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A New Robust Interference Reduction Scheme for Low Complexity Direct-Sequence Spread-Spectrum Receivers: Optimization

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***Abstract*—We present a self-adaptive algorithm for a new robust direct-sequence spread-spectrum system with integrated interference reduction capabilities to reduce narrowband- and broadband-interference regardless of their composition. Our reliable chip accumulation detector combines a comparatively low processing gain direct-sequence spread-spectrum system with an efficient interference reduction technique based on a simple adaptive nonlinearity employed prior to spread-spectrum demodulation. The information required for adjusting the adaptive nonlinearity to track the optimum state for efficient interference reduction is solely extracted from the received signal, primarily by exploiting level-crossing information. The resulting algorithm is fast, avoids loop structures, has no stability problems, and is easy and cheap to implement in hardware. The results of our Monte-Carlo simulations reveal that the proposed receiver always achieves the minimum symbol-error-probability, even under interference conditions that vary in the range of 40 dB.**

***Keywords*-Level-Crossing Statistics, Interference Reduction, Robust Communications, Spread-Spectrum, Nonlinear Signal Processing.**

I. Introduction

In [1], we argued that future wireless applications create the need for *robust* communication approaches, which perform acceptable under unknown and varying channel conditions, and admit a simple and efficient implementation. We presented a new robust direct-sequence spread-spectrum concept with integrated interference reduction capabilities for reducing mixed narrowband- and broadband-interference, which indeed combines robustness in the presence of strong interference of unknown composition with implementation simplicity and spectral efficiency.

We achieve this goal by combining a comparatively low processing gain direct-sequence spread-spectrum system with an efficient interference reduction technique based on a simple adaptive nonlinearity employed prior to spread-spectrum demodulation. Fig. 1 shows the structure of our *reliable chip accumulation* (RCA) detector, and Fig. 2 depicts the transfer characteristics of the RCS nonlinearity (which depends on an adaptable threshold Δ).

Theoretical and simulation results presented in [1] show that our approach exhibits an excellent performance in mixed narrowband- (continuous-wave ... CW) and broadband-interference (AWGN) settings (Fig. 3), with interference signal ratios ranging over more than 40 dB. Our RCA detector thus combines spectral efficiency with interference reduction capabilities comparable to traditional military spread-spectrum systems, which typically rely on a huge processing gain that is not affordable in commercial bandwidth-limited applications.

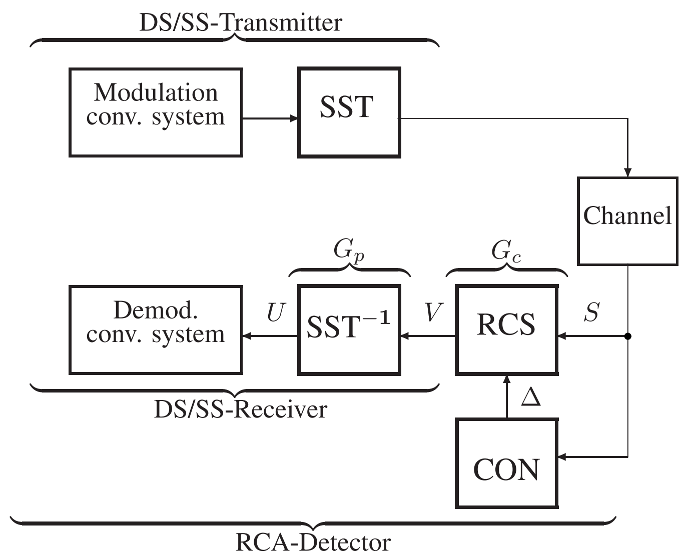

Figure 1. Structure of the investigated communication system. SST ... spread-spectrum technology, DS/SS ... direct-sequence spread-spectrum, RCS ... reliable chip selector, RCA ... reliable chip accumulator, CON ... control module, G_p ... processing gain, G_c ... conversion gain, Δ ... threshold, S, V, U ... random variables.

However, the results in [1] are based on the assumption that the threshold Δ used for adapting the nonlinearity is chosen optimally. The goal of this paper is to introduce and evaluate an approach for practical threshold adaption, with low implementation costs. Its goal is to adjust the threshold to the optimum location for achieving the lowest symbol-error-probability possible for our concept, under varying

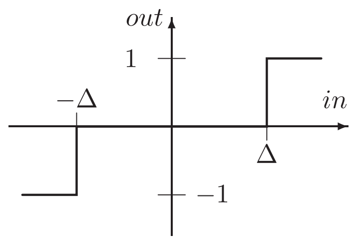

Figure 2. Transfer characteristic of the reliable chip selector.

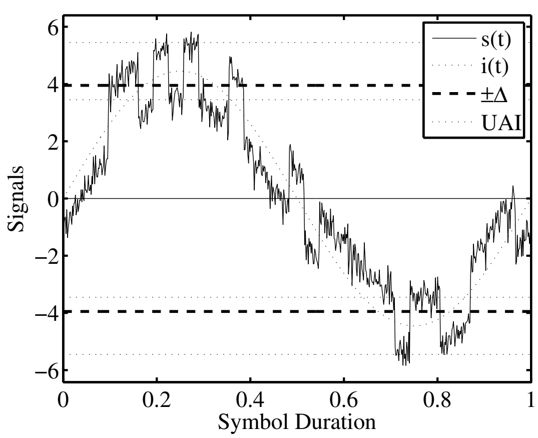

Figure 3. Sample of the investigated input signal (unfiltered). UAI ... unambiguous interval.

interference conditions. The challenge for the adaptation algorithm is the large variation of the composition of the combined interference (about 40 dB).

The strategy used in our CON module is to track the optimum state for efficient interference reduction, primarily by exploiting level-crossing information of the received signal; magnitude- as well as level-crossing statistics is also incorporated in the adaptation process. The resulting algorithm is fast, avoid loop structures, has no stability problems and is very easy and cheap to implement in hardware. The results of our Monte-Carlo simulations reveal that the proposed receiver indeed achieves always the minimum symbol-error-probability under changing interference conditions, provided that the interference variations are slow compared to the symbol duration.

The mathematical basis of the level-crossing theory can be found in [2], [3] for time series. A special form of the level-crossings are the zero-crossings of a random process [4]. The level-crossing theory was applied to estimate the level-crossing rate and the duration of fades in a carrier signal in a terrestrial mobile environment [5], [6], [7]. The authors have never seen the exploitation of the level-crossing theory for controlling a nonlinearity to reduce interference.

In the following Section III, we state the goals we want to achieve with our threshold control. Section IV presents the details of the adaption algorithm. The evaluation of the performance of the resulting receiver is presented in Section V.

II. State of the Art

The hard-limiter receiver is from comparable complexity to the proposed RCA scheme. As seen in Fig. 13 of [1] the performance measured with symbol-error-probability is rather bad for the hard-limiter receiver if continuous-wave interference is dominating. The proposed RCA detector show its superiority in this type of interference. Other schemes, like transform domain processing are too complex, need large computation power, suffer from stability problems and achieve in the best case a comparable performance as the RCA scheme.

III. Performance Goals

Before we focus on the dynamic behavior which is the goal of this paper we describe the strategy to proceed to it. In [1], we have shown that it is possible with the investigated RCA-detector to enhance the SINR_v before symbol-detection in the spread-spectrum correlator takes place. The ultimate measure of the enhancement is the conversion gain. The optimum performance measure is the minimum symbol-error-probability as derived in [1] and summarized in (1). This is a static analysis (SA) and is based on optimizing the probability density at the output of the nonlinearity to maximize the conversion gain. The degree of freedom for optimization is the threshold Δ. That is a probabilistic approach and the optimum threshold found is $\Delta_{\mathrm{opt}}^{(\mathrm{M})}$. We use this result for comparison and as baseline for the result derived in this paper. We use the following notation: The ... theoretical, (S)im ... simulation and (M)at ... mathematical.

We focus on realistic situations, that means we take the data-detection into account. Therefore we set up a Monte-Carlo simulation to derive the SEP. That means we make a waveform simulation and all the results are based on waveforms. We generate the waveforms corresponding to the actual SINR_s and the ratio I/N. We transmit symbols from a fair binary source and detect it in the proposed receiver passing the nonlinearity and spread-spectrum correlation. The estimated SEP is based on the ratio of the number of symbols in error to the total amount of transmitted symbols. We investigate two situations using Monte-Carlo simulations. First, we optimize the detection, and second we make a real simulation of the data-detection process. The optimized detection is done to calculate the minimum SEP possible under real (waveform) conditions. This optimized result for the SEP serves as reference for what we want to achieve with active and online threshold control for a permanent symbol stream. The procedure for the optimum simulation is given in (2). In this approach, we adjust the threshold Δ until the minimum of the SEP occur and note the threshold $\Delta_{\text{opt}}^{(S)}$ for reference. This situation is sketched in Fig. 4. It is easily verified with the help of Fig. 3 that the minimum of the symbol-error-probability occur within the unambiguous interval.

The real situation takes the dynamic into account (DA ... dynamic approach). The necessary changes are: (a) We need an algorithm to adjust the threshold $\Delta = \Delta_0$ to its optimum location $\Delta_{\text{opt}}^{(S)}$ (b) we need a control variable X that allows us to estimate the optimum location under changing interference situations exclusively from observations of the received signal (c) we must restrict the evaluation of the control variable to a finite time interval (observation interval). From this restrictions we expect a degradation in SEP. The formal description is given in (3).

We judge our threshold control algorithm with the following questions: (a) How close can we adjust Δ_0 to $\Delta_{\text{opt}}^{(S)}$ and (b) how close can we approach the symbol-error-probability $\text{SEP}_X^{(\text{Sim})}$ to $\text{SEP}_{\text{opt}}^{(\text{Sim})}$.

$$\begin{aligned} \text{SA[The]: } \text{SEP}_{\text{opt}}^{(\text{Mat})} &= \min\Big\{\text{SEP}\Big\} = \\ &= \text{SEP}\Big\{\max\Big\{\overbrace{G_c(\Delta)}^{\text{pdf(V)}}\Big\}\Big\} = \\ &= \text{SEP}\Big\{G_c(\Delta = \Delta_{\text{opt}}^{(\text{M})})\Big\} \end{aligned} \tag{1}$$

$$\text{SA[Sim]: } \text{SEP}_{\text{opt}}^{(\text{Sim})} = \min\{\text{SEP}\} = \underbrace{\text{SEP}\Big\{\Delta = \Delta_{\text{opt}}^{(S)}\Big\}}_{\text{Data-Detection}} \tag{2}$$

$$\text{DA[Sim]: } \text{SEP}_X^{(\text{Sim})} = \underbrace{\text{SEP}\left(\Delta_0 = f(X)\right)}_{\text{Data-Detection}} \tag{3}$$

By inspection of Fig. 3 it can be intuitively deduced that for dominating CW-interference the optimum location of $\Delta \mapsto \Delta_{opt}$ is within the unambiguous interval (UAI=$A_{cw} - A_c \leq s(t) \leq A_{cw} + A_c$) close to the inner boundary (IB=$A_{cw} - A_c$).

The optimum curves in Fig. 5 and Fig. 6 serve as reference for the performance of the threshold control algorithm to estimate the implementation loss and the reliability.

IV. Control of the Adaptive Nonlinearity

The goal of the control algorithm is to adjust the threshold of the nonlinearity to its optimum location to achieve the maximum conversion gain.

The reliability of a chip can only be measured with its information content. Unfortunately we have no information theoretic relation between the information content of a chip and measurable parameters for the decision if it should be included in the correlation process or not. Therefore we use an axiomatic approach.

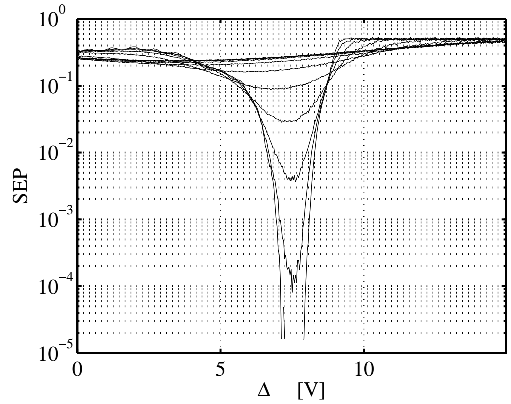

Figure 4. Sample of the Monte-Carlo optimization procedure for G_p=15 dB and varying I/N. SINR$_s$=-15 dB.

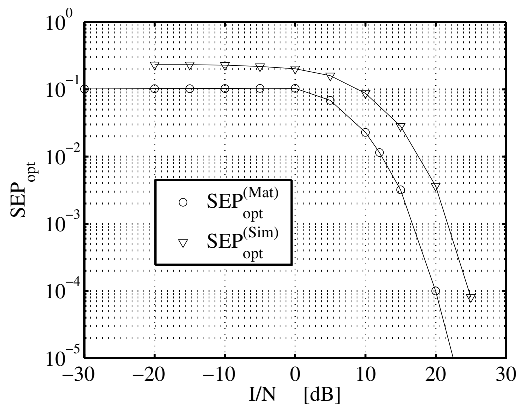

Figure 5. Static Analysis: Simulated and calculated optimum SEP in combined interference with G_p=15 dB. SINR=-15 dB.

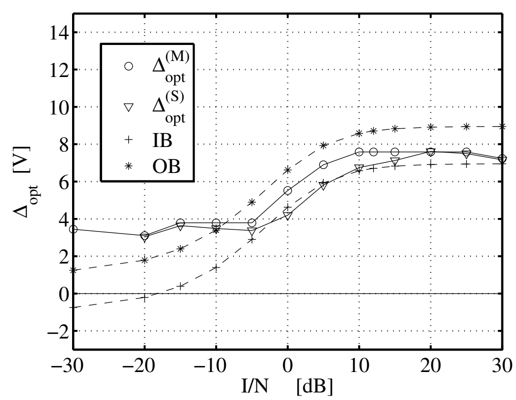

Figure 6. Static Analysis: Simulated and calculated optimum threshold locations in combined interference. SINR$_s$=-15 dB.

Axiom 1: *The mean number of level crossings is a* *measure for the rate of change in a signal at that level.*

AXIOM 2: *The highest information content in a mixture of signals is at such a magnitude where the level crossings occur most frequently.*

AXIOM 3: *The location for the threshold is most valuable when level crossings occur frequently.*

Axiom 1 refer to the rate of change in a signal and Axiom 2 point out the magnitude region for the highest information content. Axiom 3 is a consequence of Axiom 2 and indicate the strategy of the control mechanism.

The adaptive nonlinearity utilizes level-crossing information to modify the form of the nonlinearity to reduce the interference magnitude as much as possible. The only degree of freedom available is the magnitude threshold Δ. The magnitude threshold is derived from a joint measure of level-crossings, zero-crossings and magnitude probabilities.

By definition, the optimum location of Δ is that magnitude for which the quantized magnitudes exceeding this threshold and processed by the spread-spectrum signal detection deliver the minimum symbol-error probability.

The optimum threshold location is tracked by the control variable X, given in (4). This variable is constructed from magnitude information ($pshm$ ... percentage of signal outside $\pm\Delta$) and level crossing information ($pstc$ ... percentage of sign threshold crossings ($\Delta = 0$), $patc$ ... percentage of amplitude threshold crossings). The threshold Δ is adjusted very close to its optimum location Δ_{opt} if the control variable approaches zero. The specific threshold value for the condition $X = 0$ is termed Δ_0. For minimum SEP the threshold Δ_0 must approach Δ_{opt} for all ratios of I/N of the combined interference. That is verified in Fig. 7, Fig. 8 and Fig. 9. Additionally we need the constant weighting factors k_p, k_a and k_s to make $X = 0$ at the optimum threshold location. The time segment of the received signal for which the control parameters are evaluated is set to ten symbol durations (T_0) which should be small enough to cope with high dynamic interference changes. We refer to this interval as the observation interval T_{ob}). The $E[\cdot]$ is the expectation operator.

$$X(\Delta) = k_p \cdot pshm(\Delta) - k_a \cdot patc(\Delta) - k_s \cdot pstc \qquad (4)$$

$$patc(\Delta) = E[|s(t)| - \Delta = 0] \qquad (5)$$

$$pstc = E[|s(t)| = 0] = patc(0)/2 \qquad (6)$$

General remarks on the results derived from Fig. 7 to Fig. 9: (a) The curves in the figures are related to construct the control variable X following (4). (b) The shape of $pshm$ is roughly the same for all ratios of the combined interference. This means that it is impossible to use the

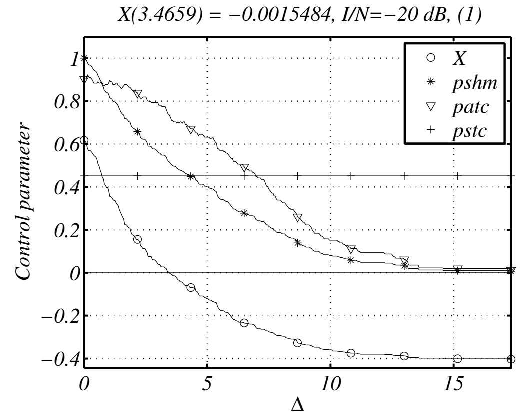

Figure 7. Sample of the control variable for I/N=-20 dB and SINR$_s$=-15 dB with k_p=1.44, k_a=0.46 and k_s=0.90. $T_{ob} = 10\ T_0$.

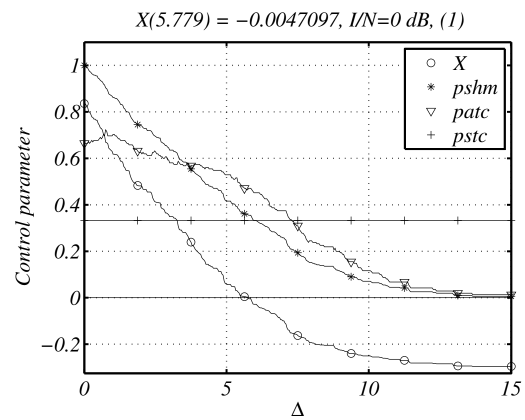

Figure 8. Sample of the control variable for I/N=0 dB and SINR$_s$=-15 dB with k_p=1.44, k_a=0.46 and k_s=0.90. $T_{ob} = 10\ T_0$.

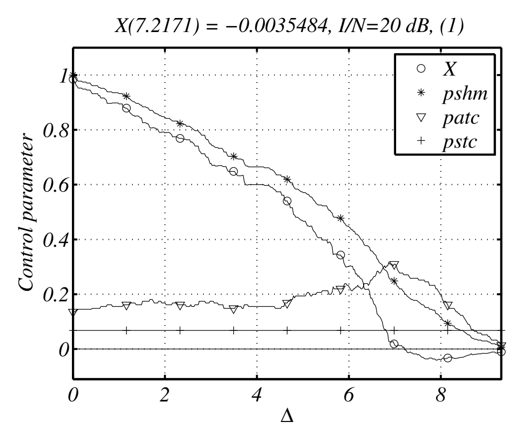

Figure 9. Sample of the control variable for I/N=20 dB and SINR$_s$=-15 dB with k_p=1.44, k_a=0.46 and k_s=0.90. $T_{ob} = 10\ T_0$.

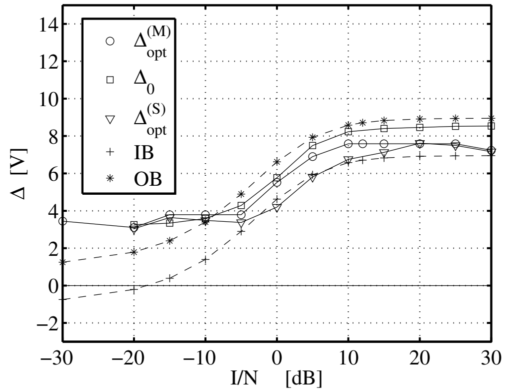

Figure 10. Comparison: Threshold allocation for combined interference. Corresponding to Fig. 11.

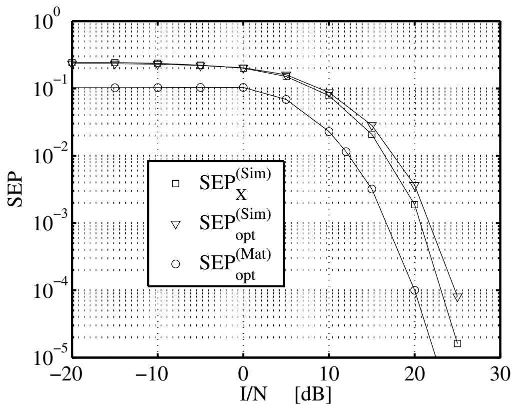

Figure 11. Comparison: Symbol error probability for combined interference. G_p=15 dB and SINR$_s$=-15 dB.

$pshm$ alone for adaptive threshold adjustment. For $pshm$ alone a stationary error will occur. (c) The inclusion of the level-crossings ($patc$ and $pstc$) solve the stationary error problem under changing interference conditions. Consult the next section for details. (d) The steepness at $X = 0$ is satisfactory. That guarantees less insensitivity to adjustment errors.

V. Performance

The performance of the new receiver is evaluated with the symbol-error probability under static and dynamic conditions. A detailed discussion of the static symbol-error probability is given in the companion paper in [1]. The results are included in Fig. 10 and Fig. 11.

The performance depends on how well and how fast the threshold can be adjusted to its optimum value. From Fig. 10 we derive that the threshold for the real behavior is in a wide range close to the mathematical derived threshold and differ slightly for dominating CW-interference. If we take the restrictions into account we have made to implement the theory to a real operating receiver we conclude that the thresholds agree with satisfactory accuracy. The corresponding symbol-error-probabilities are drawn in Fig. 11. The symbol-error-probability for the real receiver is very close to the simulated optimum symbol-error-probability. That the real receiver did it slightly better depends on the number of transmitted symbols in the Monte-Carlo simulations. We have transmitted 62000 symbols for the real receiver and 2000 symbols for the optimum receiver with equal magnitude resolution (400 threshold steps).

The error sources for the threshold adjustment are divided in stationary errors and dynamical errors. The stationary error is modest for dominating CW-interference. The nature of the dynamical error is dependent on the question if the adjustment procedure is fast enough to adapt to a new interference situation. This question can be answered by comparing the symbol-error-probabilities. The symbol-error-probabilities match perfect and therefore the adjustment must be very fast because no additional symbol-errors occur during an interference change. Therefore the implementation loss is negligible.

VI. Conclusion

This paper has proven that it is possible under varying interference conditions from dominating AWGN-interference to dominating CW-interference to adjust the threshold of the adaptive nonlinearity reliable and fast to meet the optimum symbol-error-probability with negligible implementation loss.

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