A ROBUST TRANSMITTER DIVERSITY SCHEME FOR CDMA IN IMPULSIVE NOISE

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ABSTRACT

In this paper we propose and evaluate different robust detectors for a transmitter diversity scheme which can be used for the downlink of a direct-sequence code division multiple access (CDMA) system in impulsive noise environments. It is well known that the performance of the linear detector is severely degraded when impulsiveness occurs. The proposed non-linear detectors are based on M-estimation and use non-linear score functions. Simulation results show that they perform considerably better than the linear detector when impulsive noise is present and do not loose much of their performance in the Gaussian case. A comparison of the robust detectors in terms of performance and complexity is provided.

1. INTRODUCTION

Diversity concepts are needed to cope with multipath fading in wireless communications. The idea is to transmit the same information several times over channels that fade independently. Time and frequency diversity lead to lower data rates and are therefore inconvenient in many applications. In [1], Alamouti proposed a spatial diversity method with two transmit and one receive antennae. This method ensures full data rate while maintaining the same total transmit power that a single-transmitter antenna would have used. This method has been adopted in [2] for a CDMA system so as to improve the quality of the downlink channel where the assumption of Gaussian noise was made.

However, in reality, this assumption is not always true. In particular, impulsive noise can occur in urban areas due to switching transients in powerlines, automobile ignition, fluorescent lighting and other electromagnetic interference sources [3]. The presence of impulsive (i.e. non-Gaussian) noise causes conventional techniques to have poor performance.

Hence, robust detectors are required whose performance is near optimal in the Gaussian case and does not degrade significantly if the underlying noise distribution changes. In this paper, we consider the transmitter diversity scheme proposed in [2] when the underlying noise distribution is impulsive. We suggest different robust detectors which are able to cope with impulsive noise environments.

The paper is structured as follows: In Section 2, the system model is explained and Section 3 introduces an impulsive noise model. In Section 4, three different robust detectors are presented and their computational complexity is evaluated in Section 5 by means of the O-notation. Simulation results are shown in Section 6 and conclusions are drawn in Section 7.

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2. SYSTEM MODEL

We consider a system of two transmitter and one receiver antennae [2]. At the transmitter we have the following signal model for the signals transmitted from antenna t_1 and t_2

$$\begin{aligned} \mathbf{t}_1 &= 1/\sqrt{2}(b_1\mathbf{c}_1 + b_2\mathbf{c}_2) \\ \mathbf{t}_2 &= 1/\sqrt{2}(b_2\mathbf{c}_1 - b_1\mathbf{c}_2). \end{aligned} \tag{1}$$

where b_1, b_2 are the transmitted *Binary Phase Shift Keying* (BPSK) symbols and $\mathbf{c}_1, \mathbf{c}_2$ are orthogonal spreading sequences with unit norm and length N. We assume a Rayleigh fading channel which is constant across two consecutive symbols. The ith element of the received signal is

$$r_i = h_1 t_{1i} + h_2 t_{2i} + n_i, \quad i = 1, \ldots, N, \tag{2}$$

where h_1 and h_2 are the complex channel coefficients and n_i is i.i.d. complex noise with probability density function (pdf) $f_n(x)$. The signal model can be written in matrix form as

$$\mathbf{r} = A\mathbf{S}\theta_{\mathbf{c}} + \mathbf{n} \tag{3}$$

where A is the transmit amplitude, $\mathbf{S} = [\mathbf{c}_1\ \mathbf{c}_2]$ is the code matrix and $\theta_{\mathbf{c}} = \mathbf{H}\mathbf{b}$ is to be estimated. In [2] it was claimed that no extra spreading codes are required and the method works with any orthogonal codes and thus we could generate a code $\mathbf{c}_1 = [\mathbf{c};\ \mathbf{0}]$ and $\mathbf{c}_2 = [\mathbf{0};\ \mathbf{c}]$ which reduces the complexity of the system.

To recover θ_c one performs matched filtering or decorrelating where the received signal is correlated with the spreading sequences.$\theta_c = \mathbf{S}^\top \mathbf{r}$. In order to demodulate the symbols b_1 and b_2, the decorrelated signal $\theta_{\mathbf{c}} = [\theta_{c1}\ \theta_{c2}]^T$ is multiplied by the hermitian of the channel matrix $\mathbf{H} = [h_1\ h_2; -h_2\ h_1]$ where full *channel state information* (CSI) is assumed at the receiver and only the real part is considered to recover the BPSK symbols, i.e. $\hat{\mathbf{b}} = sgn(\Re\{\mathbf{H}^\dagger \theta_{\mathbf{c}}\})$ [2]. If $\mathbf{n}$ has a Gaussian pdf the estimates of θ_{c1} and θ_{c2} obtained by a linear decorrelator are optimal.

However, if the distribution of $\mathbf{n}$ is not Gaussian but has impulsive behaviour, the estimates $\hat{\theta}_{c1}$ and $\hat{\theta}_{c2}$ are degraded severely and the BER increases.

We propose a robust non-linear detector, developed in [4], for decorrelating the received space-time spreading (STS) sequences, i.e. to estimate θ_{c1} and θ_{c2} in a robust way. Stacking the real and imaginary parts of the model of Equation (3) in one vector, one obtains the extended system model

$$\mathbf{y} = A\mathbf{\Gamma}\theta + \mathbf{v}. \tag{4}$$

$$\begin{aligned} \mathbf{y} &= \begin{pmatrix} \Re\{\mathbf{r}\} \\ \Im\{\mathbf{r}\} \end{pmatrix} \quad & \mathbf{\Gamma} &= \begin{pmatrix} \mathbf{S} & \mathbf{0} \\ \mathbf{0} & \mathbf{S} \end{pmatrix} \\ \theta &= \begin{pmatrix} \Re\{\theta_{\mathbf{c}}\} \\ \Im\{\theta_{\mathbf{c}}\} \end{pmatrix} \quad & \mathbf{v} &= \begin{pmatrix} \Re\{\mathbf{n}\} \\ \Im\{\mathbf{n}\} \end{pmatrix} \end{aligned} \tag{5}$$

and $\mathbf{0}$ is a $N \times 2$ matrix of zero elements. If we consider one user with two orthogonal spreading codes the problem then becomes one of solving

$$\hat{\theta} = \arg\min_{d} \sum_{i=1}^{2N} -\log f_n\left(y_i - \sum_{k'=1}^{2} (\mathbf{\Gamma})_{ik'}\theta_{k'}\right). \tag{6}$$

Note that, the system model may easily be extended to multiple users by allowing the sum in brackets to range over $k' = 1$ to $2M$, where M is the number of users. In this case, when several user communicate at the same time, Equation (6) requires the spreading sequences of the other users in order to decorrelate the signal.

As in [2], we restrict ourselves to the one user case in order to demonstrate the method. Assuming that the noise distribution $f_n(x)$ has a single maximum we obtain a unique solution by solving the following equation system

$$\sum_{i=1}^{2N} \mathbf{\Gamma}_{ik}\varphi\left(y_i - \sum_{k'=1}^{2} (\mathbf{\Gamma})_{ik'}\theta_{k'}\right) = 0 \quad k = 1, 2, \tag{7}$$

where $\varphi(x) = -\partial \log f_n(x)/\partial x$ is the location score function which equals x/σ^2 in the Gaussian case and reduces Equation (7) to least squares. $\theta_{\mathbf{c}}$ is obtained from θ by the simple transformation

$$\theta_{\mathbf{c}} = \begin{pmatrix} 1 & 0 & j & 0 \\ 0 & 1 & 0 & j \end{pmatrix} \theta. \tag{8}$$

3. IMPULSIVE NOISE MODEL

In [3] a canonical model based on measurements and statistical-physical modelling was developed. Due to its complexity this model is mathematically impractical. An approximation, the ε-contaminated Gaussian mixture model, is used in this work in order to simulate impulsive noise behaviour. The model consists of two Gaussian components

$$f_n(x) = (1-\varepsilon) f_G(x; 0, \nu^2) + \varepsilon f_G(x; 0, \kappa\nu^2). \tag{9}$$

where $f_G(x; \mu, \sigma^2)$ is a Gaussian pdf with mean μ and variance σ^2. Typically values for ε and κ are $0.01 \le \varepsilon \le 0.1$ and $10 \le \kappa \le 100$ for wireless communication channels where impulsive noise occurs [5]. Note that the variance of the second term is significantly larger than that of the nominal first term and hence leads to impulsive behaviour. The total noise power is

$$\sigma^2 = (1-\varepsilon)\nu^2 + \varepsilon\kappa\nu^2. \tag{10}$$

We will study the impact of changes of the shape of the noise distribution by varying the parameter ε and κ while the overall variance is fixed to unity.

4. ROBUST APPROACHES

In Section 2, it was mentioned that outliers have a deleterious effect on the estimates. However, if one replaces the Gaussian location score function by another influence function, this effect could be eliminated. Several parametric and non-parametric approaches have been considered [7, 8]. How to choose the influence function is described in this section.

4.1. M-estimator and One-step M-estimator

Huber [4] proposed an estimator which minimises the maximum asymptotic variance of the least favourable noise distribution over the class of ε-contaminated Gaussian mixture

$$n_i \sim (1-\varepsilon)\mathcal{N}(0, \nu^2) + \varepsilon\mathcal{H} \tag{11}$$

where $0 \le \varepsilon \le 1$, $\mathcal{N}(0, \nu^2)$ is the Gaussian pdf with mean 0 and variance ν^2 and $\mathcal{H}$ is any symmetric zero-mean pdf.

The influence function of this minimax estimator, also known as the soft-limiter, can be expressed as [4]

$$\psi(x) = \begin{cases} \frac{x}{\nu^2} & |x| \le k\nu^2 \\ k sign(x) & |x| > k\nu^2 \end{cases} \tag{12}$$

where k, ε and ν are connected through

$$\frac{\Phi(k\nu)}{k\nu} - Q(k\nu) = \frac{\varepsilon}{2(1-\varepsilon)}, \tag{13}$$

$\Phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ and $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-\frac{x^2}{2}} dx$. In practice ε and κ are not known. For this reason the influence function of Equation (12) was approximated in [5] as

$$\psi(x) = \begin{cases} \frac{x}{\sigma^2} & |x| \leq k\sigma^2 \\ ksign(x) & |x| > k\sigma^2 \end{cases} \tag{14}$$

where $k = 1.5/\sigma$. Note that σ^2 is the overall variance of the noise distribution and ν^2 is the variance of the nominal distribution.

The estimation procedure for determining θ in a robust way is as follows First, obtain an initial estimate θ^i using linear decorrelation and determine the residuals. Second, perform one iteration step of a Newton-Raphson algorithm in order to find the next estimate θ^{i+1}. This is repeated until convergence is reached, i.e.

$$\begin{aligned} \mathbf{z}^i &= \psi(\mathbf{y} - \mathbf{\Gamma}\theta^i) \\ \theta^{i+1} &= \theta^i + \mu(\mathbf{\Gamma}^\mathsf{T}\mathbf{\Gamma})^{-1}\mathbf{\Gamma}^\mathsf{T}\mathbf{z}^i, \quad i = 0, 1, .. \end{aligned} \tag{15}$$

where $\mu = 1/\sigma^2$ is a step size parameter. The algorithm stops when $|\hat{\theta}^{i+1} - \hat{\theta}^i| > \epsilon \cdot |\hat{\theta}^{i+1}|$ where $\epsilon \in \mathbb{R}$ is a small number. Note that the pseudoinverse $(\mathbf{\Gamma}^\mathsf{T}\mathbf{\Gamma})^{-1}\mathbf{\Gamma}^\mathsf{T}$ can be computed offline.

Many other influence functions $\psi(x)$ may be suggested, for example $\tanh(x/\sigma)$ which is a smoothed version of the soft-limiter.

Another possibility is to apply only one step of the Newton-Raphson algorithm. This does not necessarily lead to best results but still provides robustness while maintaining computational complexity on a low level. This is known as the one-step M-estimator.

4.2. Parametric Estimator

In the previous subsection, an M-estimator used for estimating θ with a static influence function was described. This M-estimator, like any minimax estimator, may be far from optimal, away from the least favorable distribution. In order to provide more flexibility to the underlying noise distribution, we consider an adaptive M-estimator, developed in [6,7], which uses an adaptive influence function constructed from a linear combinations of B basis functions

$$\psi(x) = \sum_{b=1}^{B} a_b g_b(x) = \mathbf{a}^\mathsf{T}\mathbf{g}(x). \tag{16}$$

The basis functions $g_1(x), .., g_B(x)$ are contained in the vector $\mathbf{g}(x)$ and $\mathbf{a}$ contains the corresponding coefficients. The bases have to be chosen in such a way that they provide a good approximation of φ.

The criterion used for estimating the coefficients $\mathbf{a}$ is to minimise the mean square error between the model $\psi(x)$ and the true score function $\varphi(x)$, i.e.,

$$\hat{\mathbf{a}} = \arg\min_{\mathbf{a}} E\left[(\psi(x) - \varphi(x))^2\right]. \tag{17}$$

1. *Initialisation*
   Set i=0. Obtain an initial estimate of θ^0
2. *Determine the residuals*
   $\hat{\mathbf{v}} = \mathbf{r} - \mathbf{\Gamma}\hat{\theta}^i$
3. *Estimate the weights* $\mathbf{a}$ *and construct the influence function*
   $\hat{\mathbf{a}} = E[\mathbf{g}(\hat{\mathbf{v}})\mathbf{g}(\hat{\mathbf{v}})^\mathsf{T}]^{-1}E[\mathbf{g}'(\hat{\mathbf{v}})]$
   $\psi(x) = \hat{\mathbf{a}}^\mathsf{T}\mathbf{g}(x)$
4. *Update the parameter estimates*
   $\mathbf{z}^i = \psi(\hat{\mathbf{v}})$
   $\theta^{i+1} = \theta^i + \mu(\mathbf{\Gamma}^\mathsf{T}\mathbf{\Gamma})^{-1}\mathbf{\Gamma}^\mathsf{T}\mathbf{z}^i$
   where $\mu = 1/max(|\psi'(\hat{\mathbf{v}})|)$
5. *Check for convergence*
   If $|\frac{\hat{\theta}^{i+1} - \hat{\theta}^i}{\hat{\theta}^{i+1}}| > \epsilon$, stop, where $\epsilon \in \mathbb{R}$ is a small number.
   otherwise $i \to i + 1$ and go to step 2,

Under certain conditions one obtains the optimal least squares solution as [6]

$$\hat{\mathbf{a}} = E[\mathbf{g}(x)\mathbf{g}(x)^\mathsf{T}]^{-1}E[\mathbf{g}'(x)] \tag{18}$$

where $E[\cdot]$ is the sample mean in practice. In [7] it has been shown that the small sample performance of this estimator is improved when the constraints $\sum_{b=1}^{B} a_b = 1$ and $a_b \geq 0$ are met. The first constraint controls the scale while the second constraint ensures the estimated influence function is antisymmetric and positive for $x > 0$.

The asymptotic variance of this estimator for $N \to \infty$ is given by [7]

$$V(F, \varphi) = \frac{\mathbf{a}^\mathsf{T}E[\mathbf{g}\mathbf{g}^\mathsf{T}]\mathbf{a}}{(\mathbf{a}^\mathsf{T}E[\dot{\mathbf{g}}])^2}. \tag{19}$$

However, if ones applies this estimator to the received signal considered in Section 2 the following steps have to be performed. The algorithm is similar to Equation (15) with the difference that an estimate of the score function replaced by the influence function.

4.2.1. Choice of basis function

It is clear that the more bases included in the set $\mathcal{B}$ the better the asymptotic performance ($N \to \infty$) of the estimator. On the other hand, for small samples, the more bases the more parameter to estimate and hence the more uncertainty in the estimation procedure. In addition to that the complexity of the algorithm increases by increasing the number of bases.

Hence, a tradeoff between performance and complexity has to be achieved. In Section 3, we introduced the Gaussian mixture pdf as a common model in wireless communications where impulsive noise occurs.
Without loss of generality, the basis set used here, $\mathcal{B} = \{g_1, g_2, g_3, g_4\}$, consists of four Gaussian mixture score functions with parameters (ε, κ) of $(0.01, 10)$, $(0.1, 50)$, $(0.02, 100)$ and $(0.1, 100)$ respectively. Each is standardised to a distribution with unit variance. These four bases are positioned in the (ε, κ) parameter space in order to cover the parameter values expected in practice.
The choice becomes apparent if one considers the asymptotic efficiency of the adaptive algorithm as shown in Fig. 1. Using

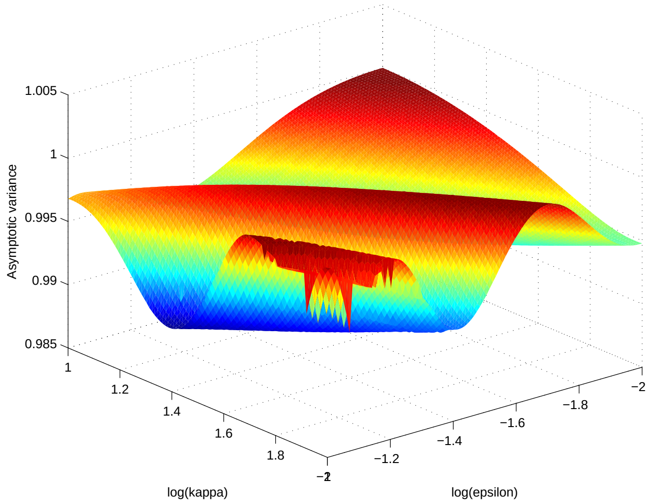

Fig. 1. Asymptotic efficiency of the adaptive algorithm.

the basis set $\mathcal{B}$ defined above, the asymptotic efficiency of the adaptive estimator is over 0.98 for practically relevant values of (ε, κ).
Furthermore, the advantage of such a scheme over Huber's minimax M-estimator is seen in Fig. 2 which shows the asymptotic relative efficiency of Huber's approach to that of the adaptive algorithm. The adaptive algorithm has lower asymptotic variance over $\{0.01 \leq \varepsilon \leq 0.1\, 10 \leq \kappa \leq 100\}$. In heavily contaminated noise environments the adaptive algorithm is seen to perform significantly better.

5. COMPUTATIONAL COMPLEXITY

If we evaluate the algorithms proposed in Section 4 in terms of computational complexity we have to consider three cost factors. The first factor is the cost of computing the pseudoinverse $(\mathbf{\Gamma}^\mathsf{T}\mathbf{\Gamma})^{-1}\mathbf{\Gamma}^\mathsf{T}$ which can be done offline and is the same for the three different algorithms. The second factor is the cost of one iteration which appears only once for the one-step M-estimator. However, for the M-estimator and the adaptive algorithm, the iteration steps are performed an un-

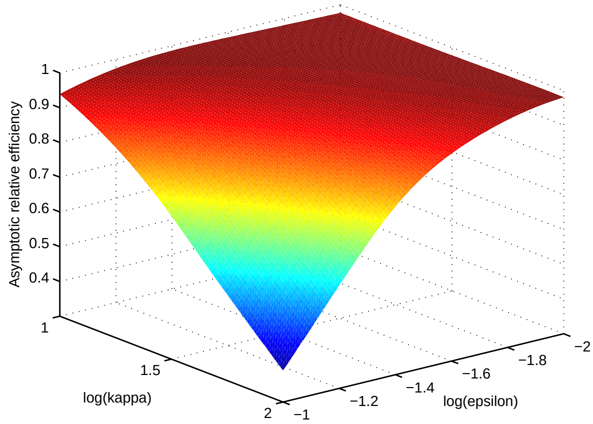

Fig. 2. Asymptotic relative efficiency of Huber's minimax M-estimator to that of the adaptive algorithm.

certain number of times and cannot be predicted beforehand because they strongly depend on the particular channel and noise environment. For the adaptive algorithm the weights of the basis functions have to be estimated for constructing the influence function, where matrix inversion is required.
In order to evaluate the computational complexity of the different algorithms we count the number of basic additions and multiplications, i.e. $O(\mathbb{R} + \mathbb{R})$ and $O(\mathbb{R} \cdot \mathbb{R})$. Each mathematical operation may be reduced to basic calculations, e.g. $O(\mathbb{C}^{N \times 2} \cdot \mathbb{R}^{2 \times N}) = 4N \cdot O(\mathbb{R} \cdot \mathbb{R}) + N \cdot O(\mathbb{R} + \mathbb{R})$. For the two M-estimators with static influence function the complexity of evaluating the function $\psi(\hat{\mathbf{v}})$ is negligible. For the parametric detector the complexity strongly depends on the choice of bases. In order to obtain a general and fair comparison which is valid for any set of bases we neglect the complexity of evaluating $\psi(\hat{\mathbf{v}})$ for all three detectors.
The computation of the pseudoinverse takes $2NM^2O(\mathbb{R} \cdot \mathbb{R}) + M(N(M-1) + M(N-1))O(\mathbb{R} + \mathbb{R}) + O(M^3)$ iterations. After several simplifications one obtains the expressions in Table 1.
B is the number of bases and I_1, I_2 are the number of iterations until convergence is reached. To summarise we can say that the one-step M-estimator has a complexity which is proportional to MN while the complexity of the other two estimators is proportional to I_1MN and I_2MN respectively. In general, it takes four to five iterations until convergence is reached for the M-estimator whereas the parametric detector needs seven to eight iterations until it converges. This is due to the fact that the influence function has to be estimated.

6. SIMULATIONS

We compare the linear decorrelator, the one-step M-estimator, the M-estimator, a smoothed version of the M-estimator with

	$O(\mathbb{R}+\mathbb{R})$	$O(\mathbb{R}\cdot\mathbb{R})$	$O(B^3)$
one-step M-estimator	$4M(2N+1)$	$16MN+4M+2N$	–
M-estimator	$I_1\cdot 4M(2N+1)$	$I_1\cdot(16MN+4M+2N)$	–
parametric detector	$I_2[B(1+B(N+1))+4M(2N+1)]$	$I_2[N(B^2+1)-2+(16MN+4M+2N)]$	I_2

Table 1. Comparison of the robust algorithms in terms of computational complexity

the influence function $\psi(x) = \tanh(x/\sigma)$ and the parametric adaptive estimator for different noise distributions. It was found out that there is hardly a difference in performance between the soft-limiter and the $\tanh(x)$ influence function used for the M-estimator. For this reason only the curves for the M-estimator are plotted in the figures. The channel is assumed as Rayleigh fading with parameter $r = 1/\sqrt{2}$ and we consider Hadamard codes for the spreading sequences with length $N = 128$. The *Bit-error-rate* (BER) is calculated over 10000 MC simulations. Simulations with different orthogonal codes, mentioned in Section 2, showed no significant difference in performance. The *Signal-to-noise-ratio* (SNR) is defined as the power of the received signal divided by the noise power before decorrelation of the spreading sequences is applied, i.e.

$$SNR = \frac{A^2(|h_1|^2+|h_2|^2)}{\sigma^2} \tag{20}$$

We want to analyse the influence of impulsive noise on a linear detector and compare its performance, i.e. BER, to robust detectors in non-Gaussian noise environments. We assume a Gaussian mixture noise pdf as presented in Section 3 in order to model impulsive noise. Simulation results are shown in Fig. 3. We observe that even for very small contamination,

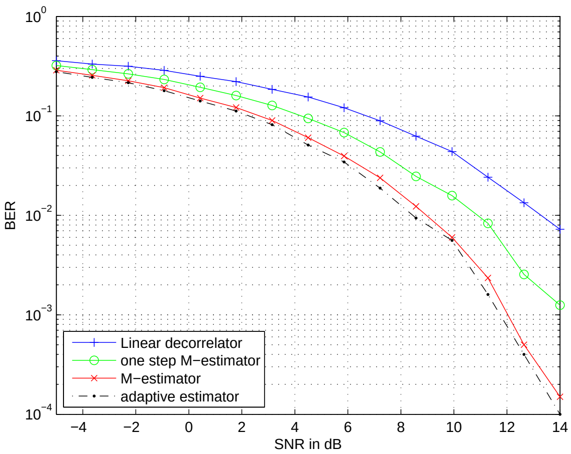

Fig. 3. SNR versus BER in Gaussian mixture noise with parameters $\varepsilon = 0.03$ and $\kappa = 75$

here $\varepsilon = 3\%$, the BER of the linear detector is significantly higher than the BER of the other non-linear detectors. We observe that the one-step M-estimator gains about $3dB$ in performance against the linear detector while we gain again $2dB$ when considering the parametric estimator and M-estimator which almost have the same performance. This is due to the fact that for this particular value of ε and κ, both estimators have the same efficiency which can be verified in Fig. 2. However, when we consider a more impulsive noise environment, i.e. we increase the percentage of contamination, we obtain a slightly different result. In Fig. 4 simulations are shown for the noise parameters $\varepsilon = 0.07$ and $\kappa = 45$. Again,

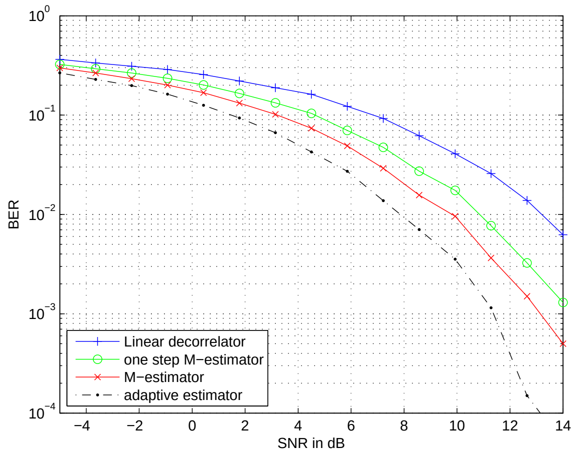

Fig. 4. SNR versus BER in Gaussian mixture noise with parameters $\varepsilon = 0.07$ and $\kappa = 45$

all three robust detector outperform the linear detector but one can notice that the parametric detector has a gain of $2dB$ over the M-estimator which is in accordance to Fig. 2.

For the next simulation we consider noise with parameter $\varepsilon = 0.1$ and $\kappa = 100$ which lies at the edge of the (ε, κ)-parameter space. Results are shown in Fig. 5. One can observe that the difference in performance among the proposed detectors increases significantly. For these particular noise parameters which represent the most impulsive noise pdf, the difference between the linear detector and the parametric detector is more than $8dB$. The parametric detector with B bases gives an improvement of $4dB$ in performance over the M-estimator. For simplification purposes we assume that the computational cost of an addition and a multiplication is the same. Then we can deduce that the computational complexity

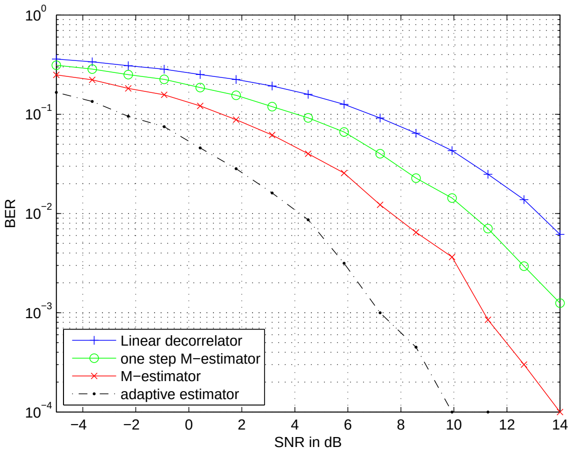

Fig. 5. SNR versus BER in Gaussian mixture noise with parameters $\varepsilon = 0.1$ and $\kappa = 100$

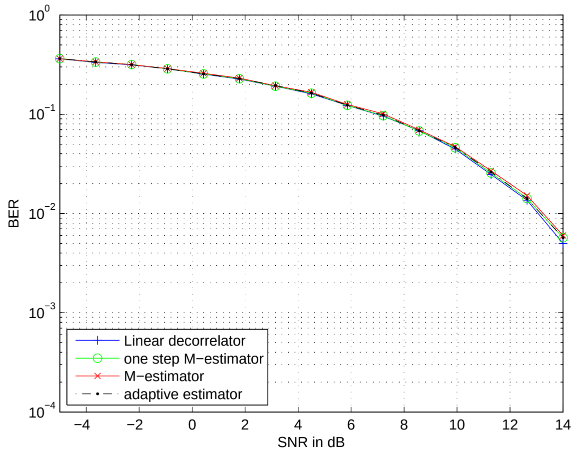

Fig. 6. SNR versus BER in Gaussian noise

is increased by a factor $2.3 \cdot I_2/I_1$ where B equals four and I_2 can be assumed in the range between six and eight. Roughly speaken, when considering the number of iterations, we can say that the computational cost of the parametric detector is increased by factor 4 over Huber's M-estimator.

Now we are interested how the robust detectors do behave in Gaussian noise environments which is shown in Fig. 6. We note that there is no significant difference in performance of the four detectors. We can summarise that the soft-limiter, with one or several iteration steps, has approximately the same performance as the linear decorrelator in the Gaussian noise environment and significantly outperforms the linear decorrelator in impulsive noise environments. Hence, in the Gaussian case there is a negligible loss in performance but when impulsive noise is present we have a large increase in performance. The same is true for the parametric detector with the addition that it significantly gains performance if the noise behaviour becomes more impulsive considering apriori knowledge about the noise model.

However, if we compare the four different detectors with each other, one can see that the more sophisticated the detectors the better the performance due to a significant increase in computational complexity.

7. CONCLUSIONS

In a transmitter diversity scheme three robust detectors have been applied in order to improve the performance in impulsive noise environments. It was shown that each of the detectors significantly outperforms the linear detector in these environments and the performance loss of the non-linear detectors in Gaussian noise environments is negligible A complexity analysis of the detector has been provided in order to tradeoff complexity versus performance. The disadvantage of the non-linear detectors is that they need to have perfect knowledge of all the spreading sequences in order to decorrelate the signal. It would be desirable to design a robust detector which blindly decorrelates the spreading sequences and is insensitive to impulsive noise. This approach will be considered in future work. Furthermore, an approach for modelling the score function, by estimating the noise pdf in a semiparametric way, is currently under investigation.

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