Low-Complexity Soft-Output Detection for Impulse-Radio Ultra-Wideband Systems Via Combining Multiple Observations

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***Abstract*—Avoiding explicit channel estimation, autocorrelation-based receivers enable low-complexity detection of impulse-radio ultra-wideband (IR-UWB) signals. In this paper, we present power-efficient IR-UWB detection schemes, which process the receive symbol stream partitioned into overlapping blocks. Properly combining the individual observations gained from each blockwise detection, a final (soft-)decision with improved reliability is obtained. By means of numerical simulations we show that the presented approach enables a reduction of the hardware complexity of the autocorrelation receiver at no degradation in performance and only slightly increased computational complexity, and is perfectly suited especially for coded transmission.**

I. Introduction

Noncoherent receivers are widely regarded as the key to low-complexity detection in impulse-radio ultra-wideband (IR-UWB) systems, which are especially well-suited for short-range low-data-rate communications, such as, e.g., in wireless-sensor networks [1]. The inherent loss in performance of conventional noncoherent autocorrelation-based differential detection (DD), as compared to coherent detection based on explicit channel estimation, can be alleviated by advanced autocorrelation-based detection schemes, which process blocks of receive symbols jointly, i.e., perform multiple-symbol differential detection (MSDD) [2]–[4] or decision-feedback differential detection (DF-DD) [5]. However, significant challenges for implementation of the autocorrelation receiver (ACR) front-end are induced, as delaying the (analog) receive signal over several symbol durations is required to compute the correlation coefficients required for these detection schemes.

In this paper, we propose to obtain multiple observations of the same symbol by processing overlapping blocks of symbols. The resulting information gained from these individual observations is then combined to obtain a final decision with improved reliability. Depending on the choice of the blockwise detection scheme (we consider MSDD and DF-DD) and the method, how the individual observations are combined, the presented scheme is able to deliver hard and soft decisions, and is thus suited for coded and uncoded transmission. The benefit of the presented scheme is to reduce the hardware implementation complexity of the ACR front-end at no degradation in performance.

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The proposed scheme can be seen as a development of subset MSDD introduced for noncoherent detection of differential phase-shift keying (DPSK, or more general differential space-time modulation) [6], [7], where similarly multiple observations are generated with an overlapping block-structure. However, as opposed to our approach, in [6], [7] most of the observations are simply treated as unreliable, thus discarded, and only a single observation is processed further.

After defining the IR-UWB system model and briefly reviewing autocorrelation-based detection in Sec. II, multiple-observations combining based on blockwise detection is introduced in Sec. III. The effectiveness of the approach is validated in Sec. IV by means of numerical simulations of uncoded and coded transmission; final remarks conclude the paper.

II. Autocorrelation-based Detection of IR-UWB

A. IR-UWB System Model

We consider differentially encoded binary pulse-amplitude-modulated IR-UWB transmission. Assuming no inter-symbol-interference (i.e., the symbol duration T is chosen sufficiently large, such that each pulse has decayed before the next pulse is received) and a time-invariant multipath channel, the sampled receive signal in the kth symbol interval may compactly be written as an $(N_\mathrm{s} = f_\mathrm{s}T)$-dimensional vector

$$\bar{\boldsymbol{r}}_k = b_k \bar{\boldsymbol{p}} + \bar{\boldsymbol{n}}_k \tag{1}$$

where f_s is the sampling frequency, b_k are differentially encoded information symbols $a_k \in \{\pm 1\}$ (i.e., $b_k = b_{k-1}a_k$ with $b_0 = 1$), and $\bar{\boldsymbol{p}}$ is the (sampled) receive pulse shape, resulting from the convolution of the transmit pulse, multipath channel and receive filter impulse response. Neglecting the reference symbol, after suitable normalization, the energy per symbol is given as $E_\mathrm{s} = 1$. $\bar{\boldsymbol{n}}_k$ collects the samples of the zero-mean additive Gaussian noise, each with variance $\sigma_n^2 = f_\mathrm{s}N_0/2$, where $N_0/2$ is the two-sided power-spectral density of the underlying additive white Gaussian noise.

B. Autocorrelation Receiver Front-End

Avoiding explicit channel estimation, autocorrelation-based detection computes the correlation of the current symbol with up to L preceeding symbols, cf., e.g., [2]–[5], [8]. Significant gains are achieved by adapting the correlation interval T_i to the channel characteristics at hand [1], i.e., considering only the relevant part $\boldsymbol{r}_k$ of $\bar{\boldsymbol{r}}_k$ for autocorrelation by selecting $N = T_\mathrm{i} f_\mathrm{s}$ successive elements (typically the first) out of N_s. This effectively reduces the time-bandwidth product to $N = f_\mathrm{s} T_\mathrm{i}$. Thus, the output of the L-branch ACR for the kth symbol is given as, for $l = 1, \ldots, L$,

$$z_{k-l,k} = \boldsymbol{r}_{k-l}^\mathsf{T} \boldsymbol{r}_k = b_{k-l} b_k + \eta_{k-l,l} \; . \tag{2}$$

Assuming that the correlation interval captures the entire pulse energy (i.e., due to normalization $\boldsymbol{p}^\mathsf{T}\boldsymbol{p} = \bar{\boldsymbol{p}}^\mathsf{T}\bar{\boldsymbol{p}} = 1$), $z_{k-l,k}$ is composed of the phase transition from b_{k-l} to b_k, and "information × noise" and "noise × noise" terms, summarized in the equivalent noise term $\eta_{k-l,l} = b_{k-l}\boldsymbol{p}^\mathsf{T}\boldsymbol{n}_k + b_k \boldsymbol{n}_{k-l}^\mathsf{T}\boldsymbol{p} + \boldsymbol{n}_{k-l}^\mathsf{T}\boldsymbol{n}_k$. It has been shown that already for moderate time-bandwidth products N this equivalent noise is well approximated as uncorrelated zero-mean Gaussian random variables with variance $\sigma_\eta^2 = 2\sigma_n^2 + N(\sigma_n^2)^2$ [8]. For clarity, we note that, given the assumptions above, this Gaussian-approximated discrete-time equivalent model is independent of the actual pulse shape, i.e., the channel realization [9]. In this paper, all simulations of the IR-UWB system use this equivalent model.

The correlation coefficients serve as input for various detection schemes [1]–[5], [8], the most simple being symbolwise differential detection (DD), evaluating only the sign of the correlation coefficient of the current symbol and its predecessor, i.e., $a_k^\mathsf{DD} = \mathrm{sign}(z_{k-1,k})$ with $L = 1$.

Finally, we point out that, due to the large signal bandwidth, implementation of the ACR is typically envisioned fully in the analog domain, instead of digital processing based on a sufficiently sampled version. This imposes a major drawback of ACR-based detection, namely the required accurate (analog) delay lines. In this paper, we aim to mitigate this drawback by means of detection schemes based on an ACR with less branches, i.e., reduced L, at no degradation in performance.

III. Soft-Output Detection based on Multiple Observations

Based on the output of an L-branch ACR, low-complexity, yet powerful detection schemes process the receive symbol stream partitioned into blocks of L symbols. Before discussing the generation and combination of multiple observations obtained from this blockwise processing, we briefly review two variants of block-based detection schemes, namely (soft-output) MSDD and DF-DD [2]–[5], which deliver individual (soft) decisions for the symbols within each block.

A. Obtaining an Individual Observation

Keeping notation simple, we consider an arbitrary block of information symbols grouped into a vector $\boldsymbol{a} \in \{\pm 1\}^L$ with all indices to be understood as intra-block indices.

1) Soft-Output Multiple-Symbol Differential Detection: MSDD delivers the blockwise-optimal sequence [3], [5], i.e., the sequence with minimum decision metric

$$\boldsymbol{a}^\mathsf{MSDD} = \operatorname*{argmin}_{\tilde{\boldsymbol{a}} \in \{\pm 1\}^L} \Lambda(\tilde{\boldsymbol{a}}) \tag{3}$$

where the decision metric is defined as

$$\Lambda(\tilde{\boldsymbol{a}}) = \sum_{k=1}^{L} \left(\sum_{l=0}^{k-1} \left(|z_{l,k}| - \tilde{b}_l \tilde{b}_k \, z_{l,k} \right) \right) \tag{4}$$

and $\tilde{b}_k$, $0 \le k \le L$, and $z_{l,k}$, correspond to the differentially encoded hypothesis $\tilde{\boldsymbol{a}}$, and the correlation coefficients (cf., (2)) of the considered block, respectively.

Soft decisions, i.e., reliability information on the decision of each symbol, is obtained by extending MSDD to so-called soft-output MSDD (SO-MSDD) [4]. In terms of (max-log approximated) log-likelihood ratios (LLRs), soft output for the kth (binary) information symbol is given as

$$\mathrm{LLR}_k = \frac{1}{\sigma_n^2 (L+1)} \left[a_k^\mathsf{MSDD} \left(\Lambda_k^{\overline{\mathsf{MSDD}}} - \Lambda^\mathsf{MSDD} \right) \right] \tag{5}$$

where $\Lambda^\mathsf{MSDD} = \Lambda(\boldsymbol{a}^\mathsf{MSDD})$ denotes the metric associated with the MSDD estimate (3), and

$$\Lambda_k^{\overline{\mathsf{MSDD}}} = \min_{\tilde{\boldsymbol{a}} \in \{\pm 1\}^L, \, \tilde{a}_k = -a_k^\mathsf{MSDD}} \Lambda(\tilde{\boldsymbol{a}}) \tag{6}$$

the decision metric of the corresponding counter hypothesis, i.e., the minimum metric with the restriction $\tilde{a}_k = -a_k^\mathsf{MSDD}$.

Utilizing the triangular structure of the decision metric, MSDD can be viewed as a tree-search-problem, which in turn can efficiently be solved employing the single-tree-search soft-output sphere decoder (SO-SD) [10], [4]. To further reduce the computational complexity of the SO-SD in particular at low SNR, LLR clipping during the SO-SD search process (clippling level $\mathrm{LLR}_\mathsf{max}$) [10], [4] is applied. In addition, we employ an optimized decision order within the search process. This sorting of the SD input is based on the same optimization criterion as of DF-DD (cf. Sec. III-A2 and [5]), and requires some modifications to the original SO-SD algorithm [4]. Minimum throughput of the MSDD device, despite the varying complexity of the SD, can effectively be guaranteed by introducing a cumulative maximum complexity limit (e.g., per codeword) similar to [10]. Due to space limitiations, these techniques are not described in greater detail.

2) Decision-Feedback Differential Detection: A closely-related detection scheme is blockwise DF-DD [5], which decides the symbols within each block in a successive manner taking into account the feedback from already decided symbols within the block. In [5] it has been shown that DF-DD achieves close-to-optimum performance at very low, and in particular constant computational complexity, if the decision order is optimized, such that in each step the most reliable symbol is decided next (taking into account the actual correlation coefficients and the previous decisions, see [5] for details).

B. Obtaining Multiple Observations

In the related context of noncoherent detection of DPSK (and more general unitary differential space-time modulation), in [6], [7] it has been proposed to employ MSDD in combination with an overlapping block-structure. Since multiple blocks thus contain the same symbol, processing of each block delivers (possibly different) beliefs on the same symbol, i.e., multiple observations are available. Observing that the reliability of the estimates degrades at the block edges for

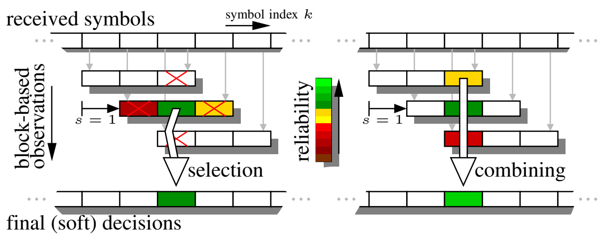

Fig. 1. Illustration of subset MSDD (left) and multiple-observations combining (right). Blocksize $L = 3$, maximum overlap (mutual shift $s = 1$).

DPSK [6], [7], only the middle part of each block is processed further, so-called subset MSDD, as illustrated in the left part of Fig. 1. Already available observations of symbols at the block edges are treated as unreliable and are simply discarded.

Avoiding to discard already available observations, we propose to suitably combine all observations obtained from processing of each block, resulting in a (possibly more reliable) final decision. The basic concept is illustrated on the right hand side of Fig. 1. There are different options how to combine multiple observations to deliver a final (soft) decision for the respective symbol, as discussed in Sec. III-C. In addition note that, in the context of MSDD of IR-UWB, significantly different reliabilities within each block cannot be observed, and, as we employ an optimized decision order within each block (cf., [5] and Sec. III-A), the positions of the most reliable symbols are no longer limited to the block center.

Of course, the generation of multiple observations, i.e., processing of overlapping blocks, leads to an increased computational complexity and processing delay; however, the analog ACR front-end remains unchanged. As we aim for a flexible tradeoff between performance and computational complexity, we vary the mutual shift $s = 1, \ldots, L$ of adjacent blocks (i.e., overlap of $L - s$ symbols) to adjust the number of multiple observations for each symbol. Thus, we obtain on average L/s observations per symbol (for finite symbol streams this value can be ensured by reducing the blocksize at the beginning and at the end), with maximum overlap for $s = 1$, and the traditional single observation per symbol for $s = L$. Note that blocksize and overlap are defined based on the information symbols; the respective blocks of $L+1$ differentially encoded symbols overlap by at least one symbol.

C. Combining Multiple Observations

Depending on the employed blockwise detection scheme, different options can be considered how multiple observations are combined to a final estimate of the information symbol.

1) Combining Multiple Soft Decisions: If soft decisions are available for each individual observation, as obtained from SO-MSDD, we may consider these observations as independent (though independence cannot be assured), and obtain the resulting final estimate according to the principle of parallel information combining [11]. In terms of LLRs, the resulting LLR for each symbol is then directly given as the sum of the corresponding individual LLRs.

In the case of coded transmission, the resulting LLR can directly be passed to the subsequent (soft-input) channel decoder. Since LLR clipping affects each SO-SD run, the maximum absolute input value is $L \cdot \mathrm{LLR}_{\mathsf{max}}$. Final hard-decisions can be obtained by evaluating only the sign of the sum of the LLRs, corresponding to combining the individual hard decisions according to their reliability.

2) Combining Multiple Hard Decisions: Based on multiple hard decisions, here obtained from DF-DD (of course, hard-output MSDD is also possible, but not considered for brevity), a final hard decision is directly given following the majority of the individual decisions (i.e., evaluating the sign of the sum of the individual estimates), which effectively treats each observation with equal reliability (in case of a draw, we choose ± 1 at random). Clearly, this strategy leads to improved performance only if more than two observations are available per symbol, i.e., only if $s < L/2$.

However, the most interesting option is to combine multiple hard decisions of the same symbol to form a single soft decision. Exemplarily, consider the case that three (possibly different) hard decisions are available. If these coincide, the reliability of this symbol is three times as large as the reliability of only a single observation, whereas if only two coincide and one differs, the reliability is reduced to the case of a single observation. This method can be implemented by using the sum of the individual hard-decisions as (quantized and scaled) “soft-output”. Depending on the employed channel decoder, scaling of these soft-output values may be neglected if the decoding metric is scale-invariant (e.g., in a convolutional coded system employing the Viterbi algorithm for soft-decision decoding). However, e.g., in an LDPC-coded system, the soft output should be scaled to match the decoder input range.

IV. Performance and Complexity

Modeling a realistic IR-UWB scenario [1], for numerical simulations we set the time-bandwidth product to $N = 400$, corresponding, e.g., to an ACR correlation interval of $T_{\mathrm{i}} = 33$ ns and a Nyquist frequency of 6 GHz ($f_{\mathrm{s}} = 12$ GHz). Typically, the symbol duration is chosen larger (e.g., $T = 75$ ns) to preclude inter-symbol interference.

We evaluate the effectiveness of the presented approach based on the key figures performance (i.e., the required energy per bit E_{b} vs. spectral noise density N_0) and computational complexity at a desired bit error rate (BER) operating point. As a measure for the computational complexity of MSDD we use the average number of visited nodes per symbol of the SO-SD tree-search process. Due to LLR clipping and the optimized decision order, its variance is relatively low and can effectively be upper-bounded by introducing a cumulative maximum complexity limit. On the contrary, DF-DD has constant complexity, which, using its relation to SD-based tree search [5], corresponds to a single node per symbol.

First, we consider uncoded transmission ($E_{\mathrm{b}} = E_{\mathrm{s}}$), i.e., multiple observations are combined to yield a final hard decision. Fig. 2 depicts the tradeoff performance vs. (average) complexity at an operating point of $\mathrm{BER} = 10^{-3}$, obtained by adjusting the mutual shift of the blocks ($s = 1, \ldots, L$) for a blocksize $L = 3$, 5 and 10. We consider the two detection schemes combining multiple soft decisions obtained from SO-

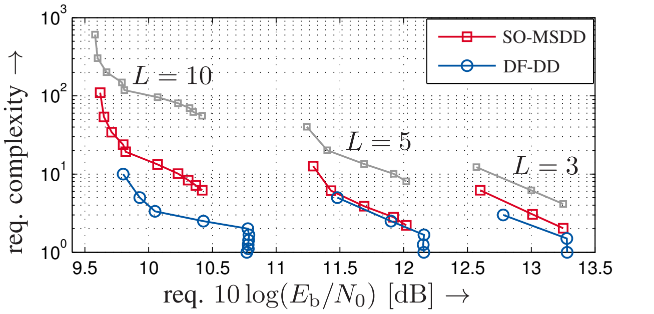

Fig. 2. Uncoded transmission: Tradeoff required E_b/N_0 for $\mathrm{BER} = 10^{-3}$ vs. complexity with $L = 3$, 5 and 10 obtained by adjusting the mutual shift between blocks $s = 1, \ldots, L$ (left to right). LLR clipping for SO-MSDD: $\mathrm{LLR}_\mathsf{max} = 15$ and $\mathrm{LLR}_\mathsf{max} = \infty$ (gray), time-bandwidth product $N = 400$.

MSDD (sign of sum of LLRs), and combining multiple hard decisions obtained from DF-DD (sign of sum of estimates). For SO-MSDD, the LLR clipping level is set to $\mathrm{LLR}_\mathsf{max} = 15$. For both cases the upper-left point corresponds to the maximum block-overlap (maximum number of L observations, $s = 1$), and the lower-right point to traditional detection with only a single observation per symbol (no overlap, $s = L$).

The performance of SO-MSDD improves with increasing number of combined individual soft-decisisions, with gains of up to $0.8\,\mathrm{dB}$ compared to traditional MSDD; the increase in complexity is proportional to the average number of observations per symbol, L/s. For comparison, tradeoff-curves employing the SO-SD without LLR clipping are also given, which prove that LLR clipping is crucial to achieve low complexity at only slight performance degradation [4], [10].

Combining multiple hard decisions (DF-DD) improvements are only achieved for $s < L/2$, as otherwise only up to two observations are available. However, as opposed to the varying complexity of SD-based MSDD, DF-DD achieves even larger gains at lower and, in particular, fixed complexity.

Finally, the performance-complexity tradeoff is evaluated for coded transmission at $\mathrm{BER} = 10^{-6}$ in Fig. 3. We consider a bit-interleaved coded modulation scheme employing maximum-free-distance convolutional codes (non-recursive, non-systematic, zero-padded encoder [12]) with constraint length $\nu = 4$, a random block-interleaver (size 1500 symbols), and, following the reasoning in [9], a code rate of $R_\mathrm{c} = 2/3$ ($E_\mathrm{b} = E_\mathrm{s}R_\mathrm{c}$). As we aim for soft-decision decoding using the Viterbi algorithm, the final soft decision is obtained by combining either multiple soft decisions (sum of LLRs) in case of SO-MSDD as blockwise detection scheme, or multiple hard decisions (sum of estimates) in case of DF-DD, cf. Sec. III-C.

It can be observed that for all blocksizes each additional observations leads to noteable gains. Combining of multiple observations is especially effective, if multiple hard decisions are combined to a single soft decision (DF-DD); the difference between the traditional single observation and L observations, e.g., amounts to almost $2\,\mathrm{dB}$ for $L = 10$. Consequently, this scheme enables to effectively tradeoff low-cost computational complexity against costly implementation complexity of the ACR front-end at no degradation in performance by processing shorter, but overlapping blocks (thus, lower maximum delay required in the ACR) and combining the multiple observations.

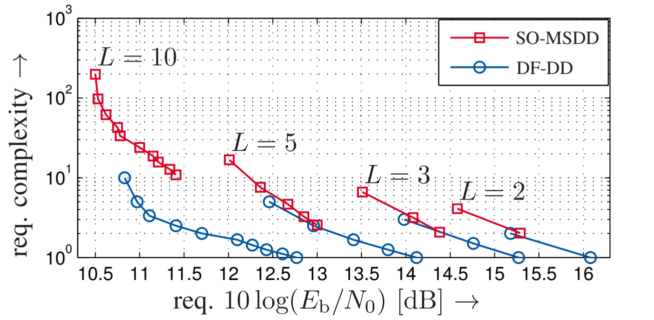

Fig. 3. Coded transmission: Tradeoff required E_b/N_0 for $\mathrm{BER} = 10^{-6}$ vs. complexity with $L = 2$, 3, 5, and 10 obtained by adjusting the mutual shift between blocks $s = 1, \ldots, L$ (left to right). LLR clipping for SO-MSDD: $\mathrm{LLR}_\mathsf{max} = 15$, convolutional code (code rate $R_\mathrm{c} = 2/3$, constraint length $\nu = 4$); time-bandwidth product $N = 400$.

V. Conclusions

In this paper, we have proposed a power-efficient, yet low-complexity detection scheme for autocorrelation-based IR-UWB receivers, which is based on combining multiple observations for the same symbol obtained from blockwise detection using an overlapping block structure. Our approach is able to deliver hard and soft decisions with improved reliability at only marginal increase in computational complexity, by, simplified speaking, repeating very-low-complexity steps multiple times and combining the individual observations. It is perfectly suited especially for coded transmission and enables to reduce the blocksize, and thus also the implementation complexity of the analog autocorrelation receiver front-end, at no degradation in performance.

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