MLSE AND SPATIO-TEMPORAL INTERFERENCE REJECTION COMBINING WITH ANTENNA ARRAYS

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ABSTRACT

By using multiple receiving antennas and modeling co-channel interference (CCI) together with the noise as additive temporally white Gaussian noise with some spatial color, CCI may be suppressed. This paper proposes spatio-temporal interference rejection combining by modeling the CCI and noise as an autoregressive Gaussian process. In this way, the joint spatial-temporal properties of the CCI may be taken into account. A training sequence based estimator is proposed, and simulations show large gains in CCI rejection as compared to only spatial processing for small antenna arrays in interference limited GSM urban scenarios. An example with data collected with a dual polarized antenna in a suburban environment is also presented.

1 INTRODUCTION

The use of wireless communication systems has undergone a rapid growth during the last decade. The physical limitations of the radio channel and the limited radio spectrum makes it non-trivial to meet the demands on higher data rates, quality and availability. Among the possibilities is a more efficient use of the spatial dimension by employing multiple antennas at different locations in space with possibly different polarizations. This work is concerned with detecting the transmitted data in the presence of co-channel interference (CCI) and intersymbol interference (ISI) using a maximum likelihood sequence estimator (MLSE) and multiple antennas at the receive side.

Previous work includes [2, 3, 9, 11], in which the CCI is modeled as a Gaussian noise process. In [2, 3], the noise process is assumed to be temporally white. Only the spatial color of the interference is taken into account, and an MLSE is implemented with a vector valued Viterbi algorithm. In [9, 11], the temporal correlation of the interference is noted, and space-time receive filters are derived to reduce the observations to a scalar statistic.

In the general case, the temporal correlation of the noise process may cause the number of states in the sequence estimator implemented with the Viterbi algorithm to become very large. In addition, with short data bursts, estimating the channel for the signal of interest and the second order statistics of the noise is a non-trivial task. Therefore, the practical implementation in [7, 8], models the noise as temporally white. If only the spatial correlation of the CCI is taken into account, the number of sensors needed may be quite large, as the CCI contribution is to be low rank in order to be effectively suppressed [7]. However, by taking the joint spatial-temporal properties of the CCI into account, the condition is that the number of interferers is to be strictly less than the number of antennas [9].

In this work, we propose modeling the CCI and noise as a Gaussian vector valued autoregressive (VAR) process. In this way, it is possible to take the joint spatial-temporal correlation of interference into account and solve the problem of CCI reduction and ISI equalization. The resulting implementation will then use the parameters of the VAR process as a vector valued FIR whitening filter to temporally whiten the noise and an MLSE, implemented with the Viterbi algorithm, to detect the transmitted data. A training sequence based estimator of the VAR parameters and the filtered channel is proposed, and performance is investigated by means of simulations of GSM scenarios. The numerical results show large gains in interference suppression for small antenna arrays. This is significant, as mobile terminals with multiple antennas may be one way to balance up and downlink performance [3]. Clearly, space limitations will prevent equipping the mobile terminals with a large number of antennas In addition, results from data collected in a suburban environment with a dual polarized antenna are included.

2 DATA MODEL

The model used to describe the symbol sampled signal received by an array with m elements is

$$\mathbf{x}(t) = \mathbf{H}\mathbf{s}(t) + \mathbf{n}(t)\,, \tag{1}$$

where $\mathbf{x}(t)$ is an $m \times 1$ vector representing the array output and $\mathbf{H}$ is an $m \times L$ matrix modeling the linear channel between the transmitter and the receiving array,

$$\mathbf{H} = [\mathbf{h}_1\ \mathbf{h}_2\ \ldots \mathbf{h}_L]\ .$$

The symbol sequence transmitted from the user of interest, $s(t)$, is used to construct $\mathbf{s}(t)$ as

$$\mathbf{s}(t) = [s(t)\ s(t-1)\ \ldots\ s(t-L+1)]^T\,.$$

Oversampling with respect to the symbol period may be modeled by increasing the number of channels.

The term $\mathbf{n}(t)$ represents noise and interference. In [2, 3, 7, 8], this term is modeled as a temporally white complex Gaussian process. This is clearly suboptimal as the CCI has the same properties as the signal of interest, finite alphabet and in the time-dispersive case, some temporal correlation. The goal of this work is to take the joint spatial-temporal correlation of the noise and CCI into account in a feasible way. An attractive model for this purpose is to use a Gaussian

VAR process. The noise is then assumed to obey the following model

$$\mathbf{n}(t) = \sum_{k=1}^{K} \mathbf{A}_k \mathbf{n}(t-k) + \mathbf{e}(t)\,, \tag{2}$$

where $\mathbf{e}(t)$ is a temporally white complex Gaussian process with some spatial color, $\mathbf{Q}$,

$$\mathrm{E}\left\{\mathbf{e}(t)\mathbf{e}^*(s)\right\} = \mathbf{Q}\delta_{t,s}\,.$$

Note that this model also is an approximation. The observations will in general not obey this AR-model. The finite alphabet property is for example not taken into account. Some attractive features for this choice are

- The whitening filter, which coincides with the Kth order best linear predictor, is given by the process parameters $\{\mathbf{A}_k\}$, and is FIR. The FIR filter introduces a finite number, K, of additional states in the sequence estimator.
- For zero thermal noise and Gaussian transmitted signals, the true moving average model for the interference may be represented by a VAR process [6]. For interference limited scenarios with the number of interferers strictly less than the number of antennas, it appears suitable.

2.1 Spatio-Temporal Formulation

It is convenient to introduce the following notation. Collect $K+1$ vectors $\mathbf{x}(t)$ into the vector $\mathcal{X}(t)$ as

$$\mathcal{X}(t) = \left[\mathbf{x}^T(t)\ \mathbf{x}^T(t-1)\ \ldots\ \mathbf{x}^T(t-K)\right]^T\,,$$

and form the $m(K+1)\times(L+K)$ block Toeplitz matrix $\mathcal{H}$,

$$\mathcal{H} = \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \cdots & \mathbf{h}_L & & \\ & \ddots & & & \ddots & \\ & & \mathbf{h}_1 & \mathbf{h}_2 & \cdots & \mathbf{h}_L \end{bmatrix}.$$

With

$$\mathcal{S}(t) = [s(t)\ s(t-1)\ \ldots\ s(t-L-K+1)]^T\,,$$

and $\mathcal{N}(t)$ defined similar to $\mathcal{X}(t)$, the following space-time model may be formulated from (1):

$$\mathcal{X}(t) = \mathcal{H}\mathcal{S}(t) + \mathcal{N}(t)\,. \tag{3}$$

In addition, with

$$\mathcal{A} = [\mathbf{A}_1\ \ldots\ \mathbf{A}_K]\,, \qquad \mathcal{W}(\mathcal{A}) = [\mathbf{I}_m\ \ -\mathcal{A}]\,,$$

the VAR model of (2) may be formulated as

$$\mathcal{W}(\mathcal{A})\mathcal{N}(t) = \mathbf{e}(t)\,. \tag{4}$$

3 ESTIMATORS

3.1 Sequence Detection

Let us for a moment assume that all parameters are known. Consider (3) and (4). Multiplying both sides of (3) with $\mathcal{W}(\mathcal{A})$ and using (4) gives

$$\mathcal{W}(\mathcal{A})\mathcal{X}(t) = \mathcal{B}\mathcal{S}(t) + \mathbf{e}(t) \tag{5}$$

where $\mathcal{B}$ defined as

$$\mathcal{B} = \mathcal{W}(\mathcal{A})\mathcal{H} = [\mathbf{b}_1\ \mathbf{b}_2\ \ldots\ \mathbf{b}_{L+K}]\,, \tag{6}$$

and represents the concatenated response of the AR-predictor $\mathcal{W}(\mathcal{A})$ and the channel $\mathbf{H}$, i.e. $\mathbf{H}$ convolved with the AR-predictor.

Sequence estimation is considered, although other detection schemes are also applicable. Due to the Gaussian property of the noise, the maximum likelihood sequence estimate is given by

$$\{\hat{s}(t)\} = \arg\min_{\{s(t)\}} \sum_t \|\mathcal{W}(\mathcal{A})\mathcal{X}(t) - \mathcal{B}\mathcal{S}(t)\|^2_{\mathbf{Q}^{-1}}\,, \tag{7}$$

where $\|\mathbf{z}\|^2_{\mathbf{W}} = \mathbf{z}^*\mathbf{W}\mathbf{z}$. Note that the metric increment, i.e. each term in the sum, is a function of $\mathcal{S}(t)$, and that the search over allowed sequences may be implemented with the Viterbi Algorithm with a memory of $L+K-1$ symbols.

Whitening the noise introduces additional intersymbol interference (ISI), and it is of interest to keep the number of states small. Similar to e.g. [11], it is possible to rewrite the sequence metric, in order to arrive at an alternative implementation with a matched space-time filter followed by an MLSE operating on a scalar signal.

3.2 An Unstructured Estimator

As is clear from the previous section, the channel and the noise parameters are needed for the sequence detection. Although the optimality of the MLSE with estimated parameters may be discussed, the approach taken is to estimate the parameters using data from a training period, and then use the estimated parameters in (7) to obtain the sequence estimate. It is assumed that the signal of interest and the interference are roughly burst-synchronized and that the scenario is time-invariant so that all parameters may be estimated during the training period. An example of such a system is the GSM system with synchronized base stations and not too large cells so that the synchronism is reasonably accurate.

A simple, unstructured approach is now taken. If the structure of $\mathcal{B} = \mathcal{W}(\mathcal{A})\mathcal{H}$ in (6) is neglected, the model of (5) may be recognized as an *ARX* model [10]. The maximum likelihood (ML) estimates of the parameters are now derived. Equation (5) may be rewritten as

$$\mathbf{x}(t) = [\mathcal{A}\ \ \mathcal{B}]\,\mathbf{z}(t) + \mathbf{e}(t)$$

where

$$\mathbf{z}(t) = \left[\mathbf{x}^T(t-1)\ \mathbf{x}^T(t-2)\ \ldots\ \mathbf{x}^T(t-K)\ \ \mathcal{S}^T(t)\right]^T\,.$$

During the training period, $s(t), t = t_1 \ldots t_N$ is known which means that $\mathbf{z}(t)$ may be formed for $t = t_{L+K} \ldots t_N$. Under the assumption that the noise and CCI are uncorrelated with the signals, the negative likelihood function is given by

$$l(\mathcal{A},\mathcal{B},\mathbf{Q}) = \ln|\mathbf{Q}| + \mathrm{trace}\ \mathbf{C}(\mathcal{A},\mathcal{B})\mathbf{Q}^{-1}\,,$$

where

$$\mathbf{C}(\mathcal{A},\mathcal{B}) = \hat{\mathbf{R}}_{xx} - \hat{\mathbf{R}}_{xz}[\mathcal{A},\mathcal{B}]^* - [\mathcal{A},\mathcal{B}]\hat{\mathbf{R}}^*_{xz} + [\mathcal{A},\mathcal{B}]\hat{\mathbf{R}}_{zz}[\mathcal{A},\mathcal{B}]^*\,,$$

$$\hat{\mathbf{R}}_{zz} = \frac{1}{N-L-K+1}\sum_{i=L+K}^{N} \mathbf{z}(t_i)\mathbf{z}^*(t_i)\,,$$

and with $\hat{\mathbf{R}}_{xz}$ and $\hat{\mathbf{R}}_{xx}$ formed as $\hat{\mathbf{R}}_{zz}$. As is well known, $l(\mathcal{A},\mathcal{B},\mathbf{Q})$ is minimized with respect to $\mathbf{Q}$ for $\hat{\mathbf{Q}} = \mathbf{C}(\mathcal{A},\mathcal{B})$. Neglecting constants, the concentrated cost function becomes

$$\begin{aligned} l(\mathcal{A},\mathcal{B}) = \log|\mathbf{C}(\mathcal{A},\mathcal{B})| = \log|&\hat{\mathbf{R}}_{xx} - \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}^{-1}_{zz}\hat{\mathbf{R}}^*_{xz} \\ &+ ([\mathcal{A},\mathcal{B}] - \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}^{-1}_{zz})\hat{\mathbf{R}}_{zz}([\mathcal{A},\mathcal{B}] - \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}^{-1}_{zz})^*| \end{aligned}$$

which is minimized for $[\mathcal{A}, \mathcal{B}] = \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}_{zz}^{-1}$ [10]. This requires $\hat{\mathbf{R}}_{zz}$ to be invertible, which it is with probability one for $Km + L + K \leq N - L - K + 1$. Thus, under the modeling assumptions, the ML estimates are given as

$$[\hat{\mathcal{A}}, \hat{\mathcal{B}}] = \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}_{zz}^{-1}, \qquad \hat{\mathbf{Q}} = \hat{\mathbf{R}}_{xx} - \hat{\mathbf{R}}_{xz}\hat{\mathbf{R}}_{zz}^{-1}\hat{\mathbf{R}}_{xz}^{*}.$$

For $K = 0$, only spatial interference rejection, the estimates coincides with the approach taken in [3, 7, 8].

The estimator is sub-optimum in the sense that the structure of $\mathcal{B} = \mathcal{W}(\mathcal{A})\mathcal{H}$ is not taken into account. This means that the model is over-parameterized, which will lead to higher variance in the estimated parameters. Formulating estimators that take the structure of $\mathcal{B}$ into account is also possible. An alternative is the iterative generalized least squares method [10]. Preliminary investigations indicate that the performance gain using a structured estimator is relatively small. However, the estimates are computed in a simple way, and for the sequence detection, an estimate of $\mathcal{B}$ is needed rather than $\mathbf{H}$. If a training sequence of length N is used, a necessary condition for identifiability is that the number of parameters to be estimated is less than the number of equations,

$$m^2 + 2Km^2 + 2(L + K)m \leq 2(N - L - K + 1)m$$

Thus, the number of unknown parameters increases with $m^2 + m$ for each extra temporal lag, K. This prevents using this form of unstructured modeling of the CCI and noise for large antenna arrays. On the other hand, for large antenna arrays, spatial interference rejection may be sufficient.

4 NUMERICAL EXAMPLES

Simulations of synchronized GSM scenarios with two and four antennas were conducted. The fading was modeled as independent from antenna to antenna, and each antenna was equipped with a fourth order Butterworth filter with a 3dB bandwidth of 200 kHz. The raw baud rate is 270 kbit/s, and GMSK modulation with $BT = 0.3$ was used [5]. The training sequence is 26 symbols long. Ideal frequency hopping was assumed, so that the channel realizations were independent from burst to burst, and the channels were assumed time-invariant during the bursts.

In the first scenario, an antenna with two elements was used, and one synchronized interferer was present. The channels for the signal of interest and the interferer were GSM typical urban (TU) from [4] with a time-dispersion of about one symbol period. Different choices of K were considered, and $K = 0$ corresponds to the previously studied spatial interference rejection in [2, 3, 7, 8]. The length of the filtered channel, $\mathcal{B}$, was held constant (2×5) so that the number of states in the sequence estimator was the same for all choices of K. The signal to noise ratio (SNR) after the receive filters was 20 dB at each antenna, and the carrier-to-interference ratio (C/I) was varied. The raw bit-error-rate (BER) after detection was considered, and in Figure 1 the results are shown. This example demonstrates that taking the spatio-temporal properties of the interference into account may give substantial gains in terms of interference rejection. For $K = 1$, the gain over the conventional spatial interference rejection is about 10 dB at BER 5%. The region of interest is usually 1-10% BER for GSM. For $K = 2$, a gain of additional 15 dB is obtained. For high C/I, the noise is the dominant error source, and the over-modeling of the temporal correlation leads to higher BER for the proposed approaches, as the number of parameters to be estimated is larger. However, for urban environments, CCI is probably the dominant problem. It is also the noise that causes the $K = 2$ curve to be flat for medium CCI. At lower SNR, the "knee" is present for higher BER.

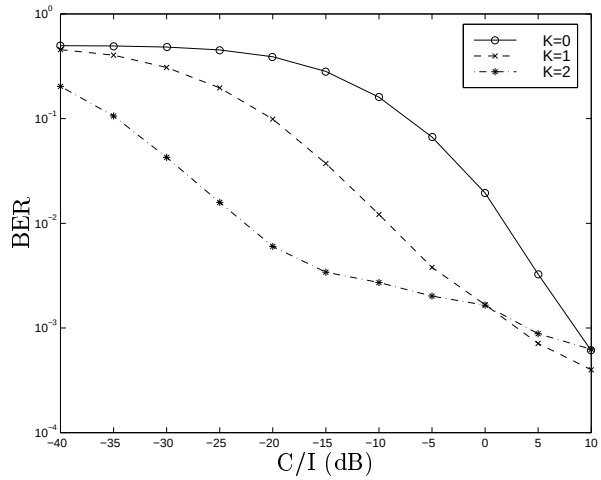

Figure 1: Typical urban scenario, two antennas, SNR 20 dB

Next, an array with four diversity channels in an interference limited scenario, SNR 20dB, was considered. Four channels with independent fading may be obtained with for example two dual polarized antennas with large separation. The channels of the signal of interest and the interferers were again the TU channel, and the number of interferers was varied. For a single interferer, spatial interference rejection usually suffices, but as can be seen in Figure 2, joint spatio-temporal processing provides gains in interference rejection also in this case. For high C/I, the scenario is noise limited, and estimation errors cause the spatio-temporal modeling to perform worse than only spatial processing with $K = 0$.

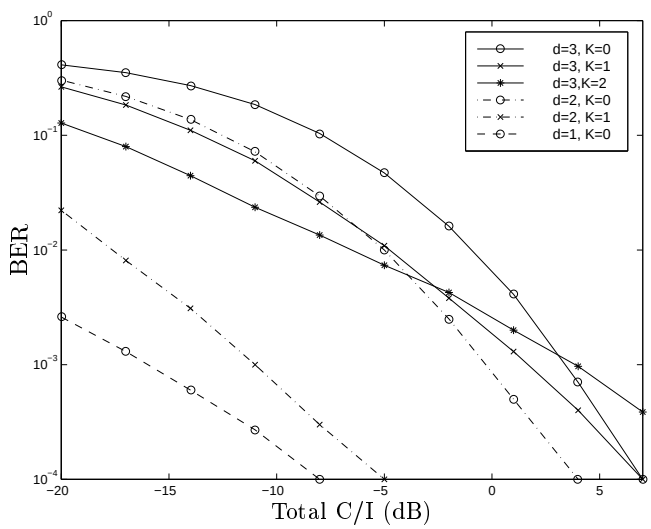

Figure 2: Typical urban scenario, $d = 1, 2, 3$ interferers, four antennas, SNR 20 dB

Finally, the impact of time-dispersion was studied . The channels of the signal of interest and the interferer were modeled as two-ray channels. The time-delays were the same for

both antennas, and the fading was assumed independent from antenna to antenna. The continuous time impulse response was thus $\mathbf{h}^0\delta(t) + \mathbf{h}^1\delta(t-\tau)$. The delay of the second was varied in steps of $T_b/4$, where T_b is the bit-period. In Figure 3, the results are shown. In this simulation, the length of the filtered channel, $\mathcal{B}$ was increased with K. As can be seen, the

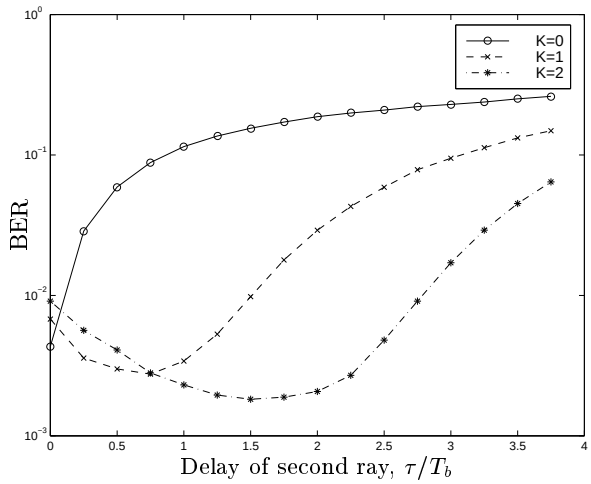

Figure 3: Two-ray channels, SNR 20 dB, C/I -6dB, two antennas

spatio-temporal modeling of the co-channel interference may handle greater time-dispersions. For zero time-dispersion, the interference is rank one, and spatial only processing suffices for interference rejection. For greater time-dispersions, joint spatio-temporal processing is required.

5 EXPERIMENTAL RESULTS

To further investigate the performance of joint spatial-temporal processing for interference rejection, data collected in a suburban environment in Düsseldorf, Germany, with a testbed for the air interface of a DCS-1800 base station [1] was processed. Two sets of data were simultaneously collected, one set with data from a dual polarized array with eight outputs and one set with data from a single dual polarized sector antenna with two outputs. One mobile transmitter and one interferer were present on the air simultaneously.

For the dual polarized sector antenna with two outputs, a gain of 3-5 dB was observed at BER 0.01-0.1. The results of processing 20000 GSM bursts are shown in Figure 4.

The time-dispersion was very small, and spatial interference rejection sufficed for interference rejection with the antenna array. In fact, estimation errors made the spatio-temporal processing perform slightly worse than spatial-only processing.

6 SUMMARY

Autoregressive modeling of the noise and CCI was proposed for the purpose of spatio-temporal interference rejection combining. A training sequence based estimator was studied in interference limited scenarios in simulations and on experimental data collected in a suburban environment. The examples illustrated that the spatio-temporal processing is advantageous for small antenna arrays. For large antenna arrays and a small number of interferers, spatial-only processing

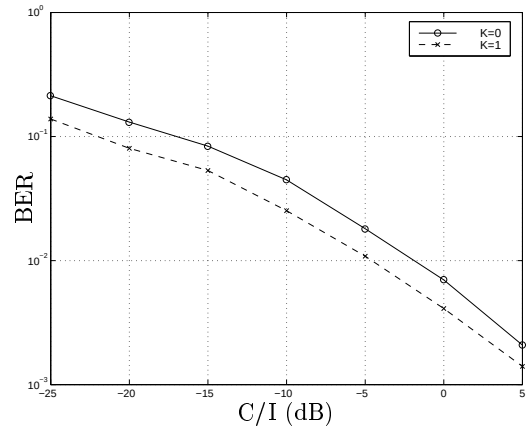

Figure 4: Experimental data, dual polarized sector antenna.

may yield satisfactory performance. In addition the simulations indicated the tradeoff between between increased interference rejection and estimation errors due to the increasing number of parameters when only a short training sequence is available.

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