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UWB RECEIVER DESIGN FOR LOW RESOLUTION QUANTIZATION

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ABSTRACT

Digital implementation of ultra-wideband receivers requires analog-to-digital conversion (ADC) at an extremely high speed, thereby limiting the available bit resolution. Herein, a new family of receiver structures optimized and tailored to quantized observations is presented. The generalized-likelihood ratio test (GLRT) based on the quantized samples is derived and shown to provide performance improvements in comparison to the infinite resolution GLRT rule employed on the quantized received signal. Furthermore, simulation results reveal that four bits of resolution are sufficient to closely approach the performance of a infinite resolution receiver.

1. 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. The large bandwidth of UWB signaling offers the potential for higher capacity, very fine timing resolution, improved penetration properties, low probability of intercept, and increased diversity due to significant multipath [1]. To achieve adequate energy capture and account for pulse distortion [2], UWB transmitted reference (TR) receivers have been reconsidered as a promising low complexity alternative to conventional RAKE receivers [3]. In conjunction with correlation receivers, TR systems and their generalizations offer high energy capture without explicit channel estimation, *i.e.* no attempt is made to resolve individual multipath components (see [4] and references therein). Implicit channel estimation significantly reduces complexity at the expense of employing a noisy template estimate which causes performance degradation.

Analog implementations for UWB systems have been previously proposed, e.g. [3]. While simplifying some of the implementation issues, such as reducing the required sampling rate considerably, our interest in digital logic is motivated by improvements in robustness, flexibility, scalability, the ability to employ sophisticated digital signal processing algorithms, and simplification of analog elements in the transceiver yielding low power operation over purely analog logic [5, 6]. A key challenge for the implementation of digital UWB systems is the required sampling rate. Realization of sampling rates on the order of GHz and the desire to keep the power consumption low, limits the available bit resolution of the ADC to very few bits [7].

Mono-bit digital receivers which obviate the need for an automatic gain control and thereby simplify the implementation of an all digital UWB receiver considerably have been shown to lead to a significant performance degradation in comparison to infinite resolution receivers [8]. To reduce the performance loss, sigma-delta modulation, which requires oversampling, can be applied. In [9], the required ADC bit resolution for an UWB matched filter receiver is investigated. It is found that four bits give a close approximation to the optimal performance. However, the analysis in [9] relies heavily on the assumption that the quantization noise can be modelled by a uniform random variable with variance $\Delta^2/12$ and a Gaussian assumption for the overall noise term (quantization and AWGN noise). Both assumptions do not appear to be justified for UWB systems employing a low bit resolution ADC (<4 bits). Exact performance analysis for an UWB direct-sequence spread spectrum (DS-SS) system employing a matched filter receiver propagating over the AWGN channel is considered in [10]. It is found that with the appropriate dynamic range of the quantizer, three bits of resolution are sufficient to closely approximate the infinite resolution case. It is not *a-priori* clear whether the results in [10] also hold in the presence of a multipath channel with a high degree of diversity.

Our approach is to design receivers based on quantized observations to determine more completely the best tradeoff between performance and complexity. TR receivers employing an idealized *infinite resolution ADC* [4] are compared to their practical counterparts that take into account a low-bit resolution ADC. To this end, the generalized likelihood ratio test (GLRT) based on the quantized received signal is derived and shown to be superior to the GLRT-U rule that is based on unquantized samples, but operates on quantized samples. Because of the high complexity of the GLRT rule, several sub-optimal detection/estimation schemes are investigated. As in [9], it is found that a four bit ADC yields close to optimal performance if the dynamic range is adjusted properly. Note that optimum quantization for signal detection has been considered previously, *e.g.* [11–13]. The authors derive quantizers for very specific scenarios and a given detection rule, requiring knowledge of the statistics of the received signal. In contrast, our focus herein is the design of new detection algorithms given a uniform quantizer.

This paper is organized as follows. In Section 2, we provide the system model. Receivers employing a low resolution ADC along with several more sub-optimal receivers are considered in Section 3. Section 4 presents simulation results and concluding remarks are drawn in Section 5.

2. SYSTEM MODEL AND RECEIVER STRUCTURES

We consider a time-hopped UWB system with antipodal modulation that uses multiple pulses per bit to convey information to achieve adequate bit energy. The transmitted signal is given by [1]

$$s(t) = \sqrt{\mathscr{E}} \sum_i a_i \sum_{j=0}^{N_f-1} g'(t - iN_fT_f - jT_f - c_jT_c), \qquad (1)$$

where $\mathscr{E}$ is the energy of the transmitted pulse, $\{a_i\}$ are the information symbols taking values ± 1 with equal probability, $g'(t)$ is the transmitted *monocycle*, N_f is the number of frames per symbol, T_f is the frame period, T_c is the chip period, and c_j, for $j = 0, \dots, N_f - 1$, is the time-hopping sequence whose elements are integer values in the range $0 \leq c_j \leq N_h$. In our experiments, we employed random time-hopping (TH) sequences drawn from a uniform distribution. We assume that there is no inter-frame interference. The multipath channel is modeled as a tapped-delay line

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with arbitrary path delays τ_l and path gains γ_l assumed to be time-invariant for the duration of one observation block. Therefore, the received waveform can be expressed as

$$r'(t) = \sqrt{\mathscr{E}}\sum_i a_i \sum_{j=0}^{N_f-1}\sum_{l=0}^{N_p-1} \gamma_l g'_l(t - iN_fT_f - jT_f - c_jT_c - \tau_l) + n'(t), \quad (2)$$

where N_p is the number of multipath components and $n'(t)$ is AWGN with two-sided PSD $\sigma^2 = N_0/2$. The received waveform is passed through a receive filter $g_R(t)$ whose output can be rewritten in a more convenient form by denoting $h(t) = \sum_{l=0}^{N_p-1}\gamma_l g_l(t-\tau_l)$, where $g_l(t) = g'_l(t) * g_R(t)$ is the convolution of the distorted received monopulse and the receive filter:

$$r(t) = \sqrt{\mathscr{E}}\sum_i a_i \sum_{j=0}^{N_f-1} h(t - iN_fT_f - jT_f - c_jT_c) + n(t). \quad (3)$$

The observation interval comprises N_s symbols out of which the first N_t symbols are known (training symbols) and the remaining $N_d = N_s - N_t$ symbols are unknown (data symbols).

After lowpass filtering, the received signal $r(t)$ is sampled with sampling period T_s. Let $\mathbf{h} = [h[0], h[1], \ldots, h[L-1]]^T$ denote the sampled version of the channel response (CR). After removing the time-hopping code (despreading), the length-LN_fN_s received vector $\mathbf{r}$ can be obtained as a concatenation of N_fN_s sub-vectors $\mathbf{r}_{i,j}$ for $i = 0,1,\ldots,N_s-1$, $j = 0,1,\ldots,N_f-1$ of length L given by

$$\mathbf{r}_{i,j} = \sqrt{\mathscr{E}}a_i\mathbf{h} + \mathbf{n}_{i,j}, \quad (4)$$

such that $\mathbf{r}_i = [\mathbf{r}_{i,0}^T, \ldots, \mathbf{r}_{i,N_f-1}^T]^T$ and $\mathbf{r} = [\mathbf{r}_0^T, \ldots, \mathbf{r}_{N_s-1}^T]^T$. The noise samples are assumed to be independent and hence the covariance matrix of the noise vector in the ith symbol and the jth frame $\mathbf{n}_{i,j}$ is given by $\mathbf{K} = \sigma^2\mathbf{I}_L$, where $\mathbf{I}_L$ is the $L \times L$ identity matrix.

3. LOW-BIT RESOLUTION RECEIVERS

We assume that a b bit uniform scalar quantizer $Q(\cdot)$ with symmetric quantization levels $q_{\pm l} = \pm\Delta(l - 1/2)$, $l = 1,2,\ldots,2^{b-1}$, centered around zero, *i.e.* $q_{-l} = -q_l$, is employed. The threshold levels $T_{\pm l}$, $l = 0,1,2,\ldots,2^{b-1}$, are given by

$$T_l = \begin{cases} 0, & l = 0 \\ (q_l + q_{l+1})/2, & l = 1,2,\ldots,2^{b-1}-1 \end{cases} \quad (5)$$

and the dynamic range of the ADC is defined as twice the maximum quantized value plus Δ, *i.e.* $D = 2q_{(2^{b-1})} + \Delta = \Delta 2^b$. If the unquantized received samples $r_{i,j}[n]$ fall out of this range, they are clipped. Since the received vector $\mathbf{r}_i$, conditioned on the ith data symbol and the channel, is Gaussian, the probability mass function (pmf) of the quantizer output $y_{i,j}[n]$ is given by [14]

$$P(y_{i,j}[n] = q_l | a_i, h[n]) = \begin{cases} 1 - Q(z_{l+1}), & l = -2^{b-1} \\ Q(z_l) - Q(z_{l+1}), & l = -2^{b-1}+1,\ldots,-1 \\ Q(z_{l-1}) - Q(z_l), & l = 1,\ldots 2^{b-1}-1 \\ Q(z_l), & l = 2^{b-1} \end{cases},$$

where $Q(x) = \int_x^\infty 1/\sqrt{2\pi}\exp(-y^2/2)dy$ is the complementary cumulative Gaussian distribution function and $z_l = (T_l - a_i\sqrt{\mathscr{E}}h[n])/\sigma$. The GLRT rule based on quantized observations for detection of the data symbol a_j is given by

$$\Lambda(\mathbf{y}_j) = \frac{\prod_{l=0}^{N_f-1}\prod_{n=0}^{L-1} P(y_{j,l}[n] | a_j = +1, \hat{h}_{+,\mathrm{ML}}[n])}{\prod_{l=0}^{N_f-1}\prod_{n=0}^{L-1} P(y_{j,l}[n] | a_j = -1, \hat{h}_{-,\mathrm{ML}}[n])} \underset{a_j=-1}{\overset{a_j=+1}{\gtrless}} 1, \quad (6)$$

where $P(y_{j,l}[n] | a_j = +1, \hat{h}_{+,\mathrm{ML}}[n])$ is the likelihood function of the quantized received samples $y_{j,l}[n]$ conditioned on the ML estimate of the template signal $\hat{h}_{\pm,ML}[n] = \hat{h}_{(a_j=\pm1,ML)}[n]$ and the data symbol $a_j = \pm1$. We emphasize that the decision rule in (6) is based on the quantized samples. In general, due to the presence of the product of Q-functions, it appears that a closed form solution for the maximum likelihood (ML) channel estimate conditioned on the data symbol $a_j = \pm1$ cannot be obtained. Therefore, we numerically solve

$$\hat{h}_{(a_j=\pm1,\mathrm{ML})}[n] = \quad (7)$$
$$\arg\max_{h[n]\in\mathscr{D}} \Bigg\{ \prod_{i=0}^{N_t-1}\prod_{l=0}^{N_f-1} P(y_{i,l}[n]|a_i, h[n]) P(y_{j,l}[n]|a_j = \pm1, h[n]) \cdot \prod_{i=1,i\neq j}^{N_s-1}\prod_{l=0}^{N_f-1}\frac{1}{2}\left(P(y_{i,l}[n]|a_i = +1, h[n]) + P(y_{i,l}[n]|a_i = -1, h[n])\right)\Bigg\}.$$

for both $a_j = +1$ and $a_j = -1$ with the range of optimization, constrained to $\mathscr{D} = [-q_{(2^{b-1})}, q_{(2^{b-1})}]$. Note that despite the constraint on the range of optimization, we refer to the estimator in (7) as the ML estimator. With this choice for the optimization range, the maximum absolute value for each estimated channel tap is identical to the largest quantization level. The ML channel estimate for all possible combinations of the received signal can be pre-calculated.

In order to reduce the complexity, we introduce two suboptimal decision rules: GLRT-U and GLRT-QS, where -U and -QS refer to unquantized and quantized, simplified, respectively. The GLRT-U scheme corresponds to the decision rule that is based on unquantized samples [4] and simply replaces the unquantized samples by the quantized samples, *i.e.* $\hat{a}_j = \mathrm{sgn}(\bar{\mathbf{y}}_j^T\hat{\mathbf{h}}_j)$ for $j = N_t, ..., N_s - 1$. Here, the frame averaged despread received signal is defined as $\bar{\mathbf{y}}_i = 1/N_f\sum_{j=0}^{N_f-1}\mathbf{y}_{i,j}$ and the template signal for the jth data symbol is given by

$$\hat{\mathbf{h}}_j = \frac{1}{\sqrt{\mathscr{E}}(N_s-1)}\left(\sum_{i=0}^{N_t-1} a_i\bar{\mathbf{y}}_i + \sum_{i=N_t,i\neq j}^{N_s-1}\hat{a}_i\bar{\mathbf{y}}_i\right). \quad (8)$$

The GLRT-QS receiver uses the decision rule in (6) but replaces the conditioned ML channel estimate by the intuitive closed form *ad-hoc* estimator

$$\hat{\mathbf{h}}_{(a_j=\pm1,\mathrm{AH})} = \frac{1}{\sqrt{\mathscr{E}}N_s}\left(\sum_{i=0}^{N_t-1} a_i\bar{\mathbf{y}}_i + \sum_{i=N_t,i\neq j}^{N_s-1}\hat{a}_i\bar{\mathbf{y}}_i \pm \bar{\mathbf{y}}_j\right). \quad (9)$$

We emphasize that this is the conditional ML estimate only if unquantized samples $r_{i,j}[n]$ are available (no numerical optimization is required). In the sequel, we argue that this ad-hoc estimator is equivalent to the ML channel estimate for several cases.

Due to the investigation of quantized signals, the development of optimized receiver structures for arbitrary values of N_d, N_t, and N_f does not yield intuitive simple forms. To gain intuition, we focus on several special cases.

Special Case: $N_d = N_t = N_f = 1$
Consider the case of a classical TR system with $N_t = N_d = N_f = 1$, *i.e.* one training symbol, one data modulated symbol, and one frame per symbol. As can be seen from (8), the decision rule for the GLRT-U receiver simplifies to $\hat{a}_1 = \mathrm{sgn}\left(a_0\mathbf{y}_0^T\mathbf{y}_1\right)$. For the ad-hoc and the conditioned ML channel estimates, we obtain $\hat{h}_{\pm,\mathrm{AH}}[n] \approx 1/(2\sqrt{\mathscr{E}})(a_0y_0[n] \pm y_1[n])$ and

$$\hat{h}_{\pm,\mathrm{ML}}[n] = \arg\max_{h[n]\in\mathscr{D}}\{P(y_0[n]|a_0, h[n]) \cdot P(y_1[n]|a_1 = \pm1, h[n])\}. \quad (10)$$

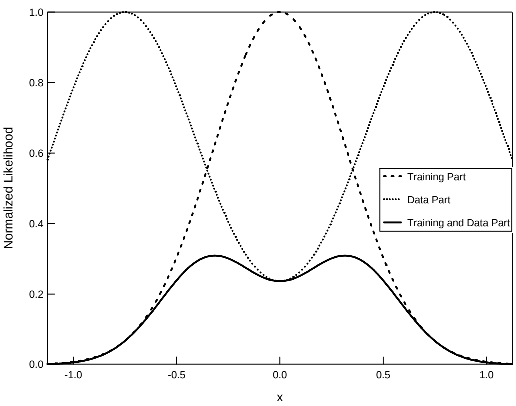

Figure 1: Likelihood function of the training and the data part of the received signal for $N_t = 1$, $N_d = 3$, $N_f = 1$, $b = 2$, and $L = 400$.

As will be seen in Section 4, for the case $N_t = N_d = N_f = 1$ no noticeable performance loss of the computationally less complex GLRT-QS scheme with respect to the GLRT-Q receiver can be observed. This suggests that the channel estimate of the GLRT-Q and the GLRT-QS schemes are similar. In fact, we can identify three different scenarios for which the ML and ad-hoc channel estimates are identical. First, denoting all combinations of $y_0[n]$ and $y_1[n]$ whose likelihood function involves the quantization bins corresponding to the maximum or minimum quantization value with infinite support, *i.e.* $y_0[n] = \pm q_{(2^{b-1})}$ or $y_1[n] = \pm q_{(2^{b-1})}$ as *asymmetric combinations*, we can prove [15] that for all *symmetric combinations* (*i.e.* all combinations which are not asymmetric) we have $\hat{h}_{\pm,\mathrm{ML}}[n] = \hat{h}_{\pm,\mathrm{AH}}[n]$, *i.e.* the ad-hoc estimator is the ML estimator. Second, asymmetric combinations for which $y_0[n] = -y_1[n] = q_l$, $q_l = -2^{b-1}, \ldots, 2^{b-1}$, we have $\hat{h}_{\pm,\mathrm{ML}}[n] = \hat{h}_{\pm,\mathrm{AH}}[n] = 0$. Third, asymmetric combinations for which $y_0[n] = y_1[n] = \pm q_{2^{b-1}}$ and the range of numerical optimization is constrained to $\mathscr{D} = [-q_{2^{b-1}}, q_{2^{b-1}}]$ we have $\hat{h}_{\pm,\mathrm{ML}}[n] = \hat{h}_{\pm,\mathrm{AH}}[n] = \pm q_{2^{b-1}}$. Note that the term symmetric relates to the fact that the likelihood function for symmetric combinations is the product of the difference of Q-functions whose argument is finite. For low SNR, the ML channel estimate for the remaining asymmetric combinations differs from the ad-hoc estimator and it appears that no closed form solution for the ML channel estimate exists. Moreover, the channel estimates corresponding to asymmetric combinations (except the zero level) are highly dependent on the range of optimization. However, in the limit of high SNR, we have observed that the ad-hoc channel estimates of the remaining asymmetric combinations converge to the ML estimates. In other words, the ad-hoc estimator is a high SNR approximation to the ML estimator in (10).

Special Case: $N_d = N_t = 1, N_f \geq 1$

If the number of frames per symbol N_f is greater than one, the ML channel estimate is given by

$$\hat{h}_{\pm,\mathrm{ML}}[n] = \arg\max_{h[n]\in\mathscr{D}} \left\{ \prod_{j=0}^{N_f-1} P(y_{0,j}[n]|a_0, h[n]) \cdot P(y_{1,j}[n]|a_1 = \pm 1, h[n]) \right\}. \quad (11)$$

For a large number of frames per symbol, *i.e.* $N_f \gg 1$ the number of possible combinations (and therefore also the complexity) increases exponentially with N_f. Therefore, we consider suboptimal schemes that are expected to provide better performance than the GLRT-QS receiver but are less complex than the GLRT-Q scheme. Instead of considering the entire received signal at once, we can proceed frame by frame, *i.e.* we compute N_f channel estimates where the

Receiver	Channel Estimator	Detector
GLRT-U	Training	Correlation
GLRT-QS	Ad-hoc	GLRT
GLRT-QF	ML-FF	GLRT
GLRT-QFW	Weighted ML-FF	GLRT
GLRT-Q	ML	GLRT
GLRT-QM	ML Modified	GLRT

Table 1: Receiver structures.

jth estimate is given by

$$\hat{h}^j_{\pm,\mathrm{QF}}[n] = \arg\max_{h[n]\in\mathscr{D}} \left\{ P(y_{0,j}[n]|a_0, h[n]) \cdot P(y_{1,j}[n]|a_1 = \pm 1, h[n]) \right\} \quad (12)$$

and average them to obtain the final estimate $\hat{h}_{\pm,\mathrm{QF}}[n] = 1/N_f \sum_{j=0}^{N_f-1} \hat{h}^j_{\pm,\mathrm{QF}}[n]$. Note that the jth channel estimate restricted to a pair of frames of the training and data symbol is ML optimal. We denote this sub-optimal scheme by GLRT-QF where QF refers to the optimal channel estimate on a frame basis. As will be seen in Section 4, the GLRT-QF receiver exhibits a small performance degradation in comparison to the GLRT-QS scheme due to the assumption that the prior density for the channel estimate within all quantization bins is flat. In other words, we consider each value for the channel estimate within a quantization bin as equally likely. While this assumption might be justified for symmetric quantization bins, *i.e.* quantization bins that do not have $\pm\infty$ as a threshold value, in the case of a asymmetric combination, where at least one quantization bin has an infinite support, this assumption does not reflect the behavior of a real system that employs an automatic-gain-control stage to adjust the quantizer to the received signal strength. For example, for the simple case $y_0 = -q_{2^{b-1}}$, $y_1 = -q_{2^{b-1}}$, $a_0 = 1$, $a_1 = 1$, and $N_f = 1$, the resulting likelihood function is a monotonically decreasing function suggesting that the ML channel estimate is $h[n] = -\infty$ (if the range of the numerical optimization is unconstrained). Certainly, this solution is not practical. If prior knowledge on the statistical description of the channel is available, we can weight the likelihood function accordingly. In the context of UWB communications, this is a challenging task, given the statistical description of the channel provided in [16]. However, it is clear that values much larger than the dynamic range of the quantizer are unlikely. Therefore, we introduce a Gaussian weighting function $\Gamma(h[n]) = 1/(\sqrt{2\pi\sigma_w^2}) \exp\left(-1/(2\sigma_w^2) h[n]^2\right)$ which acts as a prior density, but does not require knowledge of the channel statistics. The variance σ_w^2 is chosen heuristically based on the dynamic range of the quantizer. This receiver is denoted as GLRT-QFW and its jth channel estimate is given by

$$\hat{h}^j_{\pm,\mathrm{QFW}}[n] = \arg\max_{h[n]\in\mathscr{D}} \left\{ P(y_{0,j}[n]|a_0, h[n]) \cdot P(y_{1,j}[n]|a_1 = \pm 1, h[n]) \Gamma(h[n]) \right\}, \quad (13)$$

leading to the final estimate $\hat{h}_{\pm,\mathrm{QFW}}[n] = 1/N_f \sum_{j=0}^{N_f-1} \hat{h}^j_{\pm,\mathrm{QFW}}[n]$.

Special Case: $N_t = 1, N_d \geq 1, N_f = 1$

In this case the ML channel estimate conditioned on the corresponding data symbol is given by

$$\hat{h}_{(a_j=\pm 1,\mathrm{ML})}[n] = \arg\max_{h[n]\in\mathscr{D}} \left\{ P(y_0[n]|a_0, h[n]) P(y_j[n]|a_j = \pm 1, h[n]) \cdot \prod_{i=1, i\neq j}^{N_s-1} \frac{1}{2} \left(P(y_i[n]|a_i = +1, h[n]) + P(y_i[n]|a_i = -1, h[n]) \right) \right\}. \quad (14)$$

We emphasize that all of the unknown data symbols, except the one to be detected, appear as nuisance parameters over which we average the likelihood function as in [4].

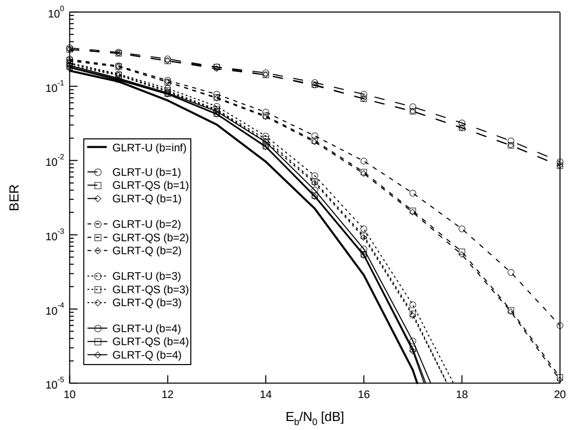

Figure 2: BER performance of the GLRT-U, GLRT-QS, and GLRT-Q decision rules for $b = 1,2,3,4$, $N_t = 1$, $N_d = 1$, and $L = 400$.

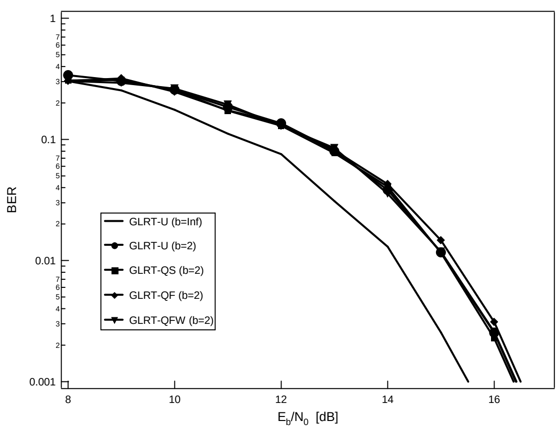

Figure 3: BER performance of the GLRT-QS, GLRT-QF, and GLRT-U for $N_t = 1$, $N_d = 1$, $N_f = 20$, $b = 2$, and $L = 400$.

In our experiments, we have observed that increasing the number of data symbols $N_d > 2$ leads to ambiguity problems. Figure 1 exhibits the likelihood function to be maximized in (14) as well as the *training part* comprising the training symbols and the data symbol to be detected $P(y_0[n]|a_0,h[n])P(y_j[n]|a_j = \pm 1,h[n])$ and the *data part* comprising the remaining unknown data symbols (nuisance parameters) $\prod_{i=1,i\neq j}^{N_s-1} \frac{1}{2}\left(P(y_i[n]|a_i = +1,h[n]) + P(y_i[n]|a_i = -1,h[n])\right)$ for $N_d = 3$, $N_t = N_f = 1$. The index of the symbol to be detected is $i = 1$ and the received samples are set to $y_0 = q_{-1}$, $y_1 = q_1$, $y_2 = q_{-2}$, and $y_3 = q_1$. Here, the nuisance parameters are a_2 and a_3. It can be observed that both the training and data part of the likelihood function are symmetric about the origin and that the training part shows a maximum at zero. However, at zero, the data part reaches its minimum, and moreover, it has two local maxima. Intuitively, this means that the training part suggests zero for the channel estimate, while the overall likelihood function exhibits two local maxima. The receiver may choose either maximum to determine the overall channel estimate leading to an ambiguity since with probability 1/2 that we select the incorrect maxima. As will be seen in Section 4, this ambiguity results in a performance degradation. To remove this ambiguity, we can modify the GLRT-Q scheme in the following manner. Whenever the maximization of the training part suggests zero as the ML channel estimate we replace this estimate by the ad-hoc estimate $\hat{h}_{\pm,\mathrm{AH}}[n]$. This scheme is refereed to as GLRT-QM. We note that this ambiguity problem of the GLRT-Q receivers also occurs for a bit resolution of $b = 3$, and an increased number of data symbols $N_d = 4,5$. However, for the case $N_d = 3$, increasing the transmit power for the training symbol by a factor of 2 or assuming only one unknown data symbol and two training symbols removes the ambiguity and the GLRT-Q outperforms the GLRT-QS receiver as expected. Table 1 summarizes the investigated receiver structures.

Next, we discuss the asymptotic complexity of the GLRT-U,-QS, and -Q receivers which theoretically can be applied to the general setting $N_f > 1$, $N_t > 1$, and $N_d > 1$. The detection rule employed by the GLRT-U scheme in (8) requires $\mathcal{O}(L)$ multiply-and-add (MPA) operations and $\mathcal{O}(N_f L)$ add-and-store operations to despread the quantized received signal $\mathbf{y}_j$. In contrast, the detection rule of the quantized receiver structures in (6) requires $\mathcal{O}(N_f L)$ MPA operations and about $\mathcal{O}(N_f L)$ table look-ups. Therefore, it appears that the complexity of the detection rule for the GLRT-QS and -Q receivers in (6) is similar to the one for the GLRT-U receiver in (8). Since the number of possible combinations of the received quantized signal is limited, the channel estimates for the GLRT-Q scheme in (11) can be pre-computed for each such combination. For example, for a b bit quantizer and $N_t = N_d = N_f = 1$ we pre-compute 2^{2b} estimates. However, the number of combinations grows exponentially with b, N_f, and N_s, *i.e.* $\mathcal{O}(e^{bN_fN_s})$, rendering the GLRT-Q receiver impractical. In contrast, the complexity of the conditioned channel estimates required for the GLRT-QS receiver can be easily calculated online based on the quantized received samples similar to the GLRT-U receiver.

4. SIMULATION RESULTS

For the simulation results presented in the sequel, we have used a monopulse $g_I(t)$ that is shaped as the second derivative of a Gaussian function and has a width of 1 ns. The frame period T_f is set equal to 110 ns, the chip period T_c is 2 ns, and the elements of the time-hopping code are randomly chosen in the interval $0 \leq c_j \leq 24$. The channel is modeled as indicated in the report [16] of the IEEE 802.15.3a task group (CM1) with a delay spread being restricted to 50 ns, as the energy of the multipath components arriving after more than 50 ns is negligible. The channel response is normalized by the maximal value, *i.e.* $\max_n\{|h[n]|\} = 1$. The receive filter has a rectangular transfer function over $\pm 4GHz$ and the sampling rate is set to 8 GHz which corresponds to $L = 400$ samples per CR. The SNR is defined as the ratio E_b/N_0, where E_b is the energy per symbol at the filter output (before sampling).

Figure 2 shows the BER performance of the GLRT-Q decision rule in (6) in comparison with the two suboptimal decision rules: GLRT-QS and GLRT-U for $N_t = N_d = N_f = 1$ and different bit resolutions. The performance of the GLRT-U scheme employing a infinite resolution ADC (GLRT-U ($b = \infty$)) is provided for reference. It can be observed that the decision rules based directly on the quantized samples $y_{i,j}[n]$, *i.e.* GLRT-Q and GLRT-QS, provide modest performance gains over the heuristic GLRT-U rule that assumes a infinite resolution ADC. At BER $= 10^{-3}$, the improvement of the GLRT-Q and the GLRT-QS schemes are 0.3, 0.5, 0.2, 0.1 dB for $b = 1,2,3,4$, respectively. As expected, no noticeable performance loss of the computationally less complex GLRT-QS scheme (no numerical optimization) with respect to the GLRT-Q receiver can be observed.

The BER performance of the GLRT-U, QS, -QF, and -QFW for $N_t = 1$, $N_d = 1$, $N_f = 20$, $b = 2$, and $L = 400$ is exhibited in Figure 3. It can be observed that the GLRT-U and GLRT-QS receivers show similar performance while the GLRT-QF receiver exhibits a small but noticeable degradation of about 0.25 dB. Intuitively, since the GLRT-QF scheme employs the frame by frame ML channel estimate as in (12) it should outperform the GLRT-QS and the GLRT-U receiver. However, as explained in Section 4, by maximizing the product of likelihood functions according to (12) for a given received, quantized signal with respect to the channel, we implicitly assume that the prior density for the channel estimate in a particular quantization bin is flat, an assumption that is not justified for the lowest and largest quantization bin. The GLRT-QFW receiver

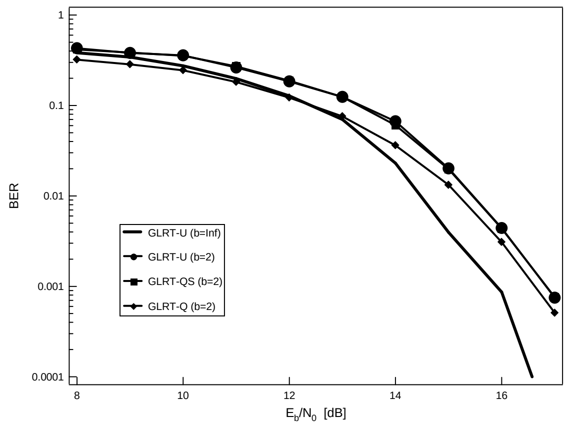

Figure 4: BER performance of the GLRT-Q, GLRT-QS, and GLRT-U for $N_t = 1$, $N_d = 2$, $N_f = 1$, $b = 2$, and $L = 400$.

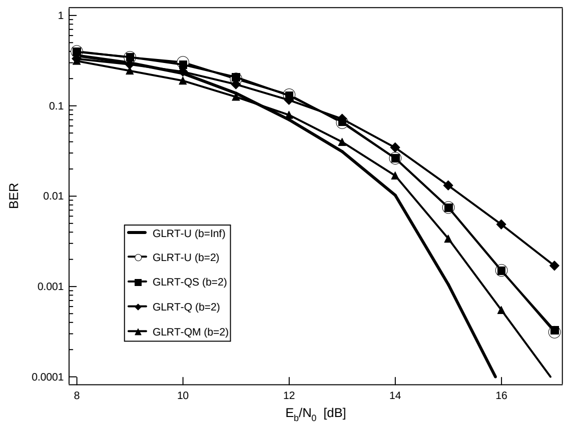

Figure 5: BER performance of the GLRT-Q, GLRT-QS, and GLRT-U for $N_t = 1$, $N_d = 3$, $N_f = 1$, $b = 2$, and $L = 400$.

that employs a weighting function with a heuristically chosen variance of $\sigma_w^2 = 1/16$ exhibits no performance loss with respect to the GLRT-QS receiver. In our experiments we have observed that the GLRT-QFW scheme is fairly robust against the choice of the variance. Note that the weighting of the likelihood function can in principal also be applied to the GLRT-Q scheme. However, we expect the performance improvements to be modest.

Figures 4 shows the BER of the GLRT-Q, -QM, -QS, and -U receiver for $b = 2$, $N_d = 2,3$, and $L = 400$. We observe that for $N_d = 2$ the GLRT-Q scheme exhibits a performance gain of about 0.3 dB in comparison to the GLRT-QS receiver which employs a simplified channel estimate. While for $N_d = 3$, in Figure 5 the ambiguity of the GLRT-Q scheme as described in the previous section causes performance degradation compared to the GLRT-QS receiver, the modified scheme, GLRT-QM, exhibits a performance gain of about 0.5 dB.

In summary, the GLRT decision rules based on the quantized received signal can lead to performance improvements. Particularly, for the traditional TR setting, *i.e.* $N_t = N_d = N_f = 1$ and a low resolution ADC with $b = 2$ bits, performance improvements with reasonably complex receiver structures can be observed. The generalization to a larger number of data symbols, training symbols, or number of frames can lead to further performance improvements at the cost of considerably more complex receiver structures. The computationally efficient GLRT-U scheme yields good performance even in the presence of a low resolution ADC and in addition can be easily adapted to different parameter settings.

5. CONCLUSIONS

In this paper, the effect of low resolution quantization of the received samples on the BER performance for UWB TR receivers is investigated. The generalized-likelihood ratio test receiver (GLRT-Q) based on the quantized samples is derived and shown to lead to performance gains in comparison to the conventional GLRT receiver operating on quantized observations. The cost for this performance gain is an exponential complexity in the number of frames, training, and data symbols. To reduce the complexity several sub-optimal detection schemes with a linear complexity showing marginal performance loss are derived. Simulation results reveal that a four bit ADC can provide a performance close to a infinite resolution ADC.

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