ML Timing Estimation for Generalized UWB-IR Energy Detection Receivers

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***Abstract*—Timing estimation of the receive pulse is a crucial component for communication systems as well as localization with ultra wideband impulse radio. Standard timing estimation algorithms might not be applicable due to stringent requirements on complexity and power consumption of the receiver. Therefore, we consider maximum likelihood timing estimation at the output of a generalized energy detection receiver, that consists of a squaring device followed by an arbitrary post-detection filter and low rate sampler. Moreover, we assume only the statistics of the channel to be known at the receiver. To the best of our knowledge, this problem has not been treated so far in this generalized set up. Known approaches for specific post-detection filters rely on a Gaussian approximation of the detector output. We show that the estimation accuracy can be improved by using the exact marginal PDF of the energy detector output. This is verified by channel model and measurements. Towards reduced complexity, we approximate the ED detector output as multivariate normally or multivariate log-normally distributed. Verification based on channel model and measured channels favors the log-normal approximation and shows that the correlation is not relevant. Accuracy down to centimeter precision can be reached.**

I. Introduction

Ultra wideband (UWB) communication is one of the most promising technologies for future wireless sensor networks [1], [2]. The very large bandwidth in the spectrum from $3.1 - 10.6$ GHz allows for innovative communication systems that are able to both transmit data very fast and efficiently and perform accurate localization and positioning. UWB impulse radio (IR) is one approach that enables very low complexity and low power transceiver architectures. Due to the frequency selective and time varying nature of the UWB channel and stringent requirements on battery autonomy, noncoherent receiver architectures attracted much interest. Among them the energy detection receiver offers a favorable compromise between complexity and performance [3]. It measures the energy, which is received in an observation window.

Timing estimation enables distance measurements based on time-of-arrival (ToA) or round-trip-time measurements and is also essential for synchronization. Hence, timing estimation is a crucial joint functional block for communication as well as localization. An overview on timing acquisition in UWB communication systems is given in [4]. Localization with UWB in general with focus on ToA estimation is described in [5]. In [6], synchronization algorithms for coherent and differential receivers are presented. With focus on low-complexity and energy detection receivers, an algorithm for synchronization has been presented and analyzed in [7]. In [8], maximum likelihood (ML) timing estimators for different IR-UWB receivers are derived, including energy detection receivers. The authors consider a conventional energy detector (ED) with rectangular integration window and invoke the Gaussian assumption for the ED output.

The work reported herein was motivated by two observations, which we made during initial investigations on the timing estimation for UWB-IR with energy detection: (i) the hardware complexity of an energy detector can be considerably reduced, if we replace the integrator by a first order lowpass [9]; (ii) for timing estimation the Gaussian assumptions may come with a considerable performance loss.

Consequently in this paper, we present a theoretical framework for timing estimation for a generalized ED receiver and normally distributed channel impulse responses. We assume, that the receiver has no channel state information, but knows the mean and covariance functions of the channel impulse response. In contrast to the conventional ED receiver the generalized version allows for an arbitrary post-detection filter after the squaring device. By adapting the parameters, timing estimation for a wide class of ED receivers and propagation environments is covered. Furthermore, low complexity algorithms are derived, which are motivated by approximations of the probability density function (PDF) of the ED output. The performance of these novel timing estimators is evaluated for measured channel impulse responses and for synthetic ones (channel model).

The remainder of this paper is structured as follows. In section II, the considered system model is described. Section III describes the ML estimation of the pulse timing, and the exact PDF of the ED output is derived in section IV. In section V lower complexity estimators based on approximations are shown. Finally, the performance of the different estimators is evaluated in section VI and a summary is given in section VII.

II. System Model

We consider a UWB impulse radio transmitter, that transmits a sequence of unmodulated pulses $p(t)$, i.e. in Fig. 1 we have $b(t) = \sum_k \delta(t - kT_{\mathrm{symb}})$. The frequency selective fading channel of the multipath environment is characterized by the delay ε_1 and the channel impulse response $h(t)$. For the theoretical part of the paper $h(t)$ is modeled as nonstationary Gaussian random process. The channel output signal is perturbed by AWGN with power spectral density

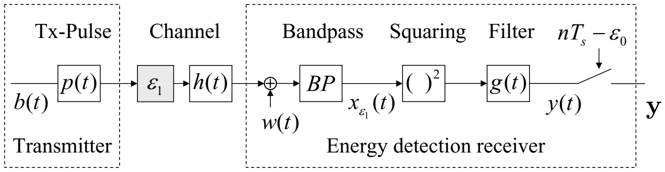

Fig. 1. Block diagram of transmitter, channel and receiver

$N_0/2$. After the receive bandpass we obtain the received signal

$$x_{\varepsilon_1}(t) = \sum_{k=-\infty}^{\infty} \tilde{h}(t - kT_{\text{symb}} - \varepsilon_1) + \tilde{w}(t),$$

where $\tilde{w}(t)$ denotes the band-limited noise and $\tilde{h}(t)$ the equivalent channel impulse response, which includes transmit pulse, channel impulse response and bandpass filter. We assume that $\tilde{h}(t) = 0$ for $t \notin [0, T_{\text{symb}}]$, i.e. no inter pulse interference occurs.

For a Gaussian channel model the equivalent channel impulse response is a sample function of an nonstationary Gaussian random process. We assume in the sequel that the receiver does not know $\tilde{h}(t)$, but has full knowledge of the statistics of it, i.e. it knows the mean and the autocorrelation function. Note that $x_\varepsilon(t)$ is a cyclostationary Gaussian random process due to the periodic transmit signal.

The delay ε_1 is unknown at the receiver. In this paper we treat the estimation of ε_1 under the aforementioned assumptions. As $x_\varepsilon(t)$ is cyclostationary, the estimation range is $[0, T_{\text{symb}}]$, i.e. we can only estimate ε_1 mod T_{symb}. The estimation is based on samples taken at time instances $nT_s - \varepsilon_0$ with the unknown sample offset $\varepsilon_0 \in [0, T_s]$ (Fig. 1). Thus the estimator actually estimates $\varepsilon_0 + \varepsilon_1$. As our system is time-invariant, we can incorporate ε_0 into the channel delay ε_1, i.e. we can assume without loss of generality $\varepsilon_0 = 0$.

The Gaussian received signal $x_\varepsilon(t)$ is detected by a generalized energy detector, which consists of a squaring device and a post-detection filter $g(t)$. For the conventional energy detector, the post-detection filter has a rectangular impulse response, i.e. it implements a rectangular integration window. Due to hardware complexity it may be beneficial to use other filters, such as a first order lowpass [9].

The maximum likelihood estimation of ε_1 requires knowledge of the multivariate PDF of the detector output signal $\{y(nT_s)\}$ for any delay ε. There is no closed form solution for this PDF, even though $x_\varepsilon(t)$ is Gaussian. For this reason in many related publications (e.g. [8]) a Gaussian assumption is invoked for $y(t)$. The present paper has been motivated by the desire to recover some of the performance loss that comes with this assumption.

III. Timing Estimation

Our receiver uses N consecutive T_s-spaced samples of the signal $y(t)$ to generate an estimate $\hat{\varepsilon}$ of the channel delay ε_1, i.e. the input to the estimator is the vector

$$\mathbf{y} = [y(T_s), y(2T_s), \ldots, y(NT_s)]^T.$$

As known from estimation theory, the maximum likelihood (ML) estimate can be formulated as follows:

$$\hat{\varepsilon} = \arg\max_{\varepsilon} p_{\mathbf{y}}(\mathbf{y}|\varepsilon), \tag{1}$$

where the probability density function (PDF) of the receive sample vector $\mathbf{y}$ conditioned on the time shift ε is denoted by $p_{\mathbf{y}}(\mathbf{y}|\varepsilon)$.

In the following, we derive an analytical expression for the marginal PDFs for each ED output sample, which are denoted by $p_y(y_n|\varepsilon)$. In order to evaluate $p_{\mathbf{y}}(\mathbf{y}|\varepsilon)$ for the maximum search, we make the additional assumption that the individual samples $y_n = y(nT_s)$ for $n = 1, ..., N$ are statistically independent, which leads to

$$p_{\mathbf{y}}(\mathbf{y}|\varepsilon) \approx \prod_{n=1}^{N} p_y(y_n|\varepsilon). \tag{2}$$

This approximation is necessary, since computation of the multivariate PDF of $\mathbf{y}$ is not feasible using the presented algorithm.

IV. Marginal PDF of Energy Detector Output for Normally Distributed Channels

For clarity, the following exposition is based on $g(t) = 0$ for $t \notin [0, T_{\text{symb}}]$. This is the most practical case and extension to arbitrary $g(t)$ is straightforward. However, note that $g(t) \geq 0$ is required. Due to the cyclostationarity of $y(t)$, we can chose without loss of generality $(nT_s - \varepsilon)$ mod T_{symb} for the calculation of the marginal PDF.

We consider now an equivalent discrete time system model, which is obtained by sampling the continuous signals with sampling period T. All system components are assumed to satisfy a sufficient low-pass characteristic and are approximately time limited that any errors from sampling expansion can be neglected. To account for the squaring operation, the sampling period T must fulfill at least $1/T > 4(B + f_c)$. Then, the sampled ED output under the hypothesis that the delay is ε, can be written as

$$y_n = \sum_{l=-L}^{L-1} g(nT_s - \varepsilon - lT) x^2(lT),$$

where $x(t - \varepsilon) = x_\varepsilon(t)$. Thus, the statistics of $x^2(lT)$ are independent of ε. Rewriting this in vector notation yields the quadratic form

$$y_n = \mathbf{x}^T \mathbf{Q}_n^{(\varepsilon)} \mathbf{x}, \tag{3}$$

where

$$\mathbf{x} = [x_{-L}, \ldots, x_{L-1}]^T \quad \text{and} \quad \mathbf{Q}_n^{(\varepsilon)} = \text{diag}([g_{-L}, \ldots, g_{L-1}]^T)$$

with $x_l = x(lT)$, $g_l = g(nT_s - \varepsilon - lT)$, and $L = T_{\text{symb}}/T$. The diagonal matrix $\mathbf{Q}_n^{(\varepsilon)}$ contains only samples of $g(t)$. Depending on the delay ε and the sample number n, the sampling of $g(t)$ is shifted. In this way, the ED output samples can be written compactly, where only $\mathbf{Q}_n^{(\varepsilon)}$ depends on the delay and sampling instance. The vector $\mathbf{x}$ is independent of

n and ε and contains the samples of the realization of two receive pulses.

Due to the assumption of Gaussian noise and Gaussian channel taps, the vector $\mathbf{x}$ is jointly Gaussian distributed. The mean $\boldsymbol{\mu}_{\mathbf{x}}$ of $\mathbf{x}$ is given by

$$\boldsymbol{\mu}_{\mathbf{x}} = \mathsf{E}(\mathbf{x}) = \mathsf{E}(\tilde{\mathbf{h}}),$$

where $\tilde{\mathbf{h}} = [\tilde{h}(T), \ldots, \tilde{h}(LT), \tilde{h}(T), \ldots, \tilde{h}(LT)]^T$. The noise vector $\tilde{\mathbf{w}}$ is assumed to be zero-mean. The covariance matrix $\boldsymbol{\Sigma}_{\mathbf{x}}$ of $\mathbf{x}$ is given by

$$\boldsymbol{\Sigma}_{\mathbf{x}} = \mathsf{E}(\mathbf{x}\mathbf{x}^T) - \boldsymbol{\mu}_{\mathbf{x}}\boldsymbol{\mu}_{\mathbf{x}}^T = \mathsf{E}(\tilde{\mathbf{w}}\tilde{\mathbf{w}}^T) + \mathsf{E}(\tilde{\mathbf{h}}\tilde{\mathbf{h}}^T) - \mathsf{E}(\tilde{\mathbf{h}})\mathsf{E}(\tilde{\mathbf{h}})^T.$$

Following the presentation in [10], let us denote λ_i and $\mathbf{u}_i$ as the eigenvalues and the eigenvectors of $\boldsymbol{\Sigma}_{\mathbf{x}}^{0.5}\mathbf{Q}_n^{(\varepsilon)}\boldsymbol{\Sigma}_{\mathbf{x}}^{0.5}$. All eigenvalues are nonnegative, due to $g(t) \geq 0$. Furthermore, let Z_i be independent Gaussian random variables with variance one, and their means given by

$$\mathsf{E}(Z_i) = \gamma_i = \left(\boldsymbol{\Sigma}_{\mathbf{x}}^{-0.5}\mathbf{u}_i\right)^T \boldsymbol{\mu}_{\mathbf{x}}.$$

Then, the quadratic form in (3) has the same PDF as the diagonalized version (cf. [11]) given by

$$\tilde{y}_n = \sum_{i=1}^{2L} \lambda_i Z_i^2. \tag{4}$$

If all λ_i are equal, y_n is distributed according to a noncentral chi-square distribution. Such a PDF is usually obtained, when the conditional PDF of y_n given a channel realization is sought (e.g. [3]). However, this would only be valid for uniform integration windows, i.e. when $g(t)$ is a rectangular function.

For arbitrary λ_i no closed form expression for $p_y(y_n|\varepsilon)$ is known. Grenander, Pollak, and Slepian presented an efficient and numerically stable approach to calculate $p_y(y_n|\varepsilon)$ for zero mean random variables Z_i ($\gamma_i = 0\ \forall i$) in [12]. This approach is based on Fourier's inversion of the characteristic function of y_n. In [10], this method is extended to the nonzero mean case. With this numerical algorithm, the exact PDF of the ED output samples for arbitrary Gaussian processes at the input and arbitrary non-negative integration filters can be computed. This enables the evaluation of the maximum likelihood rule given by (1).

Fig. 2 depicts the numerically obtained PDF for two different scenarios. First, the PDF is plotted for a sample with significant mean and less variance. This corresponds, e.g., to a sample with strong line-of-sight (LOS) component. Furthermore, the PDF of a sample with less mean and larger variance is plotted. This is related to a sample containing strong multipath components. In addition to the exact PDF, an empirical PDF is plotted. This is obtained by computing the histogram of energy detector processed channel and noise realizations drawn from the normal distribution. Furthermore, the normal and log-normal distributions with same mean and variance are plotted.

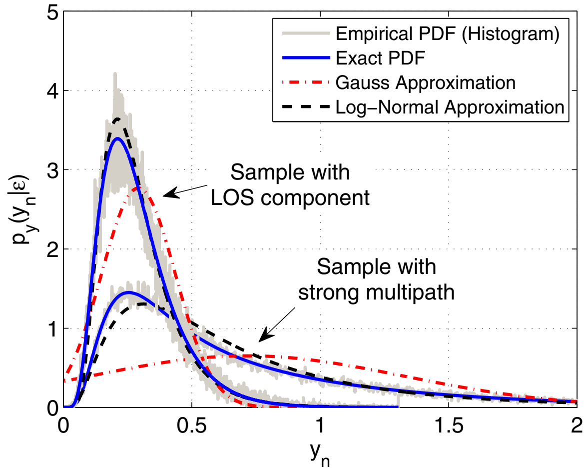

Fig. 2. Exact PDF of ED output sample compared to histogram and closed form approximations

V. Low-complexity Approximations of PDF

Even though the numeric evaluation of $p_y(y_n|\varepsilon)$ might be fast using the algorithm presented in [10], for practical system implementation it may be too complex. Therefore, we present approximations for $p_{\mathbf{y}}(\mathbf{y}|\varepsilon)$ that allow to solve the ML-estimation with lower complexity. First, we follow the approach to approximate the distribution of $\mathbf{y}$ by $\mathcal{N}(\boldsymbol{\mu}_{\mathbf{y}}, \boldsymbol{\Sigma}_{\mathbf{y}})$. The timing estimation corresponds then to the well known timing estimators as used for linear receivers [13]. Second, we approximate the ED output as log-normally distributed. Both approximations are shown in Fig. 2 in comparison to the exact PDF. It can be seen that the log-normal distribution approximates the PDF better than the Gauss approximation.

A. Gaussian Approximation

With the approximation $p_{\mathbf{y}}(\mathbf{y}|\varepsilon) \approx \mathcal{N}(\boldsymbol{\mu}_{\mathbf{y},\varepsilon}, \boldsymbol{\Sigma}_{\mathbf{y},\varepsilon})$ the ML-estimator (1) simplifies to

$$\hat{\varepsilon}_{\text{Gauss}} = \arg\max_{\varepsilon} -(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y},\varepsilon})^T \boldsymbol{\Sigma}_{\mathbf{y},\varepsilon}^{-1}(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y},\varepsilon}). \tag{5}$$

The mean and covariance matrix are given by

$$\boldsymbol{\mu}_{\mathbf{y},\varepsilon} = \mathbf{G}_\varepsilon \boldsymbol{\mu}_{\mathbf{x}^2} \quad \text{and} \quad \boldsymbol{\Sigma}_{\mathbf{y},\varepsilon} = \mathbf{G}_\varepsilon \boldsymbol{\Sigma}_{\mathbf{x}^2}\mathbf{G}_\varepsilon^T.$$

where $\mathbf{G}_\varepsilon = [g_{n,l}]_{N\times L}$ with

$$g_{n,l} = g(\text{mod}(nT_s - \varepsilon - lT, T_{\text{symb}}))).$$

Further, $\boldsymbol{\mu}_{\mathbf{x}^2} = [m_l]_{L\times 1}$ and $\boldsymbol{\Sigma}_{\mathbf{x}^2} = [s_{i,j}]_{L\times L}$ are mean and covariance matrix after the squaring device, respectively, with

$$\begin{aligned} m_l &= \mathsf{E}(x^2(lT)) = \sigma_{ll} + \mu_l^2 \\ s_{i,j} &= \mathsf{E}(x^2(iT)x^2(jT)) - m_i m_j \\ &= \sigma_{ii}\sigma_{jj} + 2\sigma_{ij}^2 + 4\mu_i\mu_j\sigma_{ij} + \mu_i^2\sigma_{jj} + \mu_j^2\sigma_{ii} + \mu_i^2\mu_j^2, \end{aligned}$$

where μ_i is the i^{th} entry of $\boldsymbol{\mu}_{\mathbf{x}}$ and σ_{ij} is the $(i,j)^{\text{th}}$ entry of $\boldsymbol{\Sigma}_{\mathbf{x}}$.

The next step towards lower complexity is to neglect correlation in the elements of $\mathbf{y}$, i.e. approximating all off-diagonal entries of the covariance matrix with zero. The ML-rule is then

$$\hat{\varepsilon}_{\text{Gauss,diag}} = \arg\max_{\varepsilon} \sum_{n=1}^{N} \frac{-(\mathbf{y}[n] - \boldsymbol{\mu}_{\mathbf{y},\varepsilon}[n])^2}{\boldsymbol{\Sigma}_{\mathbf{y},\varepsilon}[n,n]}. \qquad (6)$$

Moreover, if the variance of all output samples is approximated to be constant, i.e. $\boldsymbol{\Sigma}_{\mathbf{y},\varepsilon} \approx \sigma_y \mathbf{I}$, the estimator simplifies to

$$\hat{\varepsilon}_{\text{Gauss},\Sigma=\text{I}} = \arg\max_{\varepsilon} \mathbf{y}^T \boldsymbol{\mu}_{\mathbf{y},\varepsilon}. \qquad (7)$$

This corresponds to correlation of the received samples with the expected value and is similar to the estimator proposed in [8].

The estimator can be further simplified by the approximation $\boldsymbol{\mu}_{\mathbf{y},\varepsilon} \approx [0,\ldots,0,\mu_{k_0},0,\ldots,0]^T$ which yields

$$\hat{\varepsilon}_{\max(y)}/\Delta = \arg\max_{k} \mathbf{y}^T[k-k_0]. \qquad (8)$$

In this case, just the largest value of the receive vector is taken which might be the least complex timing estimation. This approach has been investigated in detail in [7].

B. Log-Normal Approximation

The log-normal distribution is the PDF of a random variable whose logarithm is normally distributed. The multivariate log-normal approximation of the PDF $p_{\mathbf{y}}(\mathbf{y}|\varepsilon)$ is given by

$$p_{\mathbf{y}}(\mathbf{y}|\varepsilon) \approx \frac{\exp\left(-\frac{1}{2}\left(\ln(\mathbf{y}) - \boldsymbol{\zeta}_\varepsilon\right)^T \mathbf{V}_\varepsilon^{-1}\left(\ln(\mathbf{y}) - \boldsymbol{\zeta}_\varepsilon\right)\right)}{(2\pi)^{N/2}\, |\mathbf{V}_\varepsilon|^{1/2} \prod_{n=1}^{N} y(nT_s+\varepsilon)},$$

for $y_n > 0$ and 0 otherwise. This approximation corresponds to computing element-wise the logarithm of the ED output and assuming this to be $\mathcal{N}(\boldsymbol{\zeta}_\varepsilon, \mathbf{V}_\varepsilon)$ distributed [14]. The estimation rule based on the multivariate log-normal approximation yields

$$\hat{\varepsilon}_{\text{MV}-\text{LN}} = \arg\max_{\varepsilon} -(\ln(\mathbf{y}) - \boldsymbol{\zeta}_\varepsilon)^T \mathbf{V}_\varepsilon^{-1}(\ln(\mathbf{y}) - \boldsymbol{\zeta}_\varepsilon). \quad (9)$$

The parameters $\boldsymbol{\zeta}_\varepsilon = [\zeta_1,\ldots,\zeta_N]^T$ and $\mathbf{V}_\varepsilon = [v_{i,j}]_{N\times N}$ are given by

$$\zeta_n = \ln(\boldsymbol{\mu}_{\mathbf{y},\varepsilon}[n]) - \frac{1}{2}\ln\left(1 + \frac{\boldsymbol{\Sigma}_{\mathbf{y},\varepsilon}[n,n]}{\boldsymbol{\mu}^2_{\mathbf{y},\varepsilon}[n]}\right)$$
$$v_{i,j} = \ln\left(1 + \frac{\boldsymbol{\Sigma}_{\mathbf{y},\varepsilon}[i,j]}{\boldsymbol{\mu}_{\mathbf{y},\varepsilon}[i]\boldsymbol{\mu}_{\mathbf{y},\varepsilon}[j]}\right).$$

Neglecting the correlation of the ED output samples, the distribution can be approximated by univariate log-normal. In this case, the estimation rule simplifies to

$$\hat{\varepsilon}_{\text{LN}} = \arg\max_{\varepsilon} \sum_{n=1}^{N} \frac{-(\ln(\mathbf{y}[n]) - \zeta_n)^2}{v_{n,n}}. \qquad (10)$$

An advantage of the log-normal approach is the very efficient approximation of the logarithm in a VLSI implementation.

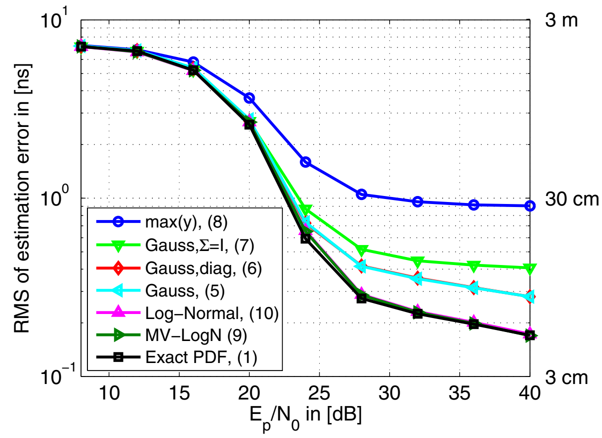

Fig. 3. Performance of timing estimators for normally distributed CIRs with exponential PDP

VI. Performance Results

This section presents the performance evaluation of the timing estimators. First, the performance is evaluated based on channel realizations drawn randomly from normal distribution with exponential power-delay profile (PDP). Second, the performance is evaluated based on measured channel impulse responses (CIR). As the figure of merit, we consider the root mean square (RMS) of the estimation error, which is obtained by Monte Carlo simulation. To find the ML-estimates, we perform an exhaustive search over ε. This is done by discretizing the time shift with step size Δ, yielding $\varepsilon_k = \Delta \cdot k$. The likelihood $p_{\mathbf{y}}(\mathbf{y}|\varepsilon_k = \Delta \cdot k)$ is determined for all $k = 1,\ldots,K$ with $K = T_{\text{symb}}/\Delta$. Then, $\hat{\varepsilon}$ is chosen corresponding to the largest likelihood value. Simulation results show that all estimators are unbiased.

System parameters are chosen as follows. The bandwidth is $B = 3$ GHz, using a center frequency of $f_c = 4.5$ GHz. The UWB pulses are band limited and flat in frequency in the desired bandwidth from 3 GHz to 6 GHz. The pulse repetition period is chosen to be $T_{\text{symb}} = 25$ ns. The sampling frequency as well as the rate of the step size to discretize ε is $1/T = 1/\Delta = 30$ GHz. For the estimation, the samples of one pulse repetition period T_{symb} are taken into account, i.e. the number of collected samples is $N = T_{\text{symb}}/T_s$.

According to the model, the performance is evaluated for channel realizations drawn randomly from a distribution $\mathcal{N}(0, \boldsymbol{\Sigma}_{\tilde{\mathbf{h}}})$. The covariance matrix $\boldsymbol{\Sigma}_{\tilde{\mathbf{h}}}$ is chosen correspondingly to an exponential PDP with RMS delay spread of 3 ns and band limitation to the spectrum from 3 to 6 GHz. The post-detection filter $g(t)$ is chosen as a rectangular function with 1 ns duration and the sampling frequency at the output of the ED is set to $1/T_s = 1$ GHz. Fig. 3 shows the performance of the timing estimators (1) and (5)-(10). The RMS of the estimation error is plotted versus the signal-to-noise ratio E_p/N_0, with E_p denoting the energy per pulse and $\frac{N_0}{2}$ the noise power spectral density. The error is given in nanoseconds as well as meters, when assuming a propagation speed of $c_0 = 3 \cdot 10^8$ m/s. For all estimators, the error of the timing estimate saturates for increasing E_p/N_0 due to

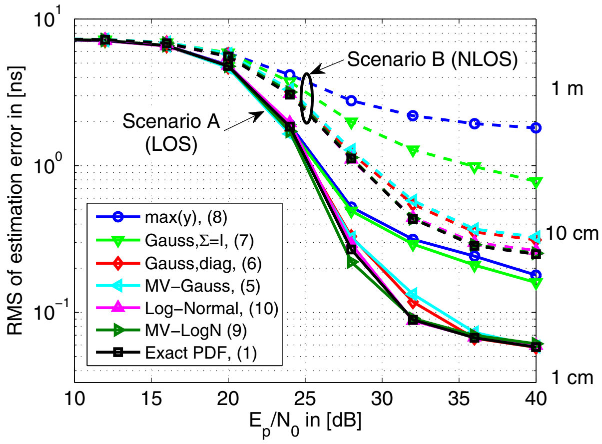

Fig. 4. Performance of Timing Estimators for LOS and NLOS Channel

the remaining uncertainty in the channel. As expected, the performance increases with increasing estimator complexity. However, with this choice of integration window and sampling at the ED output, the correlation between the samples is low. Therefore, the estimators neglecting the correlations perform very similar to the ones considering the multivariate PDF. The log-normal approximation reaches nearly the performance of the estimator using the exact PDF. This shows that the ED output samples are well modeled by log-normal distribution in this case.

Second, the performance is evaluated for measured CIRs, cf. Fig. 4. Two different scenarios are chosen, one typical LOS situation and one non-line-of-sight (NLOS) situation in an indoor environment with rich multipath propagation. For each scenario, the parameters $\boldsymbol{\mu}_{\tilde{\mathbf{h}}}$ and $\boldsymbol{\Sigma}_{\tilde{\mathbf{h}}}$ are estimated from a set of 620 measured CIRs, that are obtained by moving the receiver over an area of 27×56 cm. The measurement setup and postprocessing is described in detail in [15]. For the timing estimation the channel is chosen randomly out of the set of measured CIRs. To omit the influence of path loss the energy of each CIR is normalized. To account for the low complexity requirements of the receiver, we choose now a first-order low-pass filter after the squaring device, i.e.

$$g(t) = e^{-t2\pi f_{\text{cutoff}}} \text{ for } t > 0 \text{ and } g(t) = 0 \text{ else,} \qquad (11)$$

with cutoff frequency $f_{\text{cutoff}} = 300$ MHz.

Some interesting observations can be made from the simulation results. For the LOS channel characteristics all timing estimators perform almost similar well. Only marginal improvement can be seen for more accurate modeling of the PDF in this case. In contrast, the NLOS scenario shows larger difference in performance for the different estimators. The estimate based on (8) shows as expected the worst performance and does not give anymore a reliable timing estimate. Also the estimator based on Gauss approximation with equal variance of all ED output samples shows very poor performance. Large improvement can be seen when the variance of the different ED output samples is taken into account, cf. (6). However, this performs almost equally well as the estimator that considers also the off-diagonal elements of the covariance matrix, cf. (5). Again, the estimators based on the log-normal approximation shows great performance.

VII. Summary

Maximum likelihood estimators for timing estimation of the receive pulse for UWB impulse radio have been investigated. Based on the assumption of normally distributed channels, the PDF of the ED detector output is derived. Moreover, closed form approximation based on the normal and log-normal distribution are given. Performance evaluation shows that in LOS situations even low complexity timing estimation performs well. For NLOS scenarios the log-normal approximation shows promising results. Moreover, it is easy to implement by taking the logarithm of the energy detector output. Then, the values have to be scaled according to the variance and correlated with the expected value.

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