A WEIGHTED AUTOCORRELATION RECEIVER FOR TRANSMITTED REFERENCE ULTRA WIDEBAND COMMUNICATIONS

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ABSTRACT

Transmitted reference ultra wideband (TR-UWB) communication systems have gained increasing interest lately, because of their ability to solve the timing and channel estimation problems encountered in conventional UWB systems. Traditionally, an autocorrelation receiver is employed in a TR-UWB system, which is based on correlating the signal with a delayed version of itself. To reduce the noise squaring effect related to this autocorrelation receiver, we propose to split up the correlation interval leading to a number of smaller correlations, which are then linearly combined in some efficient manner. We refer to this receiver as a weighted autocorrelation receiver. We present both optimal and practical design algorithms for this receiver. We also carry out a number of simulations using real UWB channel measurements, and show that the weighted autocorrelation receiver significantly outperforms the conventional one. Moreover, we illustrate that the proposed TR-UWB system can compete favorably with a realistic digital implementation of a conventional UWB system.

1. INTRODUCTION

Ultra wideband (UWB) communication has attracted a lot of attention recently, for instance due to its capability to accommodate high data rates over short distances at a very low power consumption. Especially transmitted reference UWB (TR-UWB) [1] schemes turn out to be of practical use, since they ease the timing and channel estimation requirements, and allow for sampling rates far below the Nyquist rate. In the original Hoctor-Tomlinson TR-UWB system [2], the transmitter sends a reference pulse along with each data pulse. This reference pulse implicitly provides (noisy) timing and channel information at the receiver, which can be exploited by correlating the received signal with a delayed version of itself, such that the received reference pulse lines up with the received data pulse. The problem of this so-called autocorrelation receiver is that it squares the noise. To avoid this problem, some generalized TR-UWB systems have been developed in [3, 4]. These methods basically rely on an averaging operation to compute an almost noise-free version of the received reference pulse, which can then be used for matched filtering. However, this averaging operation requires large delays, which can not be implemented very accurately.

In this paper, we therefore go back to the original Hoctor-Tomlinson TR-UWB system and try to deal with the noise squaring problem in a different fashion. One way is to restrict the correlation interval to the area of interest [5]. However, this requires accurate timing, and sometimes the correct interval is missed due to noise. We go for another approach and basically split up the correlation interval leading to a number of smaller correlations, which are then linearly combined taking into account the received signal-to-noise ratio (SNR) at the output of each of these smaller correlations. We refer to this receiver as a weighted autocorrelation receiver. It is similar in spirit as the one we proposed in [6]. However, in contrast to [6], we now allow for overlapping received pulses. Both optimal and practical design algorithms for the weighted autocorrelation receiver will be investigated, and simulation results using real UWB channel measurements will be carried out.

This research was supported in part by NWO-STW under the VIDI program (DTC.6577) and the VICI program (DTC.5893).

2. DATA MODEL

We consider the original Hoctor-Tomlinson TR-UWB system in this work [2]. The transmitted signal consists of frames of duration T_f (N_f frames per symbol). Each frame consists of a reference pulse $p(t)$ and a modulated/coded version thereof. Specifically, for the nth frame, the reference pulse is modulated with the data symbol $s[\lfloor n/N_f \rfloor] \in \{+1, -1\}$ and coded with an amplitude code $c[n] \in \{+1, -1\}$ and a delay code $d[n] \in \{T_d/D, 2T_d/D, \ldots, (D-1)T_d/D, T_d\}$. Hence, the transmitted signal is given by

$$x(t) = \sum_{n=-\infty}^{\infty} p(t - nT_f) + x[n]p(t - nT_f - d[n]),$$

where the chip $x[n]$ is given by $x[n] = s[\lfloor n/N_f \rfloor]c[n]$.

The received signal can then be written as

$$y_{\rm nf}(t) = \sum_{n=-\infty}^{\infty} h_{\rm nf}(t-nT_f)+x[n]h_{\rm nf}(t-nT_f-d[n])+v_{\rm nf}(t),$$

where $h_{\rm nf}(t)$ is the response of the overall channel (including transmitter and receiver antenna effects) to the pulse $p(t)$ and $v_{\rm nf}(t)$ is additive noise. The subscript $(\cdot)_{\rm nf}$ stands for the fact that these signals are not yet filtered. In general, we of course apply a receive filter $f(t)$ to focus on the band of interest. We then obtain

$$\begin{aligned} y(t) &= f(t) * y_{\rm nf}(t) \\ &= \sum_{n=-\infty}^{\infty} h(t - nT_f) + x[n]h(t - nT_f - d[n]) + v(t), \end{aligned}$$

where $h(t) = f(t) * h_{\rm nf}(t)$ and $v(t) = f(t) * v_{\rm nf}(t)$. The received signal $y(t)$ without noise will be denoted by $\bar{y}(t)$.

3. AUTOCORRELATION RECEIVERS

The conventional autocorrelation receiver computes

$$y[n] = \int_{\epsilon+nT_f}^{\epsilon+nT_f+T_I} y(t)y(t + d[n])dt, \qquad (1)$$

where T_I is the integration interval and ϵ is the timing-offset. Note that if we take T_I large enough, e.g., $T_I \geq T_f + T_h$, where T_h

is the duration of $h(t)$, we are robust against the timing within a frame, i.e., we may assume $\epsilon \in [-T_f, 0)$. Then, the resulting sequence $y[n]$ is despread with the amplitude code $c[n]$, and the data symbols are detected by taking the sign of the despreaded sequence $z[k]$, corrected by a bias term:

$$z[k] = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]y[n],$$

$$\hat{s}[k] = \text{sign}(z[k] - \hat{b}),$$

where $\hat{b}$ is the adopted bias term.

However, some parts of the correlation interval in (1) are more affected by noise than others, which is not exploited. As in [6], we therefore split up the correlation interval in (1), leading to Q smaller correlations $y_q[n]$, $q = 0, 1, \ldots, Q-1$:

$$y_q[n] = \int_{\tau_{q,n}}^{\tau_{q+1,n}} y(t)y(t + d[n])dt, \tag{2}$$

where $\tau_{q,n} = \epsilon + nT_f + qT_I/Q$. Note that this approach resembles a fractional sampling approach, but it is different in the sense that the integration interval is inversely proportional to the oversampling factor. Similar to the conventional autocorrelation receiver, we then despread the resulting Q sequences $y_q[n]$, but we now detect the data symbols by taking the sign of a linear combination of the Q despreaded sequences $z_q[k]$, corrected by a bias term:

$$z_q[k] = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]y_q[n],$$

$$\hat{s}[k] = \text{sign}\left\{\left(\sum_{q=0}^{Q-1} \hat{a}_q z_q[k]\right) - \hat{b}\right\}, \tag{3}$$

where the $\hat{a}_q$s are the adopted linear combining weights and $\hat{b}$ is the adopted bias term. We call such an autocorrelation receiver a *weighted autocorrelation receiver*. We will show that it can significantly outperform the conventional autocorrelation receiver. Note that when $Q = 1$, the weighted autocorrelation receiver falls back to the conventional one.

Although it is possible to analyze the weighted autocorrelation receiver in a general fashion, we will now make a few assumptions, simplifying the derivations and allowing for a more comprehensive analysis. First of all, we will assume that there is no inter-chip interference (ICI) after correlation, i.e., $T_f \geq T_h + 2T_d$. Furthermore, we assume that there is a limited form of synchronization and that $\epsilon \in (-T_f + T_h, 0]$. In that case, it suffices to take $T_I = T_f$ and thus $\tau_{q,n} = \epsilon + nT_f + qT_f/Q$.

In the following sections, we will derive a data model for $y_q[n]$ and $z_q[k]$. First, let us split $y_q[n]$ into a useful signal and noise:

$$y_q[n] = \bar{y}_q[n] + v_q[n],$$

where

$$\bar{y}_q[n] = \int_{\tau_{q,n}}^{\tau_{q+1,n}} \bar{y}(t)\bar{y}(t + d[n])dt, \tag{4}$$

and

$$v_q[n] = v_q^{(1)}[n] + v_q^{(2)}[n] + v_q^{(3)}[n], \tag{5}$$

with

$$v_q^{(1)}[n] = \int_{\tau_{q,n}}^{\tau_{q+1,n}} \bar{y}(t)v(t + d[n])dt,$$

$$v_q^{(2)}[n] = \int_{\tau_{q,n}}^{\tau_{q+1,n}} v(t)\bar{y}(t + d[n])dt,$$

$$v_q^{(3)}[n] = \int_{\tau_{q,n}}^{\tau_{q+1,n}} v(t)v(t + d[n])dt.$$

Similarly, we can split $z_q[k]$ into a useful signal and noise:

$$z_q[k] = \bar{z}_q[k] + w_q[k],$$

where $\bar{z}_q[k] = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]\bar{y}_q[n]$ and $w_q[k] = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]v_q[n]$.

4. USEFUL SIGNAL MODEL

4.1. Chip Level

In this subsection, we will model the useful signal at chip level, $\bar{y}_q[n]$. Defining $R_{q,n}(\kappa_1, \kappa_2)$ as

$$R_{q,n}(\kappa_1, \kappa_2) = \int_{\tau_{q,n}}^{\tau_{q+1,n}} \bar{y}(t + \kappa_1)\bar{y}(t + \kappa_2)dt, \tag{6}$$

we can express $\bar{y}_q[n]$ as $\bar{y}_q[n] = R_{q,n}(0, d[n])$. We will now analyze the structure of the general function $R_{q,n}(\kappa_1, \kappa_2)$, since this will also be useful for the noise analysis. We will then specialize it to $\bar{y}_q[n]$.

From the noise analysis, it will be clear that we need to investigate $R_{q,n}(\kappa_1, \kappa_2)$ for a range $\kappa_1, \kappa_2 \in (-2T_d, 0]$. In order to avoid ICI for this range, we actually need $T_f \geq T_h + 3T_d$. Introducing this assumption, we can express (6) for $\kappa_1, \kappa_2 \in (-2T_d, 0]$ as

$$\begin{aligned}
&R_{q,n}(\kappa_1, \kappa_2) = \\
&\int_{\tau_{q,n}}^{\tau_{q+1,n}} [h(t - nT_f + \kappa_1) + x[n]h(t - nT_f - d[n] + \kappa_1)] \\
&\qquad \cdot [h(t - nT_f + \kappa_2) + x[n]h(t - nT_f - d[n] + \kappa_2)]dt \\
&= I_{\tau_{q,0}+\kappa_1}^{\tau_{q+1,0}+\kappa_1}(\kappa_2 - \kappa_1) + I_{\tau_{q,0}-d[n]+\kappa_1}^{\tau_{q+1,0}-d[n]+\kappa_1}(\kappa_2 - \kappa_1) \\
&\quad + x[n]I_{\tau_{q,0}-d[n]+\kappa_1}^{\tau_{q+1,0}-d[n]+\kappa_1}(d[n] + \kappa_2 - \kappa_1) \\
&\quad + x[n]I_{\tau_{q,0}+\kappa_1}^{\tau_{q+1,0}+\kappa_1}(-d[n] + \kappa_2 - \kappa_1),
\end{aligned}$$

where

$$I_{\tau_1}^{\tau_2}(s) = \int_{\tau_1}^{\tau_2} h(t)h(t + s)dt.$$

Grouping the constant and linear terms in the above equation, we obtain

$$R_{q,n}(\kappa_1, \kappa_2) = r_{\text{const},q,n}^{(\kappa_1,\kappa_2)} + x[n]r_{\text{lin},q,n}^{(\kappa_1,\kappa_2)},$$

where

$$\begin{aligned}
r_{\text{const},q,n}^{(\kappa_1,\kappa_2)} &= I_{\tau_{q,0}+\kappa_1}^{\tau_{q+1,0}+\kappa_1}(\kappa_2 - \kappa_1) + I_{\tau_{q,0}-d[n]+\kappa_1}^{\tau_{q+1,0}-d[n]+\kappa_1}(\kappa_2 - \kappa_1), \\
r_{\text{lin},q,n}^{(\kappa_1,\kappa_2)} &= I_{\tau_{q,0}-d[n]+\kappa_1}^{\tau_{q+1,0}-d[n]+\kappa_1}(d[n] + \kappa_2 - \kappa_1) \\
&\quad + I_{\tau_{q,0}+\kappa_1}^{\tau_{q+1,0}+\kappa_1}(-d[n] + \kappa_2 - \kappa_1).
\end{aligned}$$

Since $\bar{y}_q[n] = R_{q,n}(0, d[n])$, the useful signal at chip level can be expressed as

$$\bar{y}_q[n] = \tilde{\beta}_{q,n} + x[n]\tilde{\alpha}_{q,n}, \tag{7}$$

where

$$\tilde{\beta}_{q,n} = r_{\text{const},q,n}^{(0,d[n])}, \quad \tilde{\alpha}_{q,n} = r_{\text{lin},q,n}^{(0,d[n])}.$$

4.2. Symbol Level

Based on the previous results, it is easy to derive that the useful signal at symbol level, $\bar{z}_q[k]$, can be written as

$$\bar{z}_q[k] = \beta_{q,k} + s[k]\alpha_{q,k},$$

where $\beta_{q,k} = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]\tilde{\beta}_{q,n}$ and $\alpha_{q,k} = \sum_{n=kN_f}^{(k+1)N_f-1} \tilde{\alpha}_{q,n}$.

5. NOISE ANALYSIS

5.1. Chip Level

In this subsection, we will analyze the correlation function of the noise at chip level, $v_q[n]$, given by (5).

Let us first assume that the noise $v(t)$ is zero-mean with correlation function $R_v(t) = \mathrm{E}\{v(\tau)v(\tau+t)\}$. Assuming that $R_v(t) = 0$ for $|t| > T_d/D$, it is then easy to show that the noise $v_q[n]$ is also zero-mean and that the quadratic noise term is uncorrelated with the linear noise terms: $\mathrm{E}\{v_q^{(1)}[n]v_{q'}^{(3)}[n']\} = \mathrm{E}\{v_q^{(2)}[n]v_{q'}^{(3)}[n']\} = 0$. The crosscorrelation between the two linear noise terms can be derived as:

$$\begin{aligned}
&\mathrm{E}\{v_q^{(1)}[n]v_{q'}^{(2)}[n']\} \\
&= \int_{\tau_{q,n}}^{\tau_{q+1,n}} \int_{\tau_{q',n'}-\tau-d[n]}^{\tau_{q'+1,n'}-\tau-d[n]} \bar{y}(\tau)\bar{y}(\tau+t+d[n]+d[n'])R_v(t)dtd\tau \\
&\approx \delta_{q,q'}\delta_{n,n'} \int_{-\infty}^{\infty} R_{q,n}(0,t+2d[n])R_v(t)dt \\
&= \delta_{q,q'}\delta_{n,n'} \int_{-\infty}^{\infty} r_{\text{const},q,n}^{(0,t+2d[n])} R_v(t)dt \\
&\qquad + \delta_{q,q'}\delta_{n,n'} x[n] \int_{-\infty}^{\infty} r_{\text{lin},q,n}^{(0,t+2d[n])} R_v(t)dt,
\end{aligned}$$

where the approximation is obtained by changing the integration interval for t by $(-\infty, \infty)$. This approximation holds if we assume that the span of $R_v(t)$ is much smaller than T_f/Q and that T_d is much smaller than T_f/Q. Similarly, we can derive that

$$\begin{aligned}
\mathrm{E}\{v_q^{(1)}[n]v_{q'}^{(1)}[n']\} &= \delta_{q,q'}\delta_{n,n'} \int_{-\infty}^{\infty} r_{\text{const},q,n}^{(0,t)} R_v(t)dt \\
&\quad + \delta_{q,q'}\delta_{n,n'} x[n] \int_{-\infty}^{\infty} r_{\text{lin},q,n}^{(0,t)} R_v(t)dt, \\
\mathrm{E}\{v_q^{(2)}[n]v_{q'}^{(2)}[n']\} &= \delta_{q,q'}\delta_{n,n'} \int_{-\infty}^{\infty} r_{\text{const},q,n}^{(d[n],t+d[n])} R_v(t)dt \\
&\quad + \delta_{q,q'}\delta_{n,n'} x[n] \int_{-\infty}^{\infty} r_{\text{lin},q,n}^{(d[n],t+d[n])} R_v(t)dt.
\end{aligned}$$

Finally, we have to find an expression for the correlation function of the quadratic noise term. Assuming that $R_v(t) = 0$ for $|t| > T_d/(2D)$, we can show that

$$\mathrm{E}\{v_q^{(3)}[n]v_{q'}^{(3)}[n']\} \approx \delta_{q,q'}\delta_{n,n'} T_f/Q \int_{-\infty}^{\infty} R_v^2(t)dt,$$

where we have again used the assumption that the span of $R_v(t)$ is much smaller than T_f/Q.

As a result, the correlation function of the noise at chip level can be expressed as

$$\begin{aligned}
\mathrm{E}\{v_q[n]v_{q'}[n']\} &\approx \delta_{q,q'}\delta_{n,n'}(\tilde{\eta}_{q,n} + x[n]\tilde{\gamma}_{q,n}) \\
&\quad + \delta_{q,q'}\delta_{n,n'} T_I/Q \int_{-\infty}^{\infty} R_v^2(t)dt, \qquad (8)
\end{aligned}$$

where

$$\begin{aligned}
\tilde{\eta}_{q,n} &= \int_{-\infty}^{\infty} (r_{\text{const},q,n}^{(0,t)} + r_{\text{const},q,n}^{(d[n],t+d[n])} + 2r_{\text{const},q,n}^{(0,t+2d[n])})R_v(t)dt, \\
\tilde{\gamma}_{q,n} &= \int_{-\infty}^{\infty} (r_{\text{lin},q,n}^{(0,t)} + r_{\text{lin},q,n}^{(d[n],t+d[n])} + 2r_{\text{lin},q,n}^{(0,t+2d[n])})R_v(t)dt.
\end{aligned}$$

5.2. Symbol Level

Based on the previous results, it is easy to derive that the correlation function of the noise at symbol level, $w_q[k]$, can be written as

$$\begin{aligned}
\mathrm{E}\{w_q[k]w_{q'}[k']\} &\approx \delta_{q,q'}\delta_{k,k'}(\eta_{q,k} + s[k]\gamma_{q,k}) \\
&\quad + \delta_{q,q'}\delta_{k,k'} N_f T_I/Q \int_{-\infty}^{\infty} R_v^2(t)dt,
\end{aligned}$$

where $\eta_{q,k} = \sum_{n=kN_f}^{(k+1)N_f-1} \tilde{\eta}_{q,n}$ and $\gamma_{q,k} = \sum_{n=kN_f}^{(k+1)N_f-1} c[n]\tilde{\gamma}_{q,n}$.

6. OPTIMAL COMBINING

To simplify the data model after despreading, we will neglect the data dependence of the noise correlation function and approximate it by

$$\mathrm{E}\{w_q[k]w_{q'}[k']\} \approx \delta_{q,q'}\delta_{k,k'}\sigma_{q,k}^2,$$

where

$$\sigma_{q,k}^2 = \eta_{q,k} + N_f T_I/Q \int_{-\infty}^{\infty} R_v^2(t)dt.$$

We have seen in simulations (not shown here) that only a small error is made by introducing this simplification.

It is further easy to show that when we assume a short (periodic) code system, i.e., $c[n]$ and $d[n]$ are periodic with period N_f, the parameters $\alpha_{q,k}$, $\beta_{q,k}$, and $\eta_{q,k}$ (or $\sigma_{q,k}$) become independent of the symbol index k, and can be denoted as α_q, β_q, and η_q (or σ_q). Under those circumstances, the receiver architecture of (3) is optimal and the optimal linear combining weights and bias term are given by

$$a_q = f\frac{\alpha_q}{\sigma_q^2}, \qquad b = \sum_{q=0}^{Q-1} a_q\beta_q,$$

with f an arbitrary positive scaling factor. Assuming the noise $w_q[k]$ is Gaussian, which is a valid assumption in case $v(t)$ is Gaussian, the bit error rate (BER) for this optimal weighted autocorrelation receiver is given by $BER = Q(\sqrt{SNR})$, where SNR is the post-detector signal-to-noise ratio (SNR):

$$SNR = \sum_{q=0}^{Q-1} \frac{\alpha_q^2}{\sigma_q^2}.$$

In practice, we do not know the optimal linear combining weights a_q and optimal bias term b, and they have to be estimated from the received data, resulting into the linear combining weights $\hat{a}_q$ and the bias term $\hat{b}$. Since these estimated parameters generally differ from the optimal ones, the BER expression will then change into $BER = \frac{1}{2}Q(\sqrt{SNR_{+1}}) + \frac{1}{2}Q(\sqrt{SNR_{-1}})$, where SNR_{+1} and SNR_{-1} are the post-detector SNRs associated to transmitting a $+1$ and a -1, respectively:

$$\begin{aligned}
SNR_{+1} &= \frac{\left(\sum_{q=0}^{Q-1} \hat{a}_q\alpha_q + \hat{a}_q\beta_q - \hat{b}\right)^2}{\sum_{q=0}^{Q-1} \hat{a}_q^2\sigma_q^2}, \\
SNR_{-1} &= \frac{\left(\sum_{q=0}^{Q-1} \hat{a}_q\alpha_q - \hat{a}_q\beta_q + \hat{b}\right)^2}{\sum_{q=0}^{Q-1} \hat{a}_q^2\sigma_q^2}.
\end{aligned}$$

7. PRACTICAL COMBINING

In this section, we highlight some practical schemes that can be used to compute the linear combining weights $\hat{a}_q$ and bias term $\hat{b}$. Note that the algorithm we proposed in [6], which operates on the chip level and exploits the periodicity of the amplitude code, is not applicable anymore, since it requires that the chip level parameter $\tilde{\alpha}_{q,n}$ remains constant from chip to chip and that the chip level parameter $\tilde{\beta}_{q,n}$ is zero. This is only true when the received reference pulse does not overlap with the received data pulse, which is not the case in this paper. However, assuming short (periodic) amplitude and delay codes, the symbol level model parameters $\alpha_{q,k}$ and $\beta_{q,k}$ remain constant from symbol to symbol, as indicated earlier. This is what we will exploit in the methods described below.

Stacking $z_q[k]$ for the Q integration intervals: $\mathbf{z}[k] = [z_0[k], \ldots, z_{Q-1}[k]]^T$, we obtain

$$\mathbf{z}[k] = \boldsymbol{\alpha} s[k] + \boldsymbol{\beta} + \mathbf{w}[k],$$

where $\boldsymbol{\alpha} = [\alpha_0, \ldots, \alpha_{Q-1}]^T$, $\boldsymbol{\beta} = [\beta_0, \ldots, \beta_{Q-1}]^T$, and $\mathbf{w}[k] = [w_0[k], \ldots, w_{Q-1}[k]]^T$. Observe that using the above model the detection rule (3) can be rewritten as

$$\hat{s}[k] = \text{sign}(\hat{\mathbf{a}}^T \mathbf{z}[k] - \hat{b}), \tag{9}$$

where $\hat{\mathbf{a}} = [\hat{a}_0, \ldots, \hat{a}_{Q-1}]^T$. Assuming a burst of K data symbols is transmitted: $\mathbf{s} = [s[0], \ldots, s[K-1]]^T$, we can stack the K vectors $\mathbf{z}[k]$: $\mathbf{Z} = [\mathbf{z}[0], \ldots, \mathbf{z}[K-1]]$, in order to obtain

$$\mathbf{Z} = \begin{bmatrix} \boldsymbol{\alpha} & \boldsymbol{\beta} \end{bmatrix} \begin{bmatrix} \mathbf{s}^T \\ \mathbf{1}^T \end{bmatrix} + \mathbf{W}, \tag{10}$$

where $\mathbf{W} = [\mathbf{w}[0], \ldots, \mathbf{w}[K-1]]$. Based on the above data model we can now derive a very simple algorithm to compute $\hat{\mathbf{a}}$ and $\hat{b}$. First, we can estimate $\boldsymbol{\beta}$ by averaging the columns of $\mathbf{Z}$:

$$\hat{\boldsymbol{\beta}} = \frac{\mathbf{Z}\mathbf{1}}{K} = \boldsymbol{\beta} + \boldsymbol{\alpha}\frac{\mathbf{s}^T\mathbf{1}}{K} + \frac{\mathbf{W}\mathbf{1}}{K}.$$

Then, we can subtract the estimated bias from $\mathbf{Z}$:

$$\begin{aligned} \tilde{\mathbf{Z}} = \mathbf{Z} - \hat{\boldsymbol{\beta}}\mathbf{1}^T &= \boldsymbol{\alpha}\Big(\mathbf{s}^T - \frac{\mathbf{s}^T\mathbf{1}}{K}\mathbf{1}^T\Big) + \mathbf{W} - \frac{\mathbf{W}\mathbf{1}}{K}\mathbf{1}^T \\ &= \boldsymbol{\alpha}\mathbf{s}^T\Big(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^T}{K}\Big) + \mathbf{W}\Big(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^T}{K}\Big). \end{aligned} \tag{11}$$

This operation actually corresponds to projecting the rows of $\mathbf{Z}$ on the row space that is orthogonal to $\mathbf{1}^T$. Clearly, $\tilde{\mathbf{Z}}$ has rank one in the absence of noise. Hence, we can approximate $\tilde{\mathbf{Z}}$ by its best rank one approximation:

$$\tilde{\mathbf{Z}} \approx \mathbf{u}\sigma\mathbf{v}^T, \tag{12}$$

where $\mathbf{u}$ and $\mathbf{v}$ are the left and right singular vectors corresponding to the largest singular value, which is denoted by σ. From (11) and (12), it is then clear that

$$\mathbf{u} \approx \pm f_u \boldsymbol{\alpha},$$

where f_u is a positive scaling factor. Without spending more efforts to estimate the noise statistics, we then simply take $\hat{\mathbf{a}} = \mathbf{u}$ and $\hat{b} = \hat{\mathbf{a}}^T\hat{\boldsymbol{\beta}}$ in (9). The remaining sign ambiguity can be resolved by differential modulation or a few pilot signals.

Alternatively, we could look at (10) as a mixture of two sources, one of which transmits all ones. Hence, we could apply any existing source separation algorithm. Methods based on second order statistics (SOS) will estimate the mixing matrix, but only up to an invertible matrix ambiguity. Unfortunately, this ambiguity can not be completely removed by exploiting the fact that one of the sources transmits all ones. Hence, we have to resort to methods that exploit the finite alphabet property of the binary data. In that case, we end up with only an order and sign ambiguity. In theory, it is possible to remove the order ambiguity by exploiting the fact that one of the sources transmits all ones. In practice, on the other hand, this does not turn out to result in a very good performance.

One algorithm that can handle the above order ambiguity problem well is the adaptation of the real analytical constant modulus algorithm (RACMA) to a single biased source (see [7, Sec. IV]). The only difficulty is that the algorithm of [7, Sec. IV] is based on a single observation of the biased source, whereas we generally have multiple observations of the biased source (if $Q > 1$). Hence, as a first step, we transform the multiple observations into a single observation, by projecting the rows of $\mathbf{Z}$ on the row space that is orthogonal to $\mathbf{1}^T$ as in (11), resulting into the matrix $\tilde{\mathbf{Z}}$, and by observing from (11) and (12) that

$$\mathbf{v}^T \approx \pm f_v\Big(\mathbf{s}^T - \frac{\mathbf{s}^T\mathbf{1}}{K}\mathbf{1}^T\Big),$$

where f_v is a positive scaling factor. Hence, $\mathbf{v}^T$ can be viewed as the single observation of the biased source derived from $\mathbf{Z}$, and we can apply the algorithm of [7, Sec. IV] to $\mathbf{v}^T$. This results into a beamformer $[g_1, g_2]^T$ for which

$$\begin{bmatrix} g_1 & g_2 \end{bmatrix} \begin{bmatrix} \mathbf{v}^T \\ -\mathbf{1}^T \end{bmatrix} \approx \pm\mathbf{s}^T.$$

It is easy to show that the corresponding estimates for the linear combining weights and bias term are then given by $\hat{\mathbf{a}} = \mathbf{u}\sigma^{-1}g_1$ and $\hat{b} = g_2 + \hat{\mathbf{a}}^T\hat{\boldsymbol{\beta}}$. The remaining sign ambiguity can again be resolved by differential modulation or a few pilot signals. Note that the above method is equivalent to the simple method derived earlier if $g_2 = 0$. Since g_2 is approximately proportional to the mean of the symbols in $\mathbf{s}$, it is clear that when the burst length K increases, the difference in performance between the two methods decreases. This will also be illustrated by simulation results.

8. SIMULATION RESULTS

In this section, we simulate the proposed algorithms on actual UWB channel measurements that were conducted at the Delft University of Technology in the context of the Airlink project. We focus on a set of 10 measured channels $h_{\text{nf}}(t)$ that were obtained by sending a Gaussian pulse $p(t)$ with a bandwidth around 12 GHz over distances ranging from 1 m to about 20 m in line-of-sight conditions. Hence, the measurements include all the transmitter and receiver antenna effects. For simplicity reasons, we assume the additive noise $v_{\text{nf}}(t)$ is zero-mean white Gaussian noise with power spectral density N_0. To comply with the FCC spectral mask for UWB communications, we employ a simple bandpass filter $f(t)$ from 4 to 8 GHz at the receiver (in practice, we should of course also restrict the transmitted pulse $p(t)$ to this band). Since the duration of the filtered channels $h(t) = f(t) * h_{\text{nf}}(t)$ never exceeds $T_h = 50$ ns, we can satisfy the condition $T_f \geq T_h + 3T_d$, by choosing $T_f = 100$ ns and $T_d = 2$ ns. Note that it is important to keep T_d small, since this is the maximal required delay, and large delays can not be implemented very accurately. We further take $D = 4$ and $N_f = 4$ and select our codes as $c[n] = 1$ and $d[n] = (\text{mod}(n, D) + 1)T_d/D$ for $n = 0, 1, \ldots, N_f - 1$. This means that we achieve an uncoded data rate of 2.5 Gbit/s. For each channel, we randomly select a timing-offset $\epsilon \in (-T_f + T_h, 0]$ and carry out 100 (for $K = 20$) or 50 (for $K = 40$) Monte carlo runs, where we generate a new data and noise realization in each run.

Figure 1 shows the BER versus E_b/N_0 of the optimal weighted autocorrelation receiver for different values of Q [1]. We clearly observe that the performance greatly improves with increasing Q. As a result, the weighted autocorrelation receiver ($Q > 1$) can significantly outperform the conventional one ($Q = 1$). In Figure 2

[1]The received bit energy E_b is computed as $2N_f \int h_{\text{nf}}^2(t)dt$, where the factor 2 is due to the fact that we transmit two pulses per chip.

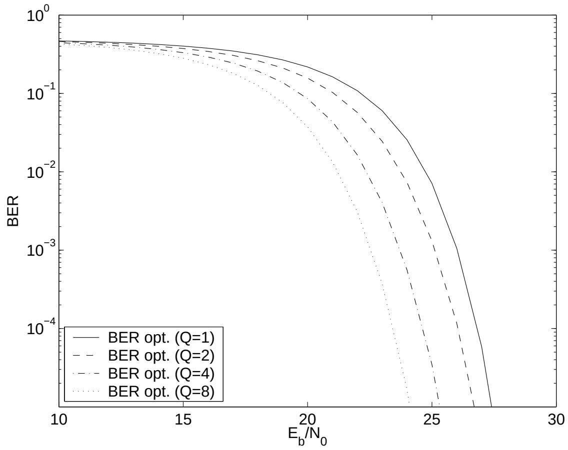

Fig. 1. Performance comparison of the optimal weighted autocorrelation receiver for different values of Q.

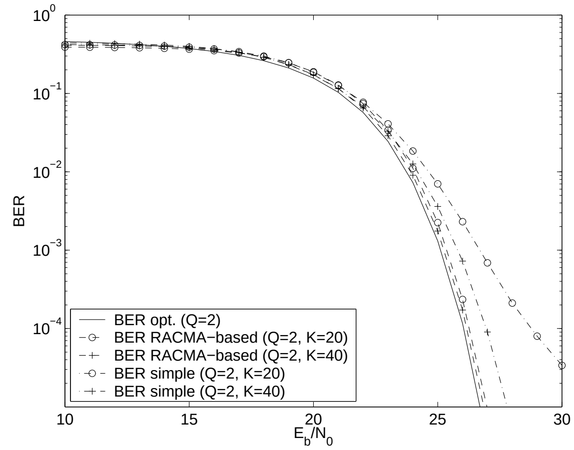

Fig. 2. Comparison of practical weighted autocorrelation receiver designs with the optimal design for $Q = 2$.

we compare the proposed practical designs with the optimal design for $Q = 2$. We see that the RACMA-based practical design is very close to the optimal design, whereas the simple practical design only works well if the burst length K is large enough.

We also compare our system with a conventional UWB system, where only one pulse per chip is transmitted and where a coherent receiver is adopted. To make a fair comparison, we consider a digital implementation of the coherent receiver with a realistic sampling rate. In other words, the received signal is first filtered with a narrow passband filter $f(t)$ with a bandwidth of B around some carrier frequency f_c, then downconverted to baseband, next sampled at a frequency of $f_s = 2B$, and finally matched filtered assuming perfect channel knowledge. We take $f_c = 5$ GHz, since this is the frequency region where a high average power is observed (within the 4-8 GHz band), and consider $B = 50, 100, 200$ MHz (hence, $f_s = 100, 200, 400$ MHz). A performance comparison between the two systems is illustrated in Figure 3 [2]. The gap between the conventional UWB system and the proposed TR-UWB system depends on the chosen design parameters. However, it is clear that for realistic sampling rates and realistic uncoded BER values, the conventional UWB system is outperformed by the proposed TR-UWB system.

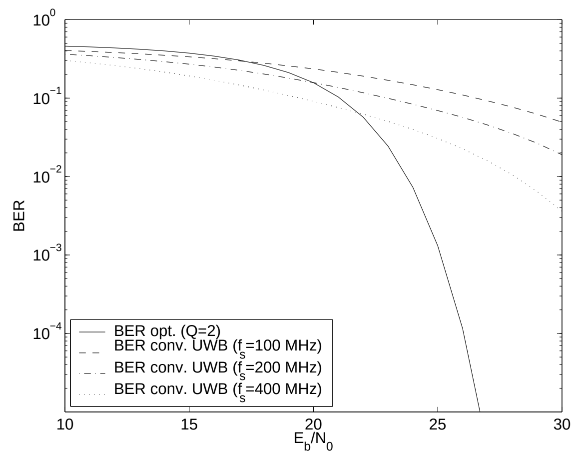

Fig. 3. Comparison of the proposed TR-UWB system with a digital implementation of a conventional UWB system.

9. ACKNOWLEDGMENT

We would like to thank Z. Irahhauten, G. Janssen, and A. Yarovoy (Delft University of Technology) for providing us with channel measurement data.

10. REFERENCES

[1] R. M. Gagliardi, "A Geometrical Study of Transmitted Reference Communication Systems," *IEEE Trans. on Communication Technologies*, pp. 118–123, Dec. 1964.

[2] R. T. Hoctor and H. W. Tomlinson, "Delay-Hopped, Transmitted-Reference RF Communications," in *Proc. Conf. on UWB Systems and Technologies (UWBST 2002)*, Baltimore, MA, May 2002.

[3] L. Yang and G. B. Giannakis, "Optimal Pilot Waveform Assisted Modulation for Ultrawideband Communications," *IEEE Trans. on Wireless Communications*, vol. 3, no. 4, pp. 1236–1249, July 2004.

[4] X. Luo and G. B. Giannakis, "Blind Timing Acquisition for Ultra-Wideband Multi-User Ad Hoc Access," in *Proc. IEEE Intl. Conf. on Acoustics, Speech, and Signal Processing (ICASSP 2005)*, Philadelphia, PA, March 2005.

[5] N. He and C. Tepedelenlioglu, "Adaptive Synchronization for Non-Coherent UWB Receivers," in *Proc. IEEE Intl. Conf. on Acoustics, Speech, and Signal Processing (ICASSP 2004)*, Montreal, Canada, May 2004.

[6] G. Leus and A.-J. van der Veen, "Noise Suppression in UWB Transmitted Reference Systems," in *Proc. IEEE Workshop on Signal Processing Advances in Wireless Communications (SPAWC 2004)*, Lisbon, Portugal, July 2004.

[7] A.-J. van der Veen, "Analytical Method for Blind Binary Signal Separation," *IEEE Trans. on Signal Processing*, vol. 45, no. 4, pp. 1078–1082, Apr. 1997.

[2]Note that for the conventional UWB system, we define the received bit energy as $E_b = N_f \int h_{\mathrm{nf}}^2(t)dt$.