Reducing the complexity of the space-time channel estimate at minimum risk

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Abstract—**In mobile communication system there is the need to define a channel length that could be useful to describe many different and varying propagation environments, over-parameterization is a simple solution. The channel matrix estimated when using an array of antennas may contain more parameters than those really needed to parsimoniously describe the space-time channel. The problem is even worse when a long channel has to be estimated from short training sequences.**

Classically the reduction of complexity is carried out by masking some samples of the channel estimate according to a theshold heuristically defined. In this paper we propose to adaptively classify (and mask) the estimated channel samples by minimizing the Bayes risk for space-time systems. The parameters of the probability densities are iteratively estimated from the estimated channel samples and contribute to define the optimum threshold. Simulation shows that in Rayleigh fading channels the adaptive threshold is close to the one that minimize the mean square error. The performance can improve by approx. 3-5dB in signal to noise ratio when the method is applied to reduce the complexity of space-time channels in CDMA system with realistic propagation environments.

I. Introduction

DS/CDMA is the preferred multiple access technique for third generation cellular systems. The capacity of CDMA systems can be increased by integrating space-time (S-T) processing and multiuser detection (S-T multiuser detection) to reduce the average level of interference (self-interference, intra-cell and inter-cell interference) [1]. This approach requires the estimation of the S-T features of the channels for all the active users. In a time-slotted CDMA system such as TDD-UTRA standard [2] the channel estimation is based on the transmission of training sequences known at the receiver. The performance is restricted by the reduced length of these training sequences and by the large number of parameters that have to be estimated for S-T processing. According to the "principle of parsimony" the number of parameters has to be restricted only to those really necessary for the S-T multiuser detection.

Even if the S-T channel has a rather complex structure due to the multipath propagation, the paths can be grouped into few temporally separated clusters (i.e., below angular and temporal resolution). This implies that the unstructured estimate of the S-T channel involves more time samples than really necessary, a simplification along the temporal axis is in order. With respect to the approach in [3] here we propose to take the least squares (LS) estimate of the S-T channel matrix $\mathbf{H}^{(k)}$ and set to zero (*mask*) only those samples of the matrix $\mathbf{H}^{(k)}$ (for the k-th user) that have small values. With respect to the routinely employed methods that pick the most significant taps of the channel samples here we propose that the S-T matrix is pre-whitened to have an uncorrelated estimation noise. In addition, the threshold value is chosen from a statistical analysis of the elements of the S-T channel matrix according to the likelihood ratio test (LRT) to minimize the Bayes risk function [4]. The statistical model of the pre-whitened channel estimates for the LRT is based on the Rayleigh mixture model, parameters of the mixture are also iteratively estimated by the LRT [5].

The paper is organized as follows: the model definition and the S-T channel estimation for CDMA systems are discussed in Section 2, the mask for reducing the complexity of S-T channel is in Section 3, Section 4 describes the adaptive threshold method based on the mixture model and it shows that in multipath Rayleigh fading the adaptive threshold approaches the one that minimize the mean square error. Performance for S-T multiuser detection in realistic propagation environments is in Section 5.

II. Space-time channel estimation

The equivalent discrete-time model for symbol synchronous DS/CDMA system is obtained by sampling at the chip rate $1/T_c$ the received signals after the chip matched filter. The signal received by a linear array of M half-wavelength spaced apart antennas for K users be simultaneously active in the same cell is

$$\mathbf{y}_n = \sum_{k=1}^{K} \mathbf{H}^{(k)}\mathbf{x}_n^{(k)} + \mathbf{n}_n. \quad (1)$$

The S-T channel matrix for the k-th user $\mathbf{H}^{(k)} = [\mathbf{h}^{(k,1)}, \ldots, \mathbf{h}^{(k,M)}]^T$ consists of M vectors, each represents the discrete-time channel impulse response $\mathbf{h}^{(k,m)}$ of length W for the link between the k-th user and the m-th antenna (here $1 \leq k \leq K$ and $1 \leq m \leq M$). The noise $\mathbf{n}_n$ is assumed to be Gaussian, with zero mean, temporally uncorrelated but spatially correlated, $E\left[\mathbf{n}_n\mathbf{n}_l^H\right] = \mathbf{R}_{ns}\delta_{l-n}$, $\mathbf{R}_{ns}$ is the space covariance matrix with $[\mathbf{R}_{ns}]_{n,n} = \sigma^2$. The estimation of $\mathbf{H}^{(k)}$ is based on the transmission of the K different training sequences $\{\mathbf{x}_n^{(k)}\}_{k=1}^K$ known at the receiver. By arranging N time samples into the matrix $\mathbf{Y} = [\mathbf{y}_1, \ldots, \mathbf{y}_N]$, the multi-user data model can be written using the standard notation

$$\mathbf{Y} = \sum_{k=1}^{K} \mathbf{H}^{(k)}\mathbf{X}^{(k)} + \mathbf{N} = \mathbf{H}\mathbf{X} + \mathbf{N}, \quad (2)$$

where $\mathbf{X}^{(k)} = [\mathbf{x}_1^{(k)}, \ldots, \mathbf{x}_N^{(k)}]$ denotes the $W \times N$ convolution Toeplitz matrix for the k-th user, $\mathbf{H} = [\mathbf{H}^{(1)}, \ldots, \mathbf{H}^{(K)}]$ and $\mathbf{X} = [\mathbf{X}^{(1)T}, \ldots, \mathbf{X}^{(K)T}]^T$ are multi-user matrices obtained by concatenating the K channels and the K training sequences, respectively.

The unstructured (or least squares) estimates of the S-T channel matrix $\mathbf{H}$ and of $\mathbf{R}_{ns}$ that takes into account for the multiaccess interference are

$$\begin{aligned}\hat{\mathbf{H}} &= \hat{\mathbf{R}}_{yx}\hat{\mathbf{R}}_{xx}^{-1}, \\ \hat{\mathbf{R}}_{ns} &= \hat{\mathbf{R}}_{yy} - \hat{\mathbf{R}}_{yx}\hat{\mathbf{R}}_{xx}^{-1}\hat{\mathbf{R}}_{xy},\end{aligned} \quad (3)$$

where $\hat{\mathbf{R}}_{yx} = \mathbf{Y}\mathbf{X}^H/N$; $\hat{\mathbf{R}}_{xx}$ and $\hat{\mathbf{R}}_{yy}$ are similarly defined. According to the block-structure of the matrix $\hat{\mathbf{H}}$ the channel estimate $\hat{\mathbf{H}}^{(k)}$ for the k-th user is obtained by selecting the k-th block of $\hat{\mathbf{H}}$. Let $\delta\mathbf{H} = \hat{\mathbf{H}} - \mathbf{H}$ be the error of the LS estimate, the covariance matrix of the estimation error can be evaluated by stacking the columns of the matrix $\delta\mathbf{H}$ into a vector $\delta\mathbf{h} = vec\{\delta\mathbf{H}\}$, it follows [3]:

$$\mathbf{R}_H = E[\delta\mathbf{h} \cdot \delta\mathbf{h}^H] = \hat{\mathbf{R}}_{xx}^{-1} \otimes \mathbf{R}_{ns}, \tag{4}$$

recall that asymptotically ($N \to \infty$) $\hat{\mathbf{R}}_{ns} \to \mathbf{R}_{ns}$, properties of Kronecker matrix product can be found in [6]. For (spatially) uncorrelated noise $\mathbf{R}_{ns} = \sigma^2\mathbf{I}_M$, training sequences with $|x_n^{(k)}| = 1$ and ideal correlation matrix $\hat{\mathbf{R}}_{xx} = \mathbf{I}_{KW}$ the mean square error (MSE) of the LS estimate is $E[||\hat{\mathbf{H}} - \mathbf{H}||^2] = \sigma^2 MKW/N$ (or equivalently, the estimation error $[\delta\mathbf{H}]_{m,w} \sim \mathcal{N}(0, \sigma_0^2)$ where $\sigma_0^2 = \sigma^2/N$). For each channel the MSE depends on the ratio between the total number of unknowns in the channel estimates MW and the training sequence length N. As N is limited and fixed, the MSE can be improved by reducing the unknowns to be estimated only to those "really necessary".

III. Reduction of the complexity of S-T channel

The reduction of complexity follows the same steps for rank-reduction of multiuser S-T matrixes as described in [3]. Let $\mathbf{h}(\boldsymbol{\theta})$ be the re-parameterization of the channel matrix for the k-th user in term of a vector of new parameters $\boldsymbol{\theta}$, the re-estimation is carried out on the LS estimate $\hat{\mathbf{h}}^{(k)} = vec\left\{\hat{\mathbf{H}}^{(k)}\right\}$ as the non linear regression

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \left\{(\mathbf{h}(\boldsymbol{\theta}) - \hat{\mathbf{h}}^{(k)})^H \mathbf{R}_H^{(k)\,-1}((\mathbf{h}(\boldsymbol{\theta}) - \hat{\mathbf{h}}^{(k)})\right\}, \tag{5}$$

where $\mathbf{R}_H^{(k)}$ is the k-th block of $\mathbf{R}_H$ (i.e., $\mathbf{R}_H^{(k)} = \mathbf{R}_{xx}^{(k)\,-1} \otimes \mathbf{R}_{ns}$). Optimization (5) implies that the re-estimation has to be carried out after temporal ($\mathbf{R}_{xx}^{(k)\,1/2}$) and spatial ($\mathbf{R}_{ns}^{-1/2}$) pre-whitening of the LS estimate. Here we propose to reduce the complexity of the S-T channel estimate by setting to zero those values of the LS estimate that are below a specified threshold obtained from the statistical analysis of the pre-whitened LS estimate. The re-parameterized channel becomes $\mathbf{h}(\boldsymbol{\theta}) = \mathbf{J}^{(k)}\hat{\mathbf{h}}^{(k)}$ where the *mask* is obtained by a diagonal matrix $\mathbf{J}^{(k)}$, entries of $\mathbf{J}^{(k)}$ are 0 or 1 depending on the value of the samples of the channel estimate. The MSE after mask can be evaluated from the error $\mathbf{h}^{(k)} - \mathbf{J}^{(k)}\hat{\mathbf{h}}^{(k)} = (\mathbf{I}_{MW} - \mathbf{J}^{(k)})\mathbf{h}^{(k)} - \mathbf{J}^{(k)}\delta\mathbf{h}^{(k)}$:

$$MSE^{(k)} = \underbrace{tr\{\mathbf{h}^{(k)}\mathbf{h}^{(k)H}(\mathbf{J}^{(k)} - \mathbf{I}_{MW})\}}_{MSE_{\mathbf{H}}} + \underbrace{tr\{\mathbf{R}_H^{(k)}\mathbf{J}^{(k)}\}}_{MSE_{\delta\mathbf{H}}}. \tag{6}$$

The two contributions in (6) are the MSE obtained by masking the channel samples ($MSE_{\mathbf{H}}$) and by unmasking the noisy LS estimates ($MSE_{\delta\mathbf{H}}$). The trade-off is obtained by selecting the mask $\mathbf{J}^{(k)}$ that minimizes the (6), as over-masking increases $MSE_{\mathbf{H}}$ and under-masking increases $MSE_{\delta\mathbf{H}}$. Recall that the following bounds holds true: $MSE_{\mathbf{H}} \leq \left\|\mathbf{h}^{(k)}\right\|^2$ and $MSE_{\delta\mathbf{H}} \leq tr\{\mathbf{R}_H^{(k)}\}$. The mask that minimizes the MSE (6) needs to be carried out indirectly from the spatially pre-whitened LS estimate only as in this paper we assume $\mathbf{R}_{xx} \simeq \mathbf{I}_{KW}$.

The method discussed below is based on the assumption that in a multipath channel with Rayleigh fading the elements of the spatially pre-whitened channel matrix can be described by simple probability density functions (pdf's). In addition, for closely spaced antennas the fading amplitude is correlated (i.e., at the first order, it differs by a phase shift depending on the direction of arrival of the path) and the mask can be chosen to be time dependent only. This is referred as *temporal-mask* (TM).

IV. The adaptive threshold

Let $\mathbf{Z} = \hat{\mathbf{R}}_{ns}^{(k)\,-H/2}\hat{\mathbf{H}}^{(k)}$ be the $M \times W$ S-T channel matrix for the k-th user obtained after spatial pre-whitening and let the effective samples of the channel L be smaller than W, under Rayleigh fading the complex valued sample $Z_{m,w} = [\mathbf{Z}]_{m,w}$ can be approximated by a random variable that belongs to two disjoint classes (or hypotheses): $Z_{m,w} \sim \mathcal{N}(0, \sigma_0^2)$ with probability $(1-p)$ (hypothesis $\mathcal{H}_0$) or $Z_{m,w} \sim \mathcal{N}(0, \sigma_1^2)$ with probability p (hypothesis $\mathcal{H}_1$), $\sigma_1^2 > \sigma_0^2$. By simplifying the notation as $z = Z_{m,w}$, the hypothesis $\mathcal{H}_0$ is the estimation noise, $z = \delta h \sim \mathcal{N}(0, \sigma_0^2)$, while hypothesis $\mathcal{H}_1$ denotes the combination of channel samples (h) and estimation noise, $z = h + \delta h \sim \mathcal{N}(0, \sigma_1^2)$. The multipath channel samples are chip-spaced with independent and identically distributed Rayleigh fading with variance σ_h^2 so that $\sigma_1^2 = \sigma_0^2 + \sigma_h^2$. The pdf of $|z|$ can be described by the Rayleigh mixture

$$f(|z|) = p\mathcal{R}[|z|; \sigma_1^2] + (1-p)\mathcal{R}[|z|; \sigma_0^2]; \tag{7}$$

the conditional pdf are $p(|z|\ |\mathcal{H}_0) = \mathcal{R}[|z|; \sigma_0^2]$ and $p(|z|\ |\mathcal{H}_1) = \mathcal{R}[|z|; \sigma_1^2]$ (according to the fading assumption); $\mathcal{R}[|\mu|; \sigma^2] = (|\mu|/\sigma^2)\exp(-|\mu|^2/2\sigma^2)$ is the Rayleigh pdf. Here we propose to estimate the mask by selecting those samples $|z|$ that are classified to belong to the hypothesis $\mathcal{H}_1$ from the estimation of the parameters of the mixture (7).

The binary hypothesis test based on the Bayes criterion [4] yields to the likelihood ratio test (LRT)

$$\mathcal{L}(|z|; \sigma_0^2, \sigma_1^2) = \frac{\mathcal{R}[|z|; \sigma_1^2]}{\mathcal{R}[|z|; \sigma_0^2]} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{1-p}{p} \tag{8}$$

that discriminates each of the sample $|z|$ belonging to the noisy channel estimate ($\mathcal{H}_1$) or noise ($\mathcal{H}_0$). The LRT can be reduced to the amplitude threshold

$$|z| \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} S(\sigma_0^2, \sigma_1^2, p) = \left[2\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right)^{-1} \ln\left(\frac{\sigma_1^2}{\sigma_0^2} \cdot \frac{1-p}{p}\right)\right]^{1/2} \tag{9}$$

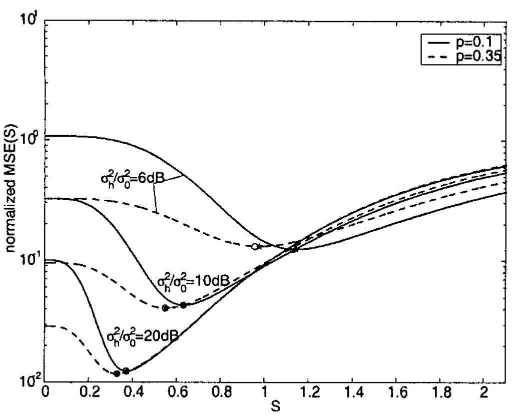

Fig. 1. MSE vs threshold S for varying distribution parameters $\sigma_0^2, \sigma_1^2, p$. Superimposed are the optimum threshold S_{MSE} (marker $\times$) and the LRT threshold from estimated pdf parameters $S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$ (marker ○).

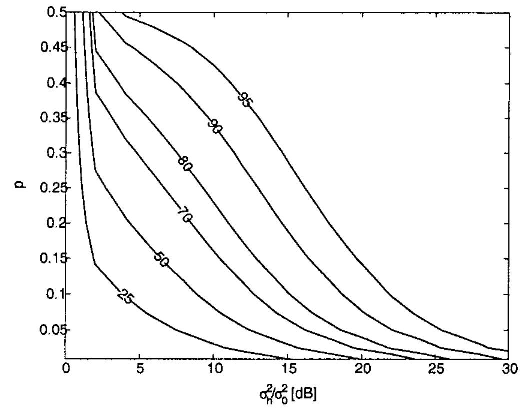

Fig. 2. Optimum energy threshold η from the MSE threshold S_{MSE} for varying distribution parameters $(p, \sigma_h^2/\sigma_0^2)$.

which is more easy to be implemented once the pdf parameters $(\sigma_0^2, \sigma_1^2, p)$ are known. This classification is carried out from the $M \cdot W$ samples of the pre-whitened S-T channel estimate. Since the mask is based on the minimization of the probability of incorrect classification, there is no proof that this classification minimizes the MSE (6). The loss of optimality with respect to the minimum MSE is negligible as shown below.

The pdf parameters $(\sigma_0^2, \sigma_1^2, p)$ can be estimated iteratively from a limited number of samples of the set $\{|z|\}$ according to the decision-directed method for Rayleigh mixture [5]. Let $S^{(i)}$ be the threshold at the i-th iteration obtained from the pdf parameters $(\sigma_0^{(i)2}, \sigma_1^{(i)2}, p^{(i)})$, according to $S^{(i)}$ the whole samples $\{|z|\}$ can be partitioned into two sub-sets $\{|z_{\mathcal{H}_0}^{(i)}|\}$ and $\{|z_{\mathcal{H}_1}^{(i)}|\}$ so that $\{|z_{\mathcal{H}_0}^{(i)}|\} \cup \{|z_{\mathcal{H}_1}^{(i)}|\} = \{|z|\}$. The sample variances and frequency from this partition are an estimate of the new set of pdf parameters $(\sigma_0^{(i+1)2}, \sigma_1^{(i+1)2}, p^{(i+1)})$ for the next iteration. This recursive algorithm converges to an estimate of the pdf parameters $(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$ when $S^{(i)} = S^{(i+1)}$. The pdf parameters estimated with the decision-directed algorithm are biased [5], however the threshold $S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p}) = \hat{S}$ for these estimated values is close to the optimum threshold (i.e., the threshold that minimizes the MSE). Recall that the mask matrix is chosen to set to zero those samples of the set $|Z_{m,w}| < S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$.

A. Mean Square Error (MSE)

The threshold $\hat{S} = S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$ is estimated iteratively to minimize the probability of incorrect classification, the loss of optimality with respect to the threshold that minimizes the MSE can be evaluated for the simple case of Rayleigh mixture (7). Let us consider a large sample size so that (asymptotically) the MSE terms in (6) can be evaluated from the expectations over the single sample

$$MSE_{\mathbf{H}} = P_m E[|h|^2 | \, |h+n| < S] \quad (10a)$$

$$MSE_{\delta\mathbf{H}} = P_{fa} E[|n|^2 | \, |n| > S] + P_d E[|n|^2 | \, |h+n| \quad (10b)$$

expectations $E[.]$ are for the conditional pdf's, P_{fa}, P_d, and P_m denotes the probability of a false alarm, detection and missing, respectively. The $MSE(S) = MSE_{\mathbf{H}}(S) + MSE_{\delta\mathbf{H}}(S)$ can be evaluated analytically from (10a-10b) as function of the threshold S. Fig.1 shows the $MSE(S)$ normalized to the mean channel norm (i.e., $p\sigma_h^2$) vs. S for Rayleigh mixtures with varying $\sigma_h^2/\sigma_0^2 = \{6, 10, 20\}dB$ and $p = \{.1, .35\}$. The threshold S that minimize the MSE (S_{MSE}) is indicate on each plot together with the threshold obtained by the decision directed algorithm $S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$. It can be noticed that for large σ_h^2/σ_0^2 (or equivalently for large signal to noise ratios as for uncorrelated noise $\sigma_0^2 = \sigma^2/N$) $S_{MSE} \simeq S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p})$ while for small σ_h^2/σ_0^2 it is $S(\hat{\sigma}_0^2, \hat{\sigma}_1^2, \hat{p}) < S_{MSE}$ with a slight loss of performance.

Standard practice is to reduce the number of channel estimate by setting a threshold with respect to the channel energy [7]. This can be easily performed in the mixture model after having sorted the MW samples $|Z_{m,w}|^2$ for decreasing values and by retaining only those samples that contribute to a specified fraction η of the overall channel estimate energy $\sum_{m,w} |Z_{m,w}|^2$. The energy fraction η that minimize the MSE depends on the statistical distribution of the channel samples and it can be easily related to the optimum threshold S_{MSE}. Analysis in Fig.2 shows that the energy fraction η that minimize the MSE cannot be fixed but it should be selected adaptively according to the channel parameters $(p, \sigma_h^2/\sigma_0^2)$.

B. Remarks

The statistical model is far from being optimum, few remarks are in order:

Remark 1: The i.i.d. Rayleigh fading model can be modified in order to take into account different power delay profiles (e.g., exponential), the LRT needs to be modified accordingly from the knowledge of the delay profile. However, it can be shown that the Rayleigh mixture (7) is still a reasonable as-

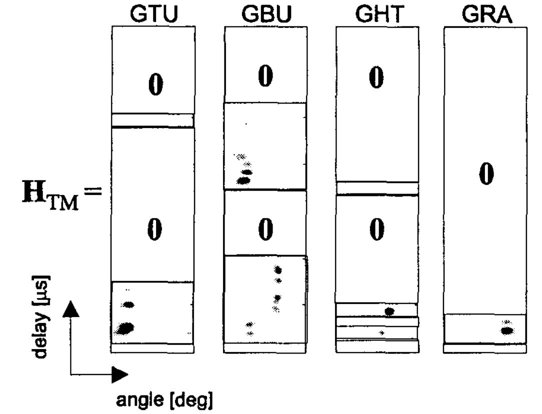

Fig. 3. Example of the power delay/angle profiles for COST 259 generalized propagation environments with the mask.

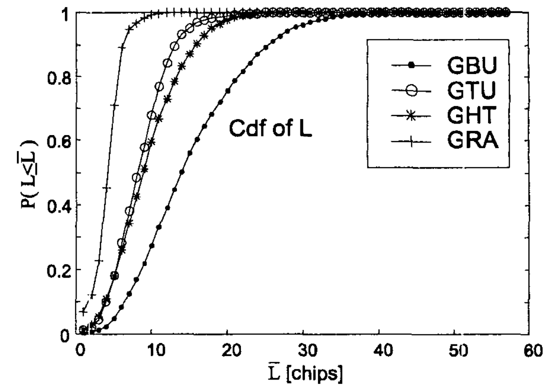

Fig. 4. Distribution of the effective channel length for COST 259 channel models.

sumption for the selection of the threshold S.

Remark 2: In a time slotted CDMA the faded amplitudes are changing but the statistical parameters of the pdf's and the temporal locations of the mask are not changing slot-by-slot. This can be used to employ a multi-slot algorithm for complexity reduction that exploits the slot-invariance of some parameters of the S-T channel.

Remark 3: When the antennas are closely spaced as for the S-T processing considered in this paper the channel taps are spatially correlated. In a multipath model where each path is chip-spaced with one direction of arrival, the S-T channel values differs only by a linearly increasing phase shift $H_{m,w}^{(k)} \simeq H_{1,w}^{(k)} \exp(j\phi_w^{(k)}(m-1))$. The selection variable can be modified by neglecting this phase shift as $d_w = \sum_{m=1}^{M} |Z_{m,w}|^2$. The conditional pdf of d_w is chi-squared or noncentral chi-squared with $2M$ degrees of freedom depending if the hypothesis $\mathcal{H}_0$ or $\mathcal{H}_1$ hold; the noncentral parameter is $M|H_{1,w}^{(k)}|^2$. The LRT and the corresponding threshold can be re-derived for d_w. Similarly to the Rayleigh mixture model, the threshold obtained by estimating the pdf parameters according to the decision directed method with few W samples (e.g., $W \leq 57$ samples in TDD-UTRA system) is likely to yield biased estimate of the pdf parameters. Redundancy from a multi-slot analysis is advisable in this case.

V. Performance Evaluation

The performance of TM channel estimation is evaluated by simulating the time slotted CDMA system proposed for 3rd generation system (TDD-UTRAstandard [2]). Numerical results are for $M = 8$ antennas, $K = 8$ users are active and are randomly located within the tri-sector cell, the channel-length is up to $W = 57$ chips, the spreading codes are $Q = 16$ chips/symbol, the chip shaping is square raised cosine with roll-off 0.22 and chip rate is 3.84 Mchips/s (Traffic Burst 1 of TDD-UTRA). The length of the data block is $N_b = 61$ QPSK modulated symbols, training sequences are chosen according to standard specifications with length $N_m = 512$. Simulations are for spatially uncorrelated and correlated noise to highlight the importance of spatial pre-whitening in masking.

We consider the feasibility of the TM approach in the realistic propagation environments defined by the COST-259 Directional Channel Model [3]: generalized typical urban (GTU), generalized bad urban (GBU), generalized rural area (GRA), generalized hill terrain (GHT). An example of masked S-T channel matrix $\mathbf{H}$ for each propagation scenario is given in Fig. 3 and it shows that the number (L) of the effective time-samples depends on the propagation environment and on the temporal dispersion of the paths. In Fig. 4 the cumulative density function $P(L \leq \bar{L})$ of the effective length L shows that GTU and GRA channels can be described by $L \simeq 15$ and $L \simeq 8$ ($L \ll W$) temporal samples with moderate distortion (here the maximum distortion value is set to 1%).

In Fig. 5 the performance of the LS-TM channel estimate are compared with the LS estimate and fixed energy threshold η. The normalized MSE $||\Delta\mathbf{H}||^2/||\mathbf{H}||^2$ vs. the signal to noise ratio $SNR = E[(||\mathbf{h}^{(k,m)}||^2)]/\sigma^2$ is shown here for GTU channel. The Gaussian noise is spatially correlated as $[\mathbf{R}_{ns}]_{m,l} = \sigma^2\{0.9\exp(-i\pi\sin(\alpha))\}^{l-m}$ and the angle of arrival of the interference α is random within the support $[-\pi/3, \pi/3]$. The adaptive threshold approach (LS+TM) outperforms the LS estimate of approx. 5dB in SNR and it is uniformly better than fixed energy threshold η. The simulations here shows that energy thresholds η should be increased with the SNR similarly to Fig.2.

The receiver, complete of channel estimation and S-T multiuser detection, is considered in Fig. 6 for GTU channels and $K = 8$ users. Since both multiaccess and intersymbol interference arise, block-type MMSE multi-user detector is adopted. Performance is evaluated for uncorrelated and correlated noise. The correlated noise is generated by 3 intercell interferers randomly located within the 120deg support of tri-sector cellular system, propagation channel for each interferer is modelled as GTU. The top of Fig. 6 shows the (average) performance for

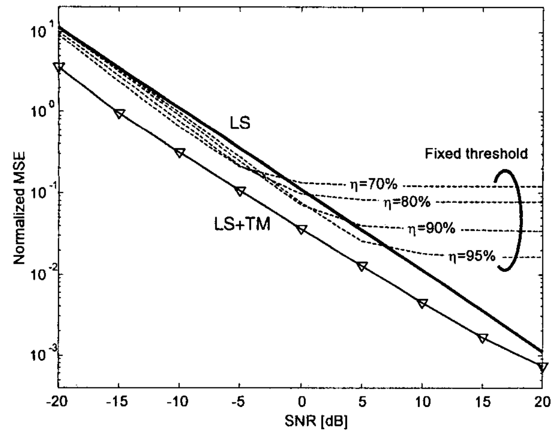

Fig. 5. Performance of TM channel estimation for GTU channel: spatially uncorrelated noise (top) and spatially correlated noise (bottom).

spatially uncorrelated noise in terms of BER for uncoded bits vs. $SNR = E_{bit}/N_0$. The BER for 3 intercell interferers is evaluated vs. signal interference ratio (SIR). The BER for perfect channel state information ($\mathbf{H}, \mathbf{R}_{ns}$ known) is shown as reference. The comparison with respect to the LS estimate of the S-T channel matrix indicates that the gain of the TM with the adaptive threshold is approx. 4÷6dB for all the SNR/SIR values considered here.

VI. Conclusions

The estimate of the channel matrix when using an array of antennas contains more parameters than those really needed to parsimoniously describe the S-T channel. In this paper the threshold of the LS estimate is obtained by classifying the samples of the LS estimate after space pre-whitening. Space pre-whitening is needed to take into account the inter-cell interference. Even if the classification is based on the simple model of Rayleigh fading for chip-spaced rays, the MSE for the classification is close to the optimum. For realistic inter-cell interferences and propagation environments and for the TDD-mode of 3rd generation system that: i) Multi-user channel estimation with adaptive threshold outperforms the least squares channel estimate by approx. 5÷7 dB in signal to noise ratio; ii) the space-time MMSE multi-user detection with reduced complexity channel provides improvements in system performance (evaluated in terms of BER) by at least 4dB in signal to interference ratio.

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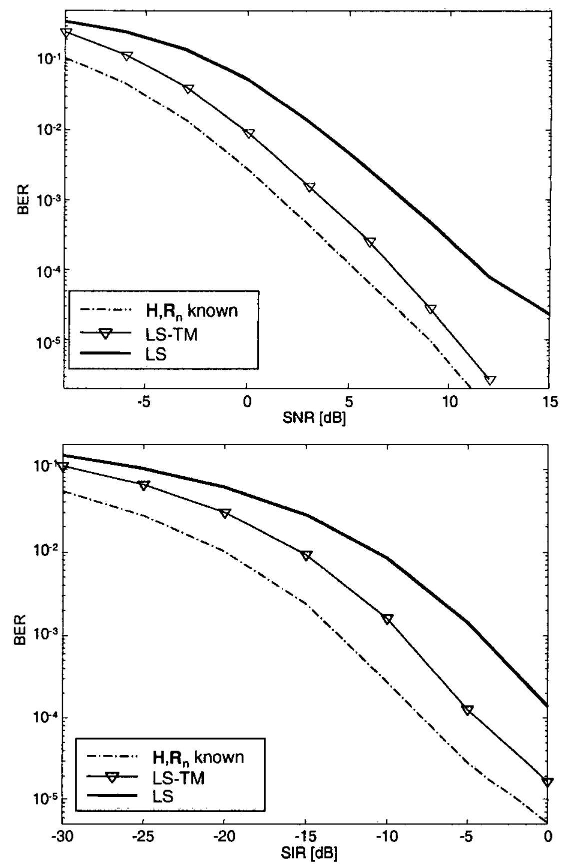

Fig. 6. Average performance of the MMSE S-T multi-user detector with LS channel estimate and LS channel estimate after adaptive threshold (LS+TM): GTU channel, $K = 8$, spatially uncorrelated noise (top) and spatially correlated noise with 3 intercell interferers (bottom).

References

[1] X. Wang, H. V. Poor, "Space-time multi-user detection in multipath CDMA channels", IEEE Trans. Signal Processing, Vol. 47, pp. 2356-2374, Sept. 1999.
[2] ETSI, "Universal Mobile Telecommunications System (UMTS):Physical channels and mapping of transport channels onto physical channels (TDD)" ETSI, TS-125 221 V3.3.0 2000-06.
[3] M. Nicoli, U. Spagnolini, "Reduced rank channel estimation and rank order selection for CDMA systems", Proc. IEEE International Conference on Communications (ICC'01), May 2001.
[4] A. D. Whalen, *Detection of signals in noise*, Academic Press, 1971.
[5] U.Spagnolini, "Cancellation of polarized impulsive noise using an azimuth-dependent conditional mean estimator", IEEE Trans. Signal Processing, vol.46, pp.3333-3344, Dec. 1998.
[6] A. Graham, *Kronecker products and matrix calculus*, Wiley Ed., 1981.
[7] V. Tripathi, A. Mantravadi, V.V. Veeravalli, "Channel acquisition for wideband CDMA signals", IEEE Journal on Selected Areas on Comm., Vol. 18, pp. 1843-1894, Aug. 2000.