac{|z-\mu|^2}{\sigma^2}}\,, \tag{6}$$

and $\sigma^2_{m,l} = \frac{m/A+\Gamma_l}{1+\Gamma_l}$. The impulsive index, $A = \lambda T_b$, is the average number of impulses within the bit interval T_b. The Gaussian factor, $\Gamma_l = \text{var}[\int_0^{T_b} n_l(t)]/\text{var}[\int_0^{T_b} i_l(t)]$, represents the power ratio of the Gaussian component n_l to the impulsive component i_l at the l^{th} receive antenna. The specified range of A and Γ_l are within $[10^{-2}\,1]$ and $[10^{-6}\,1]$, respectively. Note that (4) reduces to a Gaussian density when $A \to \infty$. The MCA density can be seen as a Gaussian distribution conditioned on the values of m, where m represents the noise state. According to (5), the noise state m is a Poisson-distributed random variable such that the probability of being in a given state is equal to α_m. Moreover, for a given noise state, m, we can indicate that there is no impulse, i.e., $m = 0$, or, impulses are present, i.e., $m \ge 1$. From (4), It is easy to show that $\text{E}(|z_l|^2) = 1$. Therefore, N_0, that appears in (1), controls the noise variance at the receiver. Since the L receivers are influenced by the same physical process creating the impulse, the elements of the received noise vector $\mathbf{z} = [z_1 \cdots z_L]$ can be assumed jointly dependent. Therefore, a complex multivariate MCA model can be used to model $\mathbf{z}$ as follows:

$$p(\mathbf{z}) = \sum_{m=0}^{\infty} \alpha_m g(\mathbf{z}; 0, \mathbf{\Sigma}_m)\,, \tag{7}$$

where

$$g(\mathbf{z};\mu,\mathbf{\Sigma}_m) = \frac{1}{(\pi)^L|\mathbf{\Sigma}_m|} e^{-(\mathbf{z}-\mu)^*\mathbf{\Sigma}_m^{-1}(\mathbf{z}-\mu)^T}\,, \tag{8}$$

where $|\cdot|$ denotes a determinant. $\mathbf{\Sigma}_m$ is the covariance matrix, which has the following form

$$\mathbf{\Sigma}_m = \begin{pmatrix} \sigma^2_{m,1} & \rho_m^{12}\sigma_{m,1}\sigma_{m,2} & \cdots & \rho_m^{1L}\sigma_{m,1}\sigma_{m,L} \\ \rho_m^{21}\sigma_{m,2}\sigma_{m,1} & \sigma^2_{m,2} & \cdots & \rho_m^{2L}\sigma_{m,2}\sigma_{m,L} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_m^{L1}\sigma_{m,L}\sigma_{m,1} & \rho_m^{L2}\sigma_{m,L}\sigma_{m,2} & \cdots & \sigma^2_{m,L} \end{pmatrix} \tag{9}$$

where ρ_m^{lk} is the correlation coefficient of the noise samples at the l^{th} and k^{th} receive antennas for a noise state m. In the case of two receive antennas, (7) can be seen as a complex extension of a bivariate MCA model [5], which has been derived through a statistical-physical modeling. Under the assumption of uncorrelated noise observations of equal variances, $\sigma^2_{m,l} = \sigma^2_{m,k}\ \forall\ l,k$, the present model (7) reduces to a multivariate MCA model considered in [6], [7].

III. Optimum Diversity Combiner

In [10], it has been shown that, for a signal transmitted over an AWGN channel, an MRC is the optimum diversity combiner. Since the impulsive noise leads to a nonlinear receiver structure, the MRC will no longer be the optimum combiner. In the following analysis, we assume that the channel coefficients h_l are perfectly known at the receiver.

Based on the observation vector $\mathbf{r} = [r_1 \cdots r_L]$, assuming equiprobable transmitted symbols, the optimum detector computes the following likelihood ratio test (LRT):

$$\Lambda(\mathbf{r}) = \frac{p(\mathbf{r}|s_1)}{p(\mathbf{r}|s_0)} \underset{s_\bullet}{\overset{s_1}{\gtrless}} 1\,, \tag{10}$$

where $p(\mathbf{r}|s_{1,0})$ are the joint conditional pdfs of the received vector $\mathbf{r}$ given s_1 or s_0 was sent. The hypotheses s_1 and s_0 correspond to $+1$ and -1, respectively. The joint conditional pdfs of the received vector $\mathbf{r}$ can be expressed as

$$p(\mathbf{r}|s_{1,0}) = e^{-A} \sum_{m=0}^{\infty} \frac{A^m}{m!} g(\mathbf{r}; s_{1,0}\mathbf{h}, \mathbf{\Sigma}_m)\,. \tag{11}$$

For a practical realization, the infinite sum in the multivariate MCA density may be truncated to a finite sum. It has been shown in [11] that the two-term approximation is sufficient in most problems. Therefore, the joint conditional pdfs may be approximated as

$$p(\mathbf{r}|s_{1,0}) \approx e^{-A} g(\mathbf{r}; s_{1,0}\mathbf{h}, \mathbf{\Sigma}_0) + (1-e^{-A}) g(\mathbf{r}; s_{1,0}\mathbf{h}, \mathbf{\Sigma}_1)\,. \tag{12}$$

The joint conditional pdf only contains two exponential functions. The natural logarithm of $p(\mathbf{r}|s_{1,0})$ cannot be used for further simplification, thereby resulting in increased complexity of evaluating the exponential functions for all (here two) possible hypotheses.

IV. Simplified ML Diversity Combiner

The two-term model of a MCA density is a sum of two scaled Gaussian densities. The first term represents the Gaussian background noise with variance $\sigma_{0,l}^2$, while the second term is thought to represent the impulse events with $\sigma_{1,l}^2 \gg \sigma_{0,l}^2$. For $L = 1$, in [8], we showed that the MCA density can be further simplified into a one-term only (either Gaussian or impulse term) over two distinct regions. Here, we extend this result to a multivariate case. Therefore, the multivariate MCA density can be simplified as

$$p(\mathbf{z}) \approx \begin{cases} \overbrace{e^{-A} g(\mathbf{z}; 0, \mathbf{\Sigma}_0)}^{p_G(\mathbf{z})} & \text{if } \mathbf{z}^* \mathbf{M} \mathbf{z}^T \leq c_0 \\ \overbrace{(1-e^{-A}) g(\mathbf{z}; 0, \mathbf{\Sigma}_1)}^{p_I(\mathbf{z})} & \text{otherwise}\,, \end{cases} \tag{13}$$

where

$$\mathbf{z}^* \mathbf{M} \mathbf{z}^T = c_0\,, \tag{14}$$

represents the boundary equation when the two terms are equal, $\mathbf{M} = \mathbf{\Sigma}_0^{-1} - \mathbf{\Sigma}_1^{-1}$, and $c_0 = \ln(\frac{|\mathbf{\Sigma}_1| e^{-A}}{|\mathbf{\Sigma}_0|(1-e^{-A})})$. Regarding this approximation, the joint conditional pdfs (11) can be approximated as

$$p(\mathbf{r}|s_{1,0}) \approx \begin{cases} \overbrace{e^{-A} g(\mathbf{r}; s_{1,0}\mathbf{h}, \mathbf{\Sigma}_0)}^{p_G(\mathbf{r}|s_{1,\bullet})} & \text{if } (\mathbf{r} - s_{1,0}\mathbf{h})^* \mathbf{M} (\mathbf{r} - s_{1,0}\mathbf{h})^T \leq c_0 \\ \overbrace{(1-e^{-A}) g(\mathbf{r}; s_{1,0}\mathbf{h}, \mathbf{\Sigma}_1)}^{p_I(\mathbf{r}|s_{1,\bullet})} & \text{otherwise}\,. \end{cases} \tag{15}$$

Since the approximated joint conditional pdf (15) contains only one term, the log-likelihood can be used to simplify the optimum combiner. To derive a closed-form expression for a diversity combiner, we start with a decision boundary analysis to determine the overlapping regions between the received observations r_l, $l = 1, \cdots, L$. The boundary equation can be expressed as

$$(\mathbf{r} - s_{1,0}\mathbf{h})^* \mathbf{M} (\mathbf{r} - s_{1,0}\mathbf{h})^T = c_0\,. \tag{16}$$

For two receive antennas ($L = 2$), this equation reduces to

$$\begin{aligned} a_1|r_1 - s_{1,0}h_1|^2 &+ a_2|r_2 - s_{1,0}h_2|^2 \\ &- 2\rho b \Re\{(r_1 - s_{1,0}h_1)^*(r_2 - s_{1,0}h_2)\} = (1-\rho^2)c_0\,, \end{aligned} \tag{17}$$

where $a_l = \frac{\sigma_{1,l}^2 - \sigma_{\bullet,l}^2}{\sigma_{1,l}^2 \sigma_{0,l}^2}$, $l = 1, 2$ and $b = \frac{\sigma_{1,1}\sigma_{1,2} - \sigma_{\bullet,1}\sigma_{\bullet,2}}{\sigma_{1,1}\sigma_{1,2}\sigma_{\bullet,1}\sigma_{\bullet,2}}$. when r_l and h_l are real signals, the boundary equation can be seen as ellipses (see Fig. 2) centered at (s_1h_1, s_1h_2) and (s_0h_1, s_0h_2) for s_1 and s_0, respectively. Figure 2 is depicted for r_l and h_l as real signals, but it is still valid for complex signals. As we can see from this figure, there are four possible overlapping regions R_i, $i = 0, \cdots, 3$. The decision boundaries of each region can be computed as follows:

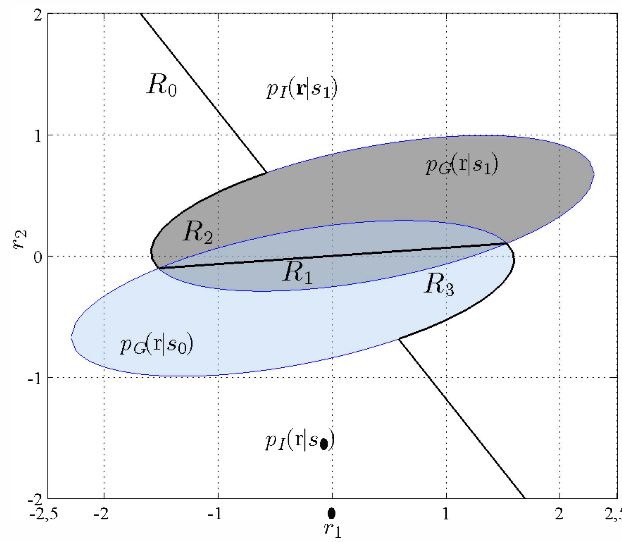

Fig. 2. Decision regions with $A = 0.01$, $\mathbf{\Gamma} = [0.1\ 0.01]$

$$\ln p(\mathbf{r} \in R_i|s_1) = \ln p(\mathbf{r} \in R_i|s_0)\,, \tag{18}$$

where $p(\mathbf{r} \in R_i|s_{1,0})$ can be simplified using (15) to be either $p_G(\mathbf{r}|s_{1,0})$ or $p_I(\mathbf{r}|s_{1,0})$. In region R_0, the joint conditional pdfs $p(\mathbf{r}|s_{1,0})$ can be approximated by $p_I(\mathbf{r}|s_{1,0})$. Then, the decision boundary can be calculated as

$$\ln p_I(\mathbf{r}|s_1) = \ln p_I(\mathbf{r}|s_0)\,, \tag{19}$$

By substituting (15) into (19), the decision boundary can be solved as

$$\Re\{\mathbf{h}^* \mathbf{\Sigma}_1^{-1} \mathbf{r}^T\} = 0\,, \tag{20}$$

which represents the combiner equation for region R_0. In region R_1, the optimum combiner can be approximated as

$$\ln p_G(\mathbf{r}|s_1) = \ln p_G(\mathbf{r}|s_0)\,, \tag{21}$$

which yields the following solution:

$$\Re\{\mathbf{h}^*\boldsymbol{\Sigma}_0^{-1}\mathbf{r}^T\} = 0\,. \tag{22}$$

Since $p_G(\mathbf{r}|s_{1,0}) \gg p_I(\mathbf{r}|s_{0,1})$, the regions R_2 and R_3 can simply be assigned to s_1 and s_0, respectively. The combining equation over these regions can be computed from the boundary equation

$$(\mathbf{r}-\mathbf{h})^*\mathbf{M}(\mathbf{r}-\mathbf{h})^T = (\mathbf{r}+\mathbf{h})^*\mathbf{M}(\mathbf{r}+\mathbf{h})^T \tag{23}$$

with the following solution:

$$\Re\{\mathbf{h}^*\mathbf{M}\mathbf{r}^T\} = 0\,. \tag{24}$$

Since $\sigma_{1,l} \gg \sigma_{0,l}$, the matrix $\mathbf{M} = \boldsymbol{\Sigma}_0^{-1} - \boldsymbol{\Sigma}_1^{-1}$ can be approximated by $\boldsymbol{\Sigma}_0^{-1}$. Therefore, the combiner of (22) can be used for overlapping regions R_2 and R_3.

In the above analysis, we showed that the optimum combiner for L diversity channels corrupted by correlated multivariate MCA impulse noise can be approximated by a linear combiner. The proposed combiner computes the boundary equations (23) to determine the noise state (Gaussian or impulsive), then it applies the corresponding noise covariance matrix ($\boldsymbol{\Sigma}_0^{-1}$ or $\boldsymbol{\Sigma}_1^{-1}$) as seen in (20) and (22).

When the receiving antennas are spaced far enough, the received interference can be assumed spatially uncorrelated. In this case $\rho_m^{lk} = 0\ \forall\ l \neq k$, then the covariance matrix of $\mathbf{z}$ becomes a diagonal matrix $\boldsymbol{\Sigma}_m = \mathrm{diag}(\sigma_{m,1}^2, \cdots, \sigma_{m,L}^2)$ and the boundary equation (16) reduces to

$$\sum_{l=1}^{L} a_l |r_l - s_{1,0}h_l|^2 = c_0\,, \tag{25}$$

and consequently the combiners of (20) and (22) reduce to

$$\sum_{l=1}^{L} \frac{1}{\sigma_{1,l}^2}\Re\{h_l^* r_l\}\,, \tag{26}$$

and

$$\sum_{l=1}^{L} \frac{1}{\sigma_{0,l}^2}\Re\{h_l^* r_l\}\,, \tag{27}$$

respectively. Now, when the L channels are effected by interference of the same Gaussian factors $\Gamma_l = \Gamma$, $l = 1, \cdots, L$, the noise variances on the L channels will be the same $\sigma_{m,l}^2 = \sigma_m^2$, $m = 0, 1$. In this case, the proposed combiners of (20), (22), and (24) reduce to the following

$$\sum_{l=1}^{L} \Re\{h_l^* r_l\}\,, \tag{28}$$

which represents the optimum combiner for Gaussian interference. That is, we can state that the conventional MRC approximates the optimum detector when the noise observations have equal variances, which justifies why the MRC offers almost the same performance of the optimum detector as reported in [7].

V. Simulation Results

In this section, we present a series of simulation results to validate our analysis by comparing the bit-error ratio (BER) of a conventional MRC, an optimum combiner, and the proposed combiner for different impulse noise environments. In all cases, we consider $L = 2$ and $L = 4$ diversity reception for BPSK signal transmission over Rayleigh fading channels. Furthermore, we assume that the parameters of impulse noise (A, $\boldsymbol{\Gamma}$, and ρ_m^{lk}) are known at the receivers. Moreover, we use the first 10 terms of a MCA density to approximate the full MCA density.

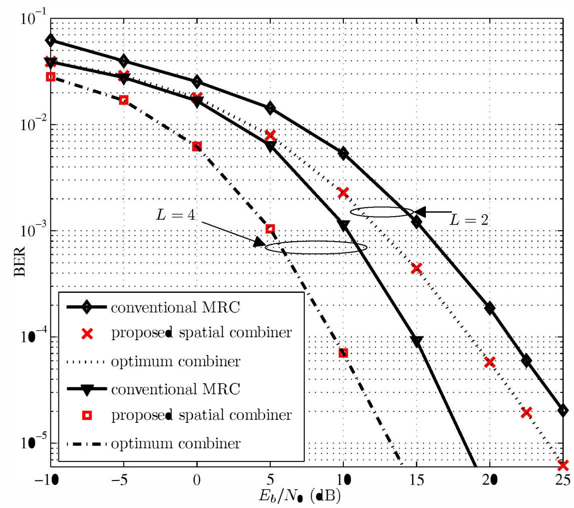

Fig. 3. Performance comparison over a correlated impulse channel

Since the received interference comes from the external sources to the receiving antennas, recent studies show that a significant level of noise correlation exists even when the antennas are far apart [3]. To simulate this scenario, we assume that the correlation coefficients ρ_m^{lk} are identical for all noise states. Therefore, the received interference has the following correlation matrices

$$\begin{pmatrix} 1 & 0.795 \\ 0.795 & 1 \end{pmatrix}$$

and

$$\begin{pmatrix} 1 & 0.795 & 0.602 & 0.372 \\ 0.795 & 1 & 0.795 & 0.602 \\ 0.602 & 0.795 & 1 & 0.795 \\ 0.372 & 0.602 & 0.795 & 1 \end{pmatrix}$$

for $L = 2$ and $L = 4$, respectively. In Fig. 3, we show the BER for the considered combiners in a moderate impulse channel ($A = 0.1$) with different Gaussian factors along the antennas, i.e., $\boldsymbol{\Gamma} = [0.01\ 0.1]$, and $\boldsymbol{\Gamma} = [0.01\ 0.1\ 0.1\ 0.01]$ for $L = 2$ and $L = 4$, respectively. As expected, as L (diversity order) increases the performance improves. The optimum and the proposed spatial combiners offer better performance than the conventional MRC. It is clear that the performance of the proposed spatial combiner approaches the optimum one. From (20) and (22), the proposed combiner decorrelates the

MCA noise (by applying Σ_m^{-1}, $m = 0, 1$) before performing the MRC, which justifies why it approaches the optimum performance.

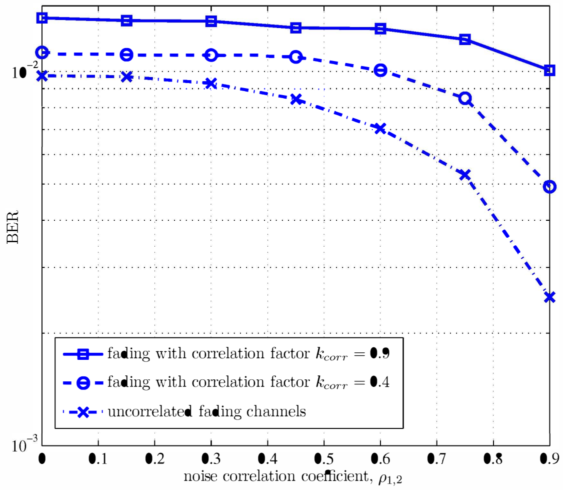

Fig. 4. Average BER versus noise correlation coefficient for $L = 2$ at E_b/N_0 = 7.5 dB

As the antenna-spacing decreases the fading channels h_l, $1, \cdots, L$ become more correlated and the assumption of independent fading envelops will no longer be true. For $L = 2$, Fig. 4 shows the BER performance versus the noise correlation coefficient $\rho_{1,2}$ at different factors of fading correlation $k_{\text{corr}} = \text{corr}(|h_1|, |h_2|)$. It is clear that the BER curves become much worse as fading channel correlation increases. A strong fading correlation of 0.9 makes the received signals suffer essentially the same fading and no diversity reception is gained. We note that the BER is improved when the Class-A noise is correlated and this improvement is maximized when the fading envelopes are uncorrelated.

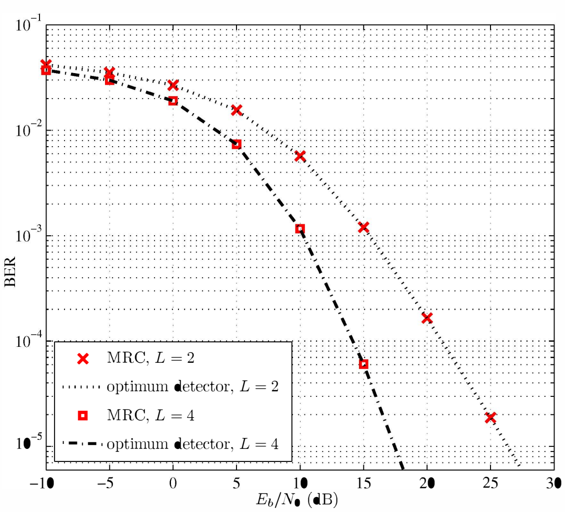

Fig. 5. Performance comparison over uncorrelated impulse channel

In [7], it was reported that the conventional MRC outperforms the other combining schemes such as selection combining and equal gain combining under the assumption of uncorrelated MCA noise and equal Gaussian factors. Regarding our analysis in Sec. IV, we show that the conventional MRC approximates the optimum detector under these assumptions. To confirm this point, Fig. 5 shows the BER of a conventional MRC and optimum detector for uncorrelated MCA noise with $\Gamma_l = 0.1$, $l = 1, \cdots, 4$.

VI. Conclusion

For spatially correlated channels, the multivariate Class-A (MCA) model can be approximated as a weighted-sum of two multivariate normal densities with different covariance matrices. Based on this model, the noise state (Gaussian or impulsive) can be determined at the receiver and subsequently, the MCA model can further be approximated as a multivariate Gaussian density. Herewith, we showed that the maximum ratio combiner (MRC) preceded by noise-whitening filters approaches the optimum combiner. The noise whitening filters are designed based on the noise state to decorrelate the Gaussian or impulse noise. For binary signaling, the maximum performance improvement is achieved when the noise is highly correlated. Additionally, we approved that the conventional MRC is still optimum when the received noise is uncorrelated.

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