On Optimal Data Detection for UWB Transmitted Reference Systems

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***Abstract*— Transmitted reference (TR) modulation schemes, initially proposed for spread-spectrum systems in the 1920's have regained popularity in the context of ultra-wideband (UWB) communications, where accurate channel estimation is a challenging task. In the conventional TR approach, a reference signal (without data modulation) is received and employed in a correlator receiver for data modulated signals. By exploiting the statistics of the received signals, optimal and suboptimal data detection schemes for a single-user UWB communication system employing antipodal modulation with TR are investigated and compared to the conventional TR receiver. The proposed schemes can cope with a variable number of reference and data modulated pulses. By construction, the modulation and demodulation methods work for arbitrary channels. The efficacy of the new methods is investigated via simulations emulating an indoor multipath channel. These simulation results reveal that the proposed detection schemes provide significant performance improvements in terms of bit error rate over the conventional TR receiver structure.**

I. Introduction

Ultra-wideband (UWB) systems transmit signals whose bandwidths exceed 20% of their center frequency or have a -10 dB bandwidth of more than 500 MHz. UWB communication systems are under consideration for wireless indoor applications. Because of the large bandwidth of UWB signals, a large number of multipath components are resolvable indicating that, in theory, diversity combining can be employed effectively. However, achieving the potential of UWB is challenging due to the difficulty in accurate channel estimation, thus inhibiting a receiver's ability to fully exploit the the multipath diversity inherent to the system. In fact, practical UWB RAKE receivers only consider a moderate number of multipath components resulting in a reduced energy capture [1]. Alternatively, transmitted reference (TR) systems in conjunction with correlation receivers can be employed offering an improved energy capture without explicit channel estimation [2], [3]. Classically, the receiver correlates the received signal with a previously received signal, or as proposed in this paper with a signal estimated from the received signal. The drawback of TR systems is a noisy template estimate that causes performance degradation. TR systems were originally proposed for spread-spectrum communications where accurate channel estimation was possible, thus TR systems were replaced by RAKE receivers. However, due to the large diversity inherent in UWB systems, correlation receivers have once again gained interest [4]–[9].

In this paper, we design decision rules for data detection in UWB TR systems using classical maximum likelihood and generalized likelihood ratio testing principles. Due to the fact that both estimators for the template signal result in a recursive expression, approximate closed form expressions are developed for template estimation. The proposed algorithms are investigated via simulations for an indoor multipath channel and compared to the conventional TR approach. As expected, maximum-likelihood and generalized likelihood ratio test based algorithms offer superior performance over traditional TR, especially for the scenario where multiple data modulated signals are transmitted for every one reference signal. Simulation results also reveal that the approximate template estimates do not result in significant performance degradations.

This paper is organized as follows. In Section II, we provide the system model. The different receiver structures are derived in Section III. Conventional correlation receivers, correlation receivers using the optimal estimate for the template signal, and receivers employing a generalized likelihood ratio test are investigated. Section IV presents numerical results for a fixed number of reference and data modulated pulses. Concluding remarks are given in Section V.

II. System Model

We consider a single user UWB system employing antipodal signaling in an indoor multipath channel with additive white Gaussian noise (AWGN) [1]. For one observation block, the channel $h(t)$ is assumed time-invariant; furthermore, within the observation block, N_r reference and N_d modulated pulses are transmitted. During one observation block, the received

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[1]We are currently investigating the modification of the proposed methods to pulse position modulation.

signal is given by

$$r(t) = \sum_{i=1}^{N_r} s(t-(i-1)T_f) + \sum_{j=1}^{N_d} b_j \cdot s(t-(j-1)T_f - N_r T_f) + n(t), \quad (1)$$

where $s(t)=h(t)*p(t)$ is the pulse response of the channel to the input pulse $p(t)$, $n(t)$ is AWGN with two sided noise variance $\sigma^2 = N_0/2$ and T_f the frame time larger than the delay spread of the channel τ_d to avoid intersymbol interference. Classically, transmitted reference (TR) systems employ correlation receivers which correlate the received data signal with the received reference signal which serves as an estimate of the pulse response $\hat{s}(t)$ denoted as the *template* signal [4]. After sampling the received signal described in (1), our discrete time signal is given by,

$$\underline{r} = \begin{bmatrix} \underline{r}_{r,1} \\ \vdots \\ \underline{r}_{r,N_r} \\ \hline \underline{r}_{d,1} \\ \vdots \\ \underline{r}_{d,N_d} \end{bmatrix} = \begin{bmatrix} \underline{s} \\ \vdots \\ \underline{s} \\ \hline b_1 \underline{s} \\ \vdots \\ b_{N_d} \underline{s} \end{bmatrix} + \begin{bmatrix} \underline{n}_{r,1} \\ \vdots \\ \underline{n}_{r,N_r} \\ \hline \underline{n}_{d,1} \\ \vdots \\ \underline{n}_{d,N_d} \end{bmatrix}, \quad (2)$$

where $\underline{r}_{r,i}$, $\underline{r}_{d,i}$ corresponds to the received vector of the ith reference, data modulated frame and $\underline{n}_{r,i}$, $\underline{n}_{d,i}$ corresponds to the ith independent AWGN noise vector of the reference, data modulated frame of length N, respectively.

III. Receiver Structures

A. Conventional Correlation Receivers

Conventional TR systems [4], [7] construct their template signal by combining only the reference pulses. In fact, the template signal is often designed by averaging all of the received reference frames in a signal observation block,

$$\hat{\underline{s}}_{\text{conv}} = \frac{1}{N_r} \sum_{i=1}^{N_r} \underline{r}_{r,i}. \quad (3)$$

To recover the data, the following decision rule is employed

$$\hat{b}_j = \begin{cases} +1, & \text{if} \quad \underline{r}_{d,j}^T \cdot \hat{\underline{s}}_{\text{conv}} \geq 0 \\ -1, & \text{if} \quad \underline{r}_{d,j}^T \cdot \hat{\underline{s}}_{\text{conv}} < 0 \end{cases}, \quad j = 1,2,...,N_d. \quad (4)$$

The premise of the current work is that each received frame contains information about the reference and thus the entire observation block should be employed to construct the template signal. Thus, we consider maximum-likelihood (ML) type estimation for the template signal over the entire observation block.

B. ML Estimate of the Template Signal with Suboptimal Correlation

In this section, we derive the ML estimator for the template signal $\underline{s}$ in the case of $N_r = 1$ reference and $N_d = 1$ data modulated pulse where the data modulation b is drawn from $\{\pm 1\}$ with probability $\frac{1}{2}$. The ML estimate of the template signal $\hat{\underline{s}}$ is given by the argument that maximizes the likelihood function $p_{\underline{r}}(\underline{r}|\underline{s})$ over all $\underline{s}$

$$\hat{\underline{s}}_{\text{ML}} = \arg\max_{\underline{s}} \left\{ p_{\underline{r}}(\underline{r}|\underline{s}) \right\}. \quad (5)$$

Assuming equal *a-priori* probabilities of the data symbols, and ignoring irrelevant constants (with respect to $\underline{s}$), the likelihood function for $\underline{s}$ is equivalent to

$$p_{\underline{r}}(\underline{r}|\underline{s}) \equiv \exp\left(-\frac{1}{2\sigma^2} \left\| \begin{bmatrix} \underline{r}_r \\ \underline{r}_d \end{bmatrix} - \begin{bmatrix} \underline{s} \\ \underline{s} \end{bmatrix} \right\|^2 \right) + \exp\left(-\frac{1}{2\sigma^2} \left\| \begin{bmatrix} \underline{r}_r \\ \underline{r}_d \end{bmatrix} - \begin{bmatrix} \underline{s} \\ -\underline{s} \end{bmatrix} \right\|^2 \right). \quad (6)$$

Taking the derivative of (6) with respect to $\underline{s}$ and equating to zero results in,

$$(\underline{s} - \underline{r}_r) \left[\exp\left(\frac{\underline{r}_d^T \underline{s}}{\sigma^2} \right) + \exp\left(-\frac{\underline{r}_d^T \underline{s}}{\sigma^2} \right) \right] + (\underline{s} - \underline{r}_d) \exp\left(\frac{\underline{r}_d^T \underline{s}}{\sigma^2} \right) + (\underline{s} + \underline{r}_d) \exp\left(-\frac{\underline{r}_d^T \underline{s}}{\sigma^2} \right) = 0. \quad (7)$$

Combining exponentials yields a recursive expression for the template,

$$\hat{\underline{s}}_{\text{ML}} = \frac{1}{2} \left[\underline{r}_r + \underline{r}_d \tanh\left(\frac{\underline{r}_d^T \hat{\underline{s}}_{\text{ML}}}{\sigma^2} \right) \right]. \quad (8)$$

The non-linear estimator in (8) has an intuitive form: $\tanh\left(\underline{r}_d^T \hat{\underline{s}}_{\text{ML}}/\sigma^2\right)$ provides a soft estimate of the unknown data symbol and averaging over all of the received frames is conducted after soft compensation for the data bit. In the case of high SNR and known data modulation, (8) can be approximated by

$$\hat{\underline{s}}_{\text{ML}} \approx \begin{cases} \frac{1}{2}(\underline{r}_r + \underline{r}_d), & \text{if} \quad b = +1 \\ \frac{1}{2}(\underline{r}_r - \underline{r}_d), & \text{if} \quad b = -1 \end{cases}. \quad (9)$$

We observe that the desired solution from (8) can be determined iteratively. In the case of N_r reference and N_d data modulated pulses the likelihood function of $\underline{s}$ is obtained by averaging over all possible permutations of the data vector, $\underline{b}^i = [b_1, b_2, ..., b_{N_d}]^T$, $i = 1, 2, ..., 2^{N_d}$,

$$p_{\underline{r}}(\underline{r}|\underline{s}) \equiv \sum_{i=1}^{2^{N_d}} \exp\left(-\frac{1}{2\sigma^2} \left\| \begin{bmatrix} \underline{r}_R \\ \underline{r}_D \end{bmatrix} - \begin{bmatrix} \underline{1}_{N_r} \otimes \underline{s} \\ \underline{b}^i \otimes \underline{s} \end{bmatrix} \right\|^2 \right), \quad (10)$$

where $\underline{r}_R = [\underline{r}_{r,1}^T, ..., \underline{r}_{r,N_r}^T]^T$ and $\underline{r}_D = [\underline{r}_{d,1}^T, ..., \underline{r}_{d,N_d}^T]^T$. The Kronecker product operator is denoted by $\otimes$ and $\underline{1}_k$ is the

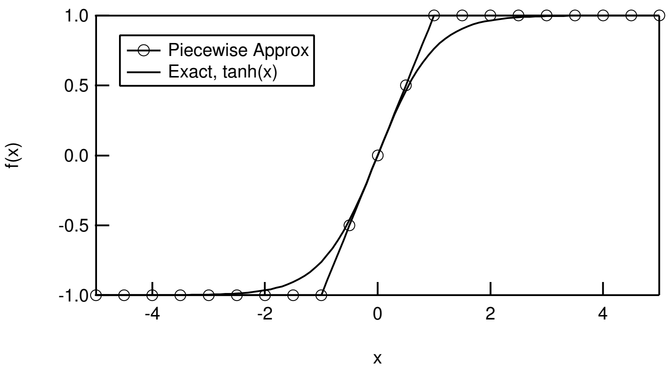

Fig. 1. Approximation of the tanh function.

$k \times 1$ vector of all ones. It can be shown that the ML estimate of the pulse response is then given by [9]

$$\underline{\hat{s}}_{\mathrm{ML}} = \frac{1}{N_r + N_d}\left[\sum_{i=1}^{N_r}\underline{r}_{r,i} + \sum_{j=1}^{N_d}\underline{r}_{d,j}\tanh\left(\frac{\underline{r}_{d,j}^T\underline{\hat{s}}_{\mathrm{ML}}}{\sigma^2}\right)\right]. \tag{11}$$

To avoid solving (8) iteratively we can approximate the $\tanh$ function in the nonlinear estimator by a piecewise linear estimator using

$$\tanh(x) \approx f(x) = \begin{cases} +1, & \text{if} \quad x > +1 \\ x, & \text{if} \quad |x| \le +1 \\ -1, & \text{if} \quad x < -1 \end{cases}. \tag{12}$$

The difference between the soft-limiter and $\tanh$ is exhibited in Fig. 1. The ML estimator can then be approximated by

$$\underline{\hat{s}}_{\mathrm{ML}} \approx \frac{1}{N_r + N_d}\left[\sum_{i=1}^{N_r}\underline{r}_{r,i} + \sum_{j=1}^{N_d}\underline{r}_{d,j} f\left(\frac{\underline{r}_{d,j}^T\underline{\hat{s}}_{\mathrm{ML}}}{\sigma^2}\right)\right]. \tag{13}$$

We define a vector $\underline{c}$

$$\underline{c} = \sum_{i=1}^{N_r}\underline{r}_{r,i} + \sum_{j=1}^{N_d}\underline{r}_{d,j}G_j, \tag{14}$$

where

$$G_j = \begin{cases} +1, & \text{if} \quad \left(\frac{\underline{r}_{d,j}^T\sum_{i=1}^{N_r}\underline{r}_{r,i}}{N_r\sigma^2}\right) > +1 \\ -1, & \text{if} \quad \left(\frac{\underline{r}_{d,j}^T\sum_{i=1}^{N_r}\underline{r}_{r,i}}{N_r\sigma^2}\right) < -1 \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

is an indicator function. Equation (13) can then be written as

$$\begin{aligned} \underline{\hat{s}}_{\mathrm{ML}} &\approx \frac{1}{N_r + N_d}\left[\underline{c} + \sum_k \frac{\underline{r}_{d,k}\underline{r}_{d,k}^T}{\sigma^2}\underline{\hat{s}}_{\mathrm{ML}}\right] & (16) \\ &= \frac{1}{N_r + N_d}\left[\underline{c} + \frac{\mathbf{R}\mathbf{R}^T}{\sigma^2}\underline{\hat{s}}_{\mathrm{ML}}\right], & (17) \end{aligned}$$

where the summation includes all terms for which $|(\underline{r}_{d,k}^T\sum_{i=1}^{N_r}\underline{r}_{r,i})/(N_r\sigma^2)| \le 1$ and

$$\mathbf{R} = \left[\underline{r}_{d,1}, ..., \underline{r}_{d,k}, ...\right]. \tag{18}$$

Note that in our use of the soft-limiter, the correlation of the estimated template with the data modulated signals is approximated by the average of the reference signals with the data modulated signal. Invoking the matrix inversion lemma the estimate for the reference signal is given by

$$\underline{\hat{s}}_{\mathrm{ML}} \approx \frac{1}{N_d + N_r}\left[\mathbf{I} - \mathbf{R}\left(\mathbf{R}^T\mathbf{R} + \sigma^2(N_d + N_r)\mathbf{I}\right)^{-1}\mathbf{R}^T\right]\underline{c}. \tag{19}$$

Note that the maximum size of the matrix to be inverted is $N_d \times N_d$.

To recover the data, we can now proceed as in the previous section; that is, correlating the received signal vectors with the template signal $\underline{\hat{s}}_{\mathrm{ML}}$. Using the ML estimate for the template signal can improve performance significantly. However, an improved decision rule for detecting the data is given by employing the generalized likelihood ratio test. This is the subject of the next section.

C. Generalized Likelihood Ratio Test

An improved decision rule for the jth data symbol is obtained by computing the generalized likelihood:

$$\begin{aligned} \Lambda_G(\underline{r}_{d,j}) &= \frac{\max_{\underline{s}:b_j=+1} p_{\underline{r}_{d,j}}\left(\underline{r}_{d,j}|b_j = +1\right)}{\max_{\underline{s}:b_j=-1} p_{\underline{r}_{d,j}}\left(\underline{r}_{d,j}|b_j = -1\right)} & (20) \\ &= \frac{p_{\underline{r}_{d,j}}\left(\underline{r}_{d,j}|b_j = +1, \underline{s} = \underline{\hat{s}}_{(b_j=+1)}\right)}{p_{\underline{r}_{d,j}}\left(\underline{r}_{d,j}|b_j = -1, \underline{s} = \underline{\hat{s}}_{(b_j=-1)}\right)}. & (21) \end{aligned}$$

The generalized likelihood ratio test (GLRT) is then given by,

$$\Lambda_G(\underline{r}_{d,j}) \underset{b_j=-1}{\overset{b_j=+1}{\gtrless}} 1, \tag{22}$$

where $p_{\underline{r}_{d,j}}\left(\underline{r}_{d,j}|b_j = \pm1, \underline{s} = \underline{\hat{s}}_{(b_j=\pm1)}\right)$ is the likelihood function of the jth received signal vector conditioned on the template signal and the data symbol $b_j = \pm1$. Using similar techniques as those described in the previous section, the template signals conditioned on the jth data symbol are given by

$$\begin{aligned} \underline{\hat{s}}_{(b_j=\pm1)} = \frac{1}{(N_r + N_d)}&\left[\sum_{i=1}^{N_r}\underline{r}_{r,i} + \right. \\ &\left.\sum_{i=1, i\neq j}^{N_d}\underline{r}_{d,i}\tanh\left(\frac{\underline{r}_{d,i}^T\underline{\hat{s}}_{(b_j=\pm1)}}{\sigma^2}\right) \pm \underline{r}_{d,j}\right]. \quad (23) \end{aligned}$$

Simplifying (22) yields,

$$\begin{aligned} &\underline{r}_{d,j}^T\left[\underline{\hat{s}}_{(b_j=-1)} + \underline{\hat{s}}_{(b_j=+1)}\right] + \\ &\qquad \frac{1}{2}\left[\left|\left|\underline{\hat{s}}_{(b_j=-1)}\right|\right|^2 - \left|\left|\underline{\hat{s}}_{(b_j=+1)}\right|\right|^2\right] \underset{b_j=-1}{\overset{b_j=+1}{\gtrless}} 0, \quad (24) \end{aligned}$$

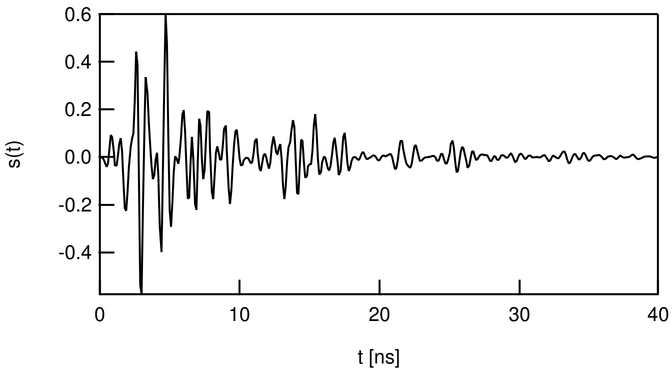

Fig. 2. Sample pulse response of the channel.

and by substituting (23) into (24), it can be shown that the GLRT receiver is equivalent to a correlator receiver with a template signal

$$\underline{\hat{s}}^j_{\mathrm{GL}} = \frac{1}{N_r + N_d - 1}\left(\sum_{i=1}^{N_r} \underline{r}_{r,i} + \sum_{i=1, i\neq j}^{N_d} \underline{r}_{d,j} \tanh\left(\frac{\underline{r}^T_{d,i}\underline{\hat{s}}^j_{\mathrm{GL}}}{\sigma^2}\right)\right), \quad (25)$$

and decision statistic

$$z = \underline{r}^T_{d,j}\underline{\hat{s}}^j_{\mathrm{GL}}. \quad (26)$$

We observe that (25) is the ML estimate of the template signal obtained from a reduced observation interval. In the case of $N_r = 1$ reference and $N_d = 1$ data modulated pulse, the GLRT reduces to

$$\underline{r}^T_r \underline{r}_d \underset{b=-1}{\overset{b=+1}{\gtrless}} 0, \quad (27)$$

which is the test employed in conventional TR systems for $N_r = N_d = 1$.

Note that the estimated reference conditioned on the jth data symbol can be approximated in the same fashion as shown in the last section. The only difference is that the jth data vector $\underline{r}_{d,j}$ has to be added or subtracted to the vector $\underline{c}$. We next evaluate the proposed algorithms via simulation.

IV. Numerical Results

In this section, simulation results for the different systems are provided and compared to the conventional TR approach. The free space received pulses are modeled as second derivative Gaussian waveforms given by

$$p(t) = A \cdot e^{-2\pi\left(\frac{t}{\tau}\right)^2}\left[\frac{4\pi t^2}{\tau^2} - 1\right], \quad (28)$$

where A is adjusted so that the maximum amplitude is 1 and τ is set to 0.7 ns. The channel under consideration is a line-of-sight (LOS) indoor multipath channel (CM1) as proposed in [10] and is depicted in Fig. 2. It is assumed that the cluster and ray arrival times follow exponential rate laws with a cluster arrival rate of $\Lambda = 0.0233$ /ns and a ray arrival rate of $\lambda = 2.5$ /ns. The received signal amplitude is modeled as a Rayleigh random variable with a mean-squared value following a double exponential law with the intercluster signal level rate of decay given by $\Gamma = 7.1$ ns and the intracluster rate of decay given by $\gamma = 4.3$ ns. The delay spread of the channel τ_d is restricted to 40 ns, as the energy of the multipath components arriving after more than 40 ns is negligible. Choosing a sampling period of 0.1 ns results in $N = 400$ samples per frame. During one observation block the channel is assumed time-invariant and we transmit $N_r = 1$ reference and $N_d = 20$ data modulated pulses. The SNR is defined as SNR $= \|\underline{s}\|^2/N_0$ where $N_0/2$ is the variance of the noise. For each SNR value we have performed Monte Carlo simulations until $N_e = 100$ errors have occurred. Figure 3 shows the mean-squared error (MSE) of the template signal $\underline{\hat{s}}$ versus the SNR in a dB scale, comparing a system using only the reference frames (the template is estimated via averaging all of the reference signals as in (3)) and our two template estimators: the iterative non-linear ML estimate in (11) and the GLRT-based estimators in (25) as well as their approximations with the modified Cramer-Rao bound [11], [12]. In the presence of nuisance parameters, *i.e.* unknown data vector $\underline{b}$, calculation of the Cramer-Rao bound (CRB) is a challenging task. Therefore, we employ the modified Cramer-Rao bound (MCRB) as a lower bound on the variance of a parameter estimator which can easily be evaluated. It can be proven that the MCRB is less tight in comparison to the CRB [11] and is given by [12]

$$\mathrm{MCRB} = \mathrm{diag}(\mathbf{J}_{\mathrm{M}}^{-1}), \quad (29)$$

where $\mathbf{J}_{\mathrm{M}}$ is a modified Fisher information matrix whose elements are

$$[\mathbf{J}_{\mathrm{M}}]_{ij} = -\mathrm{E}_{\underline{r},\underline{b}}\left\{\frac{\partial \ln p_{\underline{r}}(\underline{r}|\underline{b},\underline{s})}{\partial s_i \partial s_j}\right\}. \quad (30)$$

For the signal model provided in (2) the MCRB for each sample of the estimated template signal s_i is obtained as

$$\mathrm{Var}(s_i) \geq \frac{\sigma^2}{(N_r + N_d)}, \qquad i = 1, 2, \ldots, N. \quad (31)$$

We note that for N_m Monte Carlo runs, the MSE is defined to be

$$\mathrm{MSE} = \frac{1}{(NN_m)}\sum_{i=1}^{N_m}\|\underline{\hat{s}}(i) - \underline{s}\|^2. \quad (32)$$

It is clear from Fig. 3 that the GLRT and the ML estimators and their approximations have a significantly lower MSE in comparison to the conventional receiver. Thus, we expect to see improvements in terms of bit error rate (BER). For high SNR, the ML estimator approaches the MCRB because it uses the received signal of the whole observation interval optimally, whereas the GLRT receiver employs one less data frame for its template estimate. The approximations of the ML and GLRT estimates result in almost the same MSE as the ML and GLRT estimators themselves. Figure 4 shows the BER versus the

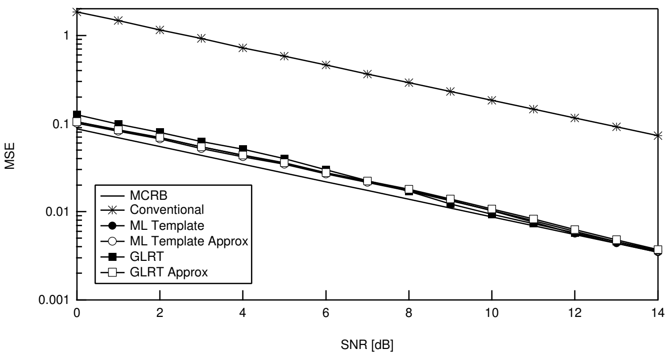

Fig. 3. MSE of the estimated template signal for $N_r = 1$ reference and $N_d = 20$ data frames.

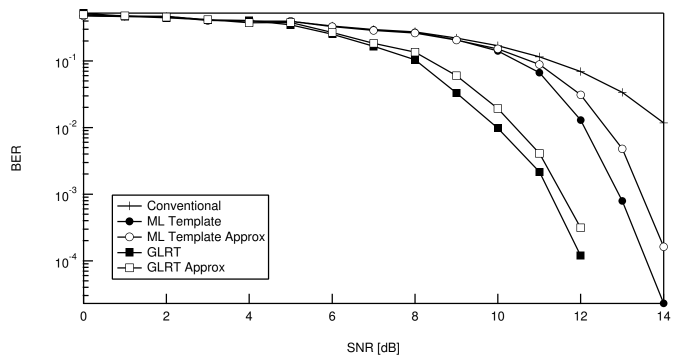

Fig. 4. BER of the systems discussed for $N_r = 1$ reference and $N_d = 20$ data frames.

SNR in a dB scale for all detector structures considered herein. In comparison with the conventional TR system, the GLRT approach and its approximation exhibit considerable performance improvements for moderate to high SNR. The ML-approach and its approximation evinces performance improvements only for high SNR in comparison to the conventional TR receiver. We observe that for low SNR, the improved MSE of the template estimate of the ML- and GLRT-based receiver compared to the conventional receiver does not translate to a lower BER because of the low SNR of the received signal itself. However, with increasing SNR, the performance improvements of both systems in comparison with conventional TR systems increase. The results also show that approximating the $\tanh$ function does not result in significant performance degradation for the SNR range we have investigated. Performance improvements of both proposed systems increase with the number of data modulated frames if the number of reference pulses is kept constant. We note that for the case of a single reference frame and a single data modulated frame, the conventional TR system and the GLRT-based receiver perform the same test. Despite an improved template estimate of the ML-based receiver it reveals a worse BER performance compared to the GLRT receiver due to the correlation between its template signal and the data signal. Analytical performance analysis of the conventional and the GLRT-based receiver is carried out in [9]. It can be shown that the BER for the conventional and a lower bound for the GLRT receiver is given by a doubly non-central F-variate.

V. Conclusions

In this paper, receiver structures for UWB TR systems operating in a dense multipath channel with AWGN were investigated. Receivers based on maximum-likelihood type estimation for the reference signal used in conjunction with a correlator structure as well as a generalized likelihood ratio detector were derived. Due to the recursive nature of both approaches, approximate receivers/estimators were designed as well. Simulation results for an exemplar UWB multipath channel are provided and compared to the conventional correlation receiver. With an increasing number of data modulated frames per reference frame, significant performance improvements in terms of BER can be obtained by employing a ML estimate of the template signal or performing a GLRT to demodulate the data. Performance analysis of the proposed systems as well as delay spread optimization to further optimize performance constitute ongoing research. Future areas of research include the application of the proposed methods to pulse-position modulation as well as the consideration of multiuser systems.

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