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UWB TRANSMITTED REFERENCE RECEIVERS IN THE PRESENCE OF CO-CHANNEL INTERFERENCE

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ABSTRACT

Non-coherent receivers such as transmitted reference receivers recently attracted much interest due to the complexity of coherent ultra wideband (UWB) receivers. In this paper, we investigate the impact of channel state information (CSI) on UWB transmitted reference (TR) maximum likelihood (ML) receivers in the presence of a UWB co-channel interferer (CCI). TR ML receivers are derived assuming the following kinds of channel state information: full CSI, knowledge of the magnitude of the channel impulse response, and no CSI. We compare the performance of these ML estimators with and without CCI by means of bit error rate simulations.

I. INTRODUCTION

According to [1], ultra wideband (UWB) systems have to use a bandwidth of at least 500MHz. Due to this large bandwidth the number of channel taps is very high and the time between adjacent channel taps very small. Thus, coherent UWB receivers are very complex and non-coherent receivers seem to be better suited for UWB devices requiring low complexity. The idea of transmitted reference (TR) systems is known for a long time [2]. To reduce receiver complexity in UWB systems, transmitted reference systems were proposed in [3]. In transmitted reference systems two signals, a reference and a data signal, are transmitted per bit. The information is contained in the sign difference of the reference and the data signal. Since both signals pass the same channel, no explicit channel estimation is necessary. Thus, the reference signal can be used as a template for correlation with the data signal in the receiver.

In many applications, such as in body area networks [4], not only one transmitter-receiver pair is present. Hence, co-channel interference (CCI) is an important issue. To the author's knowledge there exists no derivation of the optimum TR receiver considering CCI and different amount of channel state information (CSI). We consider another UWB TR systems as CCI and derive the maximum likelihood (ML) estimators assuming full CSI, knowledge of the channel impulse response (CIR) magnitudes, and no CSI. In [5], a generalized likelihood ratio test (GLRT) for a single UWB TR system is derived. GLRT derivations for a TR and a differential TR systems are derived in [6] and the performance of both systems compared. An average likelihood ratio test (ALRT) is derived in [7]. Based on the optimum receiver structure, several suboptimal receiver structures are obtained. A TR ML receiver considering interference between reference and data pulse is derived in [8].

The remainder of the paper is organized as follows. In Section II., we describe the considered TR system. The TR ML estimators assuming full CSI, knowledge of the CIR magnitudes, and no CSI are derived in the Sections III., IV., and V., respectively. Simulation results based on the derived TR ML estimators are presented in Section VI. Conclusions are given in Section VII.

II. SYSTEM DESCRIPTION

We consider two TR systems each with one reference and one data pulse transmitted per bit assuming that the delay between two adjacent pulse pairs is larger than between the reference and the data pulse. One TR system is considered as the desired user while the other system is considered as a CCI. Both TR systems are assumed to be synchronous, although it is very unlikely in reality. However, the assumption of two synchronous TR systems yields a worst case scenario. Thus, the two signals at the receiver are given by

$$\vec{d}_R = \vec{h}_1 + \vec{h}_2 + \vec{w}_R \tag{1}$$

for the reference pulses and

$$\vec{d}_D = \vec{h}_1 \cdot s_1 + \vec{h}_2 \cdot s_2 + \vec{w}_D \tag{2}$$

for the data pulses. $\vec{h}_1$ and $\vec{h}_2$ denote the channel of the desired and the interference signal, respectively, and $\vec{w}_D$ and $\vec{w}_R$ contain the additive white Gaussian noise (AWGN) both with variance σ_D^2 and σ_R^2, respectively. The transmitted bits s_1 and s_2 can each be either +1 or -1. To determine the ML estimator the probability $p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \mathrm{CSI}_1, \mathrm{CSI}_2)$ has to be maximized. CSI_1 and CSI_2 denote the amount of the desired user and interferer CSI that is known at the receiver side, respectively.

III. ML ESTIMATION WITH FULL CSI OF DESIRED SIGNAL AND CCI

In a first step, we assume perfect CSI at the receiver side, i.e., $\mathrm{CSI}_1 = \vec{h}_1$ and $\mathrm{CSI}_2 = \vec{h}_2$. Thus, the probability that has to be maximized is given by

$$\begin{aligned} &p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{h}_1, \vec{h}_2) \\ =&p(\vec{w}_R = \vec{d}_R - \vec{h}_1 - \vec{h}_2, \vec{w}_D = \vec{d}_D - \vec{h}_1 s_1 - \vec{h}_2 s_2) \end{aligned} \tag{3}$$

with

$$p(w_{Rk}) = \frac{1}{\sqrt{2\pi\sigma_R^2}} \cdot \exp\left\{ -\frac{w_{Rk}^2}{2\sigma_R^2} \right\} \tag{4}$$

and

$$p(w_{Dk}) = \frac{1}{\sqrt{2\pi\sigma_D^2}} \cdot \exp\left\{-\frac{w_{Dk}^2}{2\sigma_D^2}\right\}. \quad (5)$$

Due to the independence of w_R and w_D and assuming that $\sigma_R^2 = c \cdot \sigma_D^2$, (3) yields

$$\begin{aligned} p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{h}_1, \vec{h}_2, s_2) = \left(\frac{1}{2\pi\sigma_R\sigma_D}\right)^N \\ \cdot \exp\left\{-\sum_{k=1}^{N} \frac{(d_{R,k} - h_{1,k} - h_{2,k})^2}{2c \cdot \sigma_D^2} \right. \\ \left. + \frac{(d_{D,k} - h_{1,k}s_1 - h_{2,k}s_2)^2}{2\sigma_D^2}\right\} \end{aligned} \quad (6)$$

where c can be arbitrary but fixed. Since the transmit bit s_2 of the interferer is not known at the receiver it has to be averaged out. With $s_2 \in \{-1; +1\}$, the distribution of s_2 is given by

$$p(s_2) = \frac{1}{2}\delta(s_2 - 1) + \frac{1}{2}\delta(s_2 + 1) \quad (7)$$

with $\delta(\cdot)$ as the Dirac pulse. Considering only the for the log-likelihood ratio relevant terms in (6) one gets

$$\begin{aligned} p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{h}_1, \vec{h}_2) \propto \int_{-\infty}^{\infty} p(s_2) \cdot \\ \exp\left\{\sum_{k=1}^{N} \frac{h_{1,k}s_1d_{D,k} + h_{2,k}s_2d_{D,k} - h_{1,k}h_{2,k}s_1s_2}{\sigma_D^2}\right\} ds_2 \\ = \frac{1}{2}\exp\left\{\sum_{k=1}^{N} \frac{h_{1,k}s_1d_{D,k}}{\sigma_D^2}\right\} \\ \cdot \left(\exp\left\{\sum_{k=1}^{N} \frac{h_{2,k}d_{D,k} - h_{1,k}h_{2,k}s_1}{\sigma_D^2}\right\}\right. \\ \left. + \exp\left\{-\sum_{k=1}^{N} \frac{h_{2,k}d_{D,k} - h_{1,k}h_{2,k}s_1}{\sigma_D^2}\right\}\right). \end{aligned} \quad (8)$$

Due to $\frac{\exp\{x\}+\exp\{-x\}}{2} = \cosh\{x\}$, (8) can be written as

$$\begin{aligned} p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{h}_1, \vec{h}_2) = \exp\left\{\sum_{k=1}^{N} \frac{h_{1,k}s_1d_{D,k}}{\sigma_D^2}\right\} \\ \cdot \prod_{k=1}^{N} \cosh\left\{\frac{h_{2,k}d_{D,k} - h_{1,k}h_{2,k}s_1}{\sigma_D^2}\right\}. \end{aligned} \quad (9)$$

The likelihood ratio M with full CSI is given by

$$M = \frac{p(\vec{d}_R, \vec{d}_D | s = 1, \vec{h}_1, \vec{h}_2) \cdot P[s = 1]}{p(\vec{d}_R, \vec{d}_D | s = -1, \vec{h}_1, \vec{h}_2) \cdot P[s = -1]} \quad (10)$$

and the log-likelihood ratio L is defined as the logarithm of M, i.e.,

$$\begin{aligned} L = & \ln(M) = \ln\left(\frac{P[s = 1]}{P[s = -1]}\right) \\ & + \ln\left(p(\vec{d}_1, \vec{d}_2 | s = 1, \vec{h})\right) - \ln\left(p(\vec{d}_1, \vec{d}_2 | s = 1, \vec{h})\right). \end{aligned} \quad (11)$$

With $P[s = 1] = P[s = -1]$, the log-likelihood becomes

$$\begin{aligned} L = & 2\sum_{k=1}^{N} \frac{h_{1,k}d_{D,k}}{\sigma_D^2} \\ & + \sum_{k=1}^{N} \left[\ln\left(\cosh\left\{\frac{h_{2,k}d_{D,k} - h_{1,k}h_{2,k}}{\sigma_D^2}\right\}\right)\right. \\ & \left. - \ln\left(\cosh\left\{\frac{h_{2,k}d_{D,k} + h_{1,k}h_{2,k}}{\sigma_D^2}\right\}\right)\right] \end{aligned} \quad (12)$$

Using the approximation $\ln(\cosh(\alpha)) \approx 0.5\alpha^2$, which is valid for small α, we get for the log-likelihood ratio

$$L = \sum_{k=1}^{N} \frac{h_{1,k}d_{D,k} \cdot (\sigma_D^2 - 2h_{2,k}^2)}{\sigma_D^4}. \quad (13)$$

Without CCI (13) becomes

$$L = \sum_{k=1}^{N} \frac{h_{1,k}d_{D,k}}{\sigma_D^2}. \quad (14)$$

This result is the correlation of the received data pulse with the CIR, i.e., a realization of the matched filter.

IV. Maximum likelihood estimation with knowledge of the magnitude of the desired signal and the CCI

Usually, full CSI is not available at the receiver side. However, the CIR can be estimated by transmitting a training sequence that is known to the transmitter. Since the receiver does not know the training sequence of an interferer, it cannot estimate the CCI's CIR. However, it is possible to estimate the magnitude of the CCI's CIR without knowing the training sequence, e.g., if only the CCI is transmitting during the estimation period while the desired user is silent. Therefore, we derive the maximum likelihood estimator assuming the knowledge of the magnitude of desired signal and CCI. The channel $\vec{h}_i$ can be described by $\vec{h}_i = \vec{x}_i \odot \vec{z}_i$ with $z_{i,k} \in \{-1; 1\}$ as the sign of the k^{th} channel tap $x_{i,k}$ and $\odot$ denoting the element-wise multiplication. This yields $\text{CSI}_1 = \left|\vec{h}_1\right| = \vec{x}_1$ and $\text{CSI}_2 = \left|\vec{h}_2\right| = \vec{x}_2$. Thus, the probability that has to be maximized is given by

$$p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{x}_1, \vec{x}_2). \quad (15)$$

Since the signs $\vec{z}_1$ and $\vec{z}_2$ of the channel taps are not known, they have to be averaged out according to

$$\begin{aligned} p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{x}_1, \vec{x}_2) = \int_{-\infty}^{\infty} p(s_2) \cdot \int_{-\infty}^{\infty} \prod_{k=1}^{N} p(z_{2,k}) \\ \cdot \int_{-\infty}^{\infty} \prod_{k=1}^{N} p(z_{1,k}) \cdot p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{h}_1, \vec{h}_2) dz_1 dz_2 ds_2. \end{aligned} \quad (16)$$

With (7), $\sigma_R^2 = c \cdot \sigma_D^2$, and

$$P[z_{i,k}] = \frac{1}{2}\delta(z_{i,k} - 1) + \delta(z_{i,k} + 1) \quad (17)$$

(16) can be written as

$$\begin{aligned}
&p(\vec{d}_R, \vec{d}_D | s_1 = s_i, \vec{x}_1, \vec{x}_2) \\
&\propto \prod_{k=1}^{N} \exp\left\{-\frac{d_{D,k}(x_{2,k} + s_1 x_{1,k}(1+x_{2,k}))}{2\sigma_D^2}\right\} \\
&\cdot \left[1 + \exp\left\{\frac{d_{R,k}(1+x_{1,k})x_{2,k}}{c\sigma_D^2}\right\}\right. \\
&+ \exp\left\{\frac{d_{D,k}(1+s_1 x_{1,k})x_{2,k}}{\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{\left(d_{R,k}(1+x_{1,k})\sigma_D^2 + d_{D,k}c\sigma_D^2(1+s_1 x_{1,k})\right)x_{2,k}}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{(d_{R,k}\sigma_D^2 + d_{D,k}s_1 c\sigma_D^2)x_{1,k}(1+x_{2,k})}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) + c d_{D,k} s_1 x_{1,k}(1+x_{2,k})}{c\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{d_{R,k}x_{1,k}(1+x_{2,k}) + c d_{D,k}(s_1 x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\} \\
&\left.+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) + c d_{D,k}(s_1 x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\}\right]
\end{aligned} \tag{18}$$

considering only the for the log-likelihood ratio relevant terms. With it and with $P[s=1] = P[s=-1]$, the log-likelihood becomes

$$L = P_{s=1} - P_{s=-1} \tag{19}$$

with

$$\begin{aligned}
&P_{s=1} = \sum_{k=1}^{N} \ln\left(\exp\left\{-\frac{d_{D,k}(x_{2,k} + x_{1,k}(1+x_{2,k}))}{2\sigma_D^2}\right\}\right. \\
&\cdot \left[1 + \exp\left\{\frac{d_{R,k}(1+x_{1,k})x_{2,k}}{c\sigma_D^2}\right\}\right. \\
&+ \exp\left\{\frac{d_{D,k}(1+x_{1,k})x_{2,k}}{\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{\left(d_{R,k}(1+x_{1,k})\sigma_D^2 + d_{D,k}c\sigma_D^2(1+x_{1,k})\right)x_{2,k}}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{(d_{R,k}\sigma_D^2 + d_{D,k}c\sigma_D^2)x_{1,k}(1+x_{2,k})}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) + c d_{D,k} x_{1,k}(1+x_{2,k})}{c\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{d_{R,k}x_{1,k}(1+x_{2,k}) + c d_{D,k}(x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\} \\
&\left.\left.+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) + c d_{D,k}(x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\}\right]\right)
\end{aligned} \tag{20}$$

and

$$\begin{aligned}
&P_{s=-1} = \sum_{k=1}^{N} \ln\left(\exp\left\{-\frac{d_{D,k}(x_{2,k} - x_{1,k}(1+x_{2,k}))}{2\sigma_D^2}\right\}\right. \\
&\cdot \left[1 + \exp\left\{\frac{d_{R,k}(1+x_{1,k})x_{2,k}}{c\sigma_D^2}\right\}\right. \\
&+ \exp\left\{\frac{d_{D,k}(1-x_{1,k})x_{2,k}}{\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{\left(d_{R,k}(1+x_{1,k})\sigma_D^2 + d_{D,k}c\sigma_D^2(1-x_{1,k})\right)x_{2,k}}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{(d_{R,k}\sigma_D^2 - d_{D,k}c\sigma_D^2)x_{1,k}(1+x_{2,k})}{c\sigma_D^4}\right\} \\
&+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) - c d_{D,k} x_{1,k}(1+x_{2,k})}{c\sigma_D^2}\right\} \\
&+ \exp\left\{\frac{d_{R,k}x_{1,k}(1+x_{2,k}) + c d_{D,k}(-x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\} \\
&\left.\left.+ \exp\left\{\frac{d_{R,k}(x_{1,k}+x_{2,k}) + c d_{D,k}(-x_{1,k} + x_{2,k})}{c\sigma_D^2}\right\}\right]\right).
\end{aligned} \tag{21}$$

Without the presence of CCI the log-likelihood ratio in (19) simplifies substantially and can be written as

$$\begin{aligned}
L =& \ln\left(\prod_{k=1}^{N} \cosh\left\{\frac{(c d_{D,k} + d_{R,k})x_{1,k}}{2c\sigma_D^2}\right\}\right) \\
&- \ln\left(\prod_{k=1}^{N} \cosh\left\{\frac{(c d_{D,k} - d_{R,k})x_{1,k}}{2c\sigma_D^2}\right\}\right).
\end{aligned} \tag{22}$$

Using again the approximation $\ln(\cosh(\alpha)) \approx 0.5\alpha^2$

$$L = \sum_{k=1}^{N} \frac{2 d_{D,k} d_{R,k} x_{1,k}^2}{\sigma_D^2}. \tag{23}$$

Equation (23) is the correlation of the data pulse with the reference pulse weighted with the squared magnitude of the corresponding channel taps.

V. Maximum Likelihood Estimation without CSI

Since no CSI is available in many cases, we are also interested in the maximum likelihood estimation without CSI. In such a case the conditional error probability has to be averaged over all possible channel realizations. In [7], the maximum likelihood estimator is derived for Rayleigh distributed channel taps. Here we assume sparse channels for both desired and interfering user where the distribution of the channel tap amplitudes is given by

$$\begin{aligned}
p(h_{1,k}) =& P_U \cdot \frac{1}{\sqrt{2\pi\sigma_U^2}} \cdot e^{-\frac{h_{1,k}^2}{2\sigma_U^2}} + (1-P_U)\cdot\delta(h_{1,k}) \\
p(h_{2,k}) =& P_I \cdot \frac{1}{\sqrt{2\pi\sigma_I^2}} \cdot e^{-\frac{h_{2,k}^2}{2\sigma_I^2}} + (1-P_I)\cdot\delta(h_{2,k}).
\end{aligned} \tag{24}$$

P_U and P_I denote the probability that the user's and interferer's channel are not sparse, respectively. The probability that has to be averaged over all channel realizations is

$$
\begin{aligned}
p\left(\vec{d}_1, \vec{d}_2 | s_1 = s_{1i}, s_2 = s_{2i}, \vec{h}_1, \vec{h}_2\right) &= \left(\frac{1}{2\pi\sigma_1\sigma_2}\right)^N \\
\cdot \exp\Bigg\{ -\sum_{k=1}^{N} \Bigg(&\frac{(d_{1k} - h_{1,k} - h_{2,k})^2}{2\sigma_R^2} \\
+ \ &\frac{(d_{2k} - h_{1,k}s_{1i} - h_{2,k}s_{2i})^2}{2\sigma_D^2} \Bigg) \Bigg\}.
\end{aligned} \tag{25}
$$

Assuming separable channel taps we can compute (25) for each sample separately [7]. Thus, considering only terms relevant for the likelihood ratio we get

$$
\begin{aligned}
p\left(d_{1k}, d_{2k} | s_1 = s_{1i}\right) &\propto \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(s_2)p(h_{2,k})p(h_{1,k}) \\
\exp\Bigg\{ &-\frac{-d_{1k}h_{1,k} - d_{1k}h_{2,k} + h_{1,k}h_{2,k}}{\sigma_R^2} \\
- \ &\frac{-d_{2k}h_{1,k}s_1 - d_{2k}h_{2,k}s_2 + h_{1,k}s_1h_{2,k}s_2}{\sigma_D^2} \Bigg\} dh_{1,k}dh_{2,k}ds_2.
\end{aligned} \tag{26}
$$

For calculation of the log-likelihood ratio we assume $\sigma_R^2 = c \cdot \sigma_D^2$ and $\sigma_I^2 = b \cdot \sigma_U^2$. Thus, one gets with $P[s_1 = 1] = P[s_1 = -1]$ for the log-likelihood ratio

$$
L = \sum_{k=1}^{N} \left[P_{k,1} - P_{k,-1}\right] \tag{27}
$$

with

$$
\begin{aligned}
P_{k,1} = \ln\Bigg(1 &+ P_U \left(-1 + \exp\left\{\frac{(d_{R,k} + d_{D,k}c)^2\sigma_U^2}{2c^2\sigma_D^4}\right\}\right) \\
&+ \frac{1}{2}P_I \Bigg[(-1 + P_U) \cdot \Bigg(2 - \exp\left\{\frac{(d_{R,k} - d_{D,k}c)^2 b\sigma_U^2}{2c^2\sigma_D^4}\right\} \\
&- \exp\left\{\frac{(d_{R,k} + d_{D,k}c)^2 b\sigma_U^2}{2c^2\sigma_D^4}\right\}\Bigg) \\
&+ P_U \cdot \Bigg(-2 \cdot \exp\left\{\frac{(d_{R,k} + d_{D,k}c)^2\sigma_U^2}{2c^2\sigma_D^4}\right\} \\
&+ \frac{\exp\left\{\frac{\sigma_U^2(d_{R,k}+d_{D,k}c)^2(-2\sigma_U^2 b + c(-2\sigma_U^2 c + \sigma_D^2(1+b)))}{2c\sigma_D^2(-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b))}\right\}}{\sigma_U\sqrt{\frac{-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b)}{c^2\sigma_D^4\sigma_U^2}}} \\
&+ \frac{\exp\left\{\frac{\sigma_U^2(-\xi_k + \upsilon_k + \zeta_k)}{2c\sigma_D^2(-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b))}\right\}}{\sigma_U\sqrt{\frac{-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b)}{c^2\sigma_D^4\sigma_U^2}}}\Bigg)\Bigg]\Bigg)
\end{aligned} \tag{28}
$$

and

$$
\begin{aligned}
P_{k,-1} = \ln\Bigg(1 &+ P_U \left(-1 + \exp\left\{\frac{(d_{R,k} - d_{D,k}c)^2\sigma_U^2}{2c^2\sigma_D^4}\right\}\right) \\
&+ \frac{1}{2}P_I \Bigg[(-1 + P_U) \cdot \Bigg(2 - \exp\left\{\frac{(d_{R,k} - d_{D,k}c)^2 b\sigma_U^2}{2c^2\sigma_D^4}\right\} \\
&- \exp\left\{\frac{(d_{R,k} + d_{D,k}c)^2 b\sigma_U^2}{2c^2\sigma_D^4}\right\}\Bigg) \\
&+ P_U \cdot \Bigg(-2 \cdot \exp\left\{\frac{(d_{R,k} - d_{D,k}c)^2\sigma_U^2}{2c^2\sigma_D^4}\right\} \\
&+ \frac{\exp\left\{\frac{\sigma_U^2(d_{R,k}-d_{D,k}c)^2(-2\sigma_U^2 b + c(-2\sigma_U^2 c + \sigma_D^2(1+b)))}{2c\sigma_D^2(-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b))}\right\}}{\sigma_U\sqrt{\frac{-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b)}{c^2\sigma_D^4\sigma_U^2}}} \\
&+ \frac{\exp\left\{\frac{\sigma_U^2(\xi_k + \upsilon_k + \zeta_k)}{2c\sigma_D^2(-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b))}\right\}}{\sigma_U\sqrt{\frac{-\sigma_U^4 b - 2c\sigma_U^4 b + c^2(\sigma_D^4 - \sigma_U^4 b)}{c^2\sigma_D^4\sigma_U^2}}}\Bigg)\Bigg]\Bigg).
\end{aligned} \tag{29}
$$

In (28) and (29), ξ_k, υ_k, and ζ_k are given by

$$
\begin{aligned}
\xi_k &= 2d_{D,k}d_{R,k}c^2\sigma_D^2(b-1) \\
\upsilon_k &= d_{D,k}^2 c^2(2\sigma_U^2 b(1-c) + c\sigma_D^2(1+b)) \\
\zeta_k &= d_{R,k}^2(2\sigma_U^2 b(c-1) + c\sigma_D^2(1+b)).
\end{aligned} \tag{30}
$$

Equation (27) simplifies substantially assuming no CCI and a non-sparse channel, i.e., $P_U = 1$. Then, the log-likelihood ratio is given by

$$
L = \frac{2\sigma_U^2}{c\sigma_D^4}\sum_{k=1}^{N} d_{D,k}d_{R,k} \tag{31}
$$

Equation (31) shows that the correlation of reference and data pulse, as presented in [9], is optimum if no CSI is known at the receiver and if no CCI is present.

VI. Simulation Results

To see the impact of CCI and CSI, we compare the performance of the above derived ML estimators by means of simulation. We consider the scenario when a synchronous CCI is present, yielding the worst case performance, and the scenario without CCI, yielding the best case performance. For the simulations, we use a non-sparse channel with $K = 100$ channel taps. The channel taps are Gaussian distributed with an exponential decay α. Thus, the k^{th} channel-tap is given by

$$
h_k = c_k \cdot e^{-\alpha \cdot k} \tag{32}
$$

where $\alpha = 0.03$ and c_k is a Gaussian random variable with $\mathcal{N} \sim (0, 1)$. In Fig. 1, we plot the bit error rates (BER) assuming no CCI over the signal-to-noise ratio E_b/N_0, where E_b denotes the energy per bit and $N_0/2$ is the noise power spectral density. Although the reference pulse is not required for detection if full CSI is available, the ML with full CSI shows

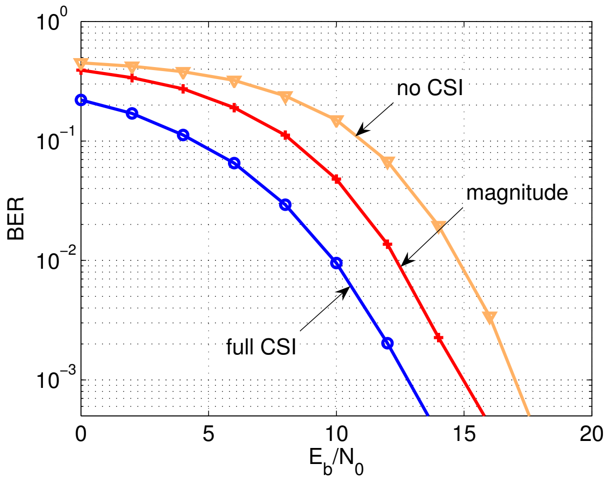

Figure 1: Bit error curves for TR ML with different CSI and without CCI .

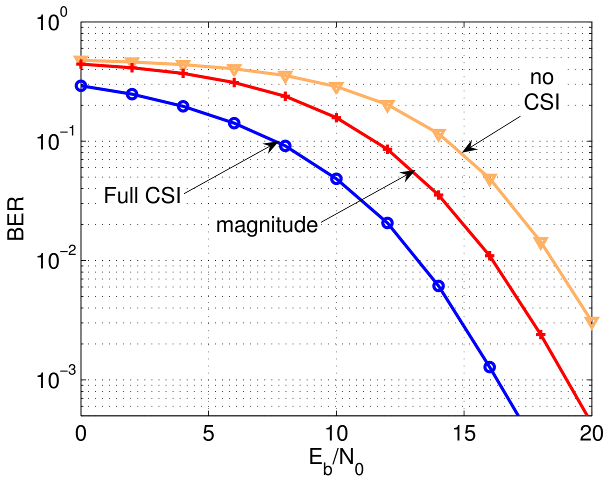

Figure 2: Bit error curves for TR ML with different CSI and CCI at a SIR of 10dB.

the best performance. Assuming knowledge of the CIR magnitudes of the desired user and the CCI, the performance is about 3dB worse. This performance loss is caused by the correlation of a noisy template signal, i.e., the reference signal, with the data signal. Due to the weighting of the correlation term with the squared magnitude of the CIR, the performance is about 2dB better compared to the ML without CSI.

The BER curves considering CCI are shown in Fig. 2. For these simulations we assume a signal-to-interference ratio SIR = 10dB. Compared to the BER curves without CCI the performance with CCI is about 4dB worse. However, the performance losses assuming different CSI are almost the same as in the case of no CSI. The ML with full CSI shows best performance and is about 3dB better compared to the ML with knowledge of the CIR magnitudes. Having no CSI available at the receiver results in a performance loss of about 5dB compared to the ML with full CSI.

VII. Conclusions

We derived in this paper ML TR estimators with and without CCI. For the derivations we considered at the receiver full CSI, knowledge of the CIR magnitude, and no CSI. We showed by means of simulation that the performance assuming knowledge of the CIR magnitude is about 3dB worse compared to full CSI at the receiver. Having no CSI at the receiver the performance compared to the receiver with full CSI is about 5dB worse.

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