ADAPTIVE POSITIVE TIME-FREQUENCY ANALYSIS IN SPREAD SPECTRUM COMMUNICATIONS

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ABSTRACT

This paper introduces a novel algorithm to excise single and multicomponent chirp-like interferences in direct sequence spread spectrum (DSSS) communications. The excision algorithm consists of two stages: adaptive signal decomposition stage and directional element detection stage based on the Hough-Radon transform (HRT). Initially, the received spread spectrum signal is decomposed into its time-frequency (TF) functions using an adaptive signal decomposition algorithm, and the resulting TF functions are mapped onto the TF plane. We then use a line detection algorithm based on the HRT that operates on the image of the TF plane and detects energy varying directional elements that satisfy a parametric constraint. Interference is modeled by reconstructing the corresponding TF functions detected by the HRT, and subtracted from the received signal.

Keywords: DSSS, Interference Excision Algorithm, Chip error rate.

1. INTRODUCTION

In spread spectrum (SS) communications, the message signal is modulated and spread over a wider bandwidth with a pseudo noise (PN) code also known at the receiver, and transmitted over the channel. The increase of the bandwidth yields a processing gain, defined as the ratio of the bandwidth of the transmitted signal to the bandwidth of the message signal, and it provides a high degree of interference suppression. However, there is a trade off between increasing the processing gain and the available frequency spectrum. In the case of a jammer with high power, the SS system may not be able to suppress the interference. Therefore, excising the interference prior to dispreading the received signal is necessary to increase the performance of the system. Most interference suppression techniques are designed to deal with narrowband interferences [1–5]. Among the time-domain approaches for narrowband interference excision, the most notable methods include adaptive notch filtering and decision-directed adaptive filtering techniques [6] While SS systems can successfully reject narrowband interferences, their performance in rejecting wideband interferences is limited. In practical systems, it is not likely to transmit high-power wideband jamming signals due to the power limitations of the interference source. Additive white Gaussian noise can be considered as the only realizable wideband interference, which is very challenging to predict and excise. Therefore, substantial amount of research has been conducted on wideband interferences with narrowband instantaneous frequency elements such as FM signals.

In [10, 11], different window length STFTs are used to localize the interference. In [12], the authors use a signal decomposition algorithm consisting of a chirp-based dictionary to represent linear chirp interferences on the TF plane. The chirp interferences can be modeled with few coefficients and the proposed method performs well with linear chirp interferences. However, the generalization of the system to include quadratic, hyperbolic, or sinusoidal FM interferences is not discussed. Earlier interference excision methods based on TFDs suffer from a tradeoff between the TF resolution and the TFD cross-terms [17–19]. They also perform the excision of limited type of interferences such as linear or sinusoidal interferences [9, 12]. Considering these two disadvantages, we propose a new excision method based on constructing a positive TFD of the received SS signal using an adaptive signal decomposition technique, the matching pursuit (MP) algorithm [20]; followed by a line detection algorithm based on the HRT. By decomposing a signal into its components, the interaction between components can be kept under control and possibly eliminated. The decomposition will allow the construction of a cross-term free TFD by combining the TFDs of the individual components generated by the decomposition.

Also, by using Gaussian functions as bases for decomposition, we can achieve a high TF resolution, since the Gaussian functions satisfy the equality in the uncertainty principle and provide optimal TF resolution [7]. Interference is recursively estimated using the discrete evolutionary and Hough transforms, and the interference is subtracted from the signal by using the singular value decomposition of the de-chirped signal. In [14], the authors propose an adaptive TF excise that decides the domain of the excision by evaluating both the time and frequency properties. We construct the TFD of the TF functions resulting from the MP, treat the TFD as an image, and detect the interfering signals using the HRT, which can detect any line satisfying a parametric equation. We then reconstruct a model of the interfering chirps using the TF functions and excise the reconstructed interference from the received signal.

II DSSS SYSTEM

Let us consider a DSSS system as shown in Figure 1. In this system, the transmitter generates an SS signal which in turn is transmitted over a communications channel as a binary phase shift keying (BPSK) modulated signal. Additive channel noise as well as jamming signal act on the transmitted signal. At the receiver, the noise and interference corrupted signal is first demodulated. The “standard” SS receiver correlates the baseband SS signal with the synchronized PN sequence, and the resulting signal is processed and input into a threshold detector to estimate the transmitted binary data sequence.

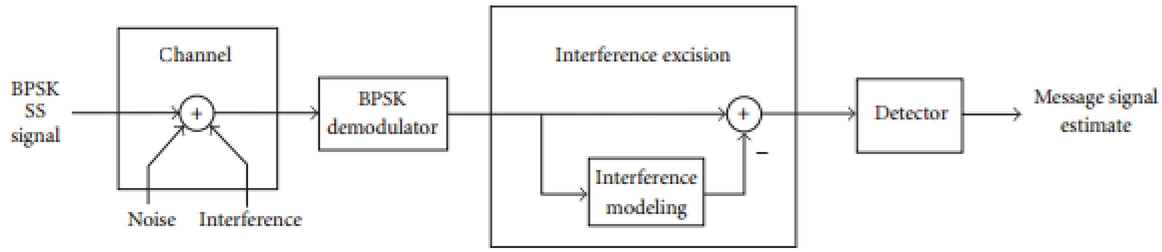

Figure 1: Bock Diagram of DSSS System

Let bk = ±1 be the kth message symbol transmitted in a DSSS system such that Wk = bk pk,

Where pk = $[c\ 0,...,c_{L-1}]^T$ for {k = 1, 2,...} is a PN sequence with a chip length L, $c_n = \pm 1$ is the nth chip of the PN sequence, and w_k is the SS signal.

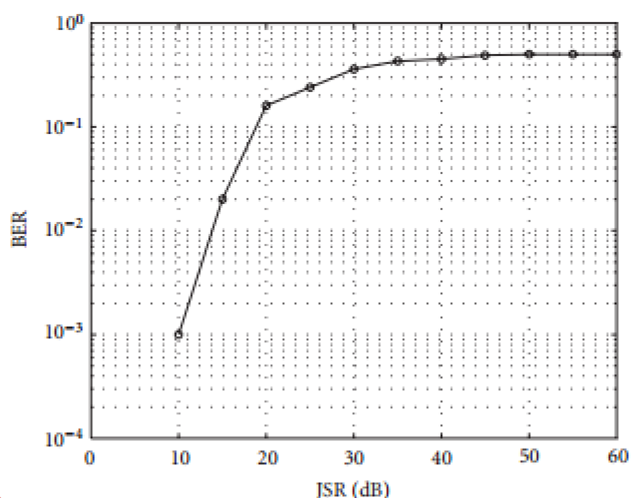

Figure 2: BER versus JSR Results for a Self-Excised SS System.

At the receiver, the received signal is first synchronized and correlated with the same spreading signal p. To estimate bk, we use the PN sequence pk to dispreads rk, and integrate the result to generate the test statistic. We define signal to-noise-power ratio (SNR) and jammer-to-signal-power ratio (JSR) as

$$\mathbf{SNR = E_w/E_n,}$$

$$\mathbf{JSR = E_i/E_w.}$$

Figure 2 shows the BER values at different JSR levels. The results presented in Figure 2 show that the SS system was able to completely self-excise the interference for JSR < 10 dB, as manifested with BER = 0. The resistance of the system to interference decreased with increasing JSR. For JSR > 40 dB, we observed BER ≈ 50% indicating that the SS system cannot suppress any part of the interference. From these observations we conclude that preprocessing of the SS signals is an essential step in expanding the operating range of SS systems in high-JSR environments. In particular, the preprocessing operations take the form of modeling the interference and excising from the SS signal before the despreading and detection steps as shown in Figure 1.

III INTERFERENCE EXCISION ALGORITHM

The interference excision algorithm is a two-step process based on the matching pursuit (MP) algorithm and the Hough-Radon transform (HRT) [21].

3.1. Matching pursuit algorithm

The MP algorithm [20] is an adaptive signal decomposition technique that can decompose the signal into its TF functions. In MP, the signal x(n) of length N is decomposed into a linear combination of TF functions in $\{g_{\gamma m}(n)\}$, and can be represented as

$$x(n) = \sum_{m=0}^{\infty} a_m g_{\gamma_m}(n),$$

where

$$g_{\gamma_m}(n) = \frac{K_{s_m}}{\sqrt{s_m}} g\left(\frac{n-p_m}{s_m}\right) e^{j((2\pi k_m/N)n+\phi_m)}.$$

3.2. The Hough-Radon transforms

The directional interferences can be energy varying. Therefore, we require a directional element detector that can detect time-varying energy values. The line detector that can satisfy our needs is a detector that uses the combination of Hough and Radon transforms proposed in [22]. This detector has been mathematically proven to be an optimal detector as it provides the maximum likelihood identification of a chirp signal [17]. The combined Hough and Radon transform, the HRT, is an efficient tool to detect directional and time-varying energy components in the TF plane. We first discuss the Hough transform and the Radon transform, and then continue to discuss the advantages of using the combined HRT for TFDs.

3.3. The Excision Algorithm

Figure:3 provides an overview of the proposed algorithm. After the interference excision, the "interference suppressed" SS signal is processed as before by first correlating with the synchronized PN sequence, integrating the resulting sequence, and estimating the transmitted data symbols using a threshold detector. For the interference excision algorithm, we assume that the information on the number and type of interference signals is available. In particular, we assume that the interference signals are linear or quadratic FM signals which can be present simultaneously. Let τ ∈ {linear, quadratic} be the type of interference, and let Mτ be the number of interference signals of type τ.

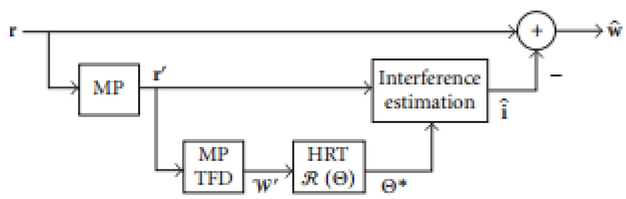

Figure 3: Interference excision

IV SIMULATION RESULTS AND DISCUSSION

The simulation results presented in this section are based on a DSSS system with L = 128 chips per message symbol bk. The transmitted message contained 100 message symbols. We assumed that the channel was non dispersive, and the received signal and the PN sequence were synchronized.

4.1. Performance measures

- *Bit error rate (BER).* For the DSSS model used in this study, we process the received signal using the interference excision algorithm, and estimate the transmitted message symbols using the detector structure. A comparison of the estimated message symbols {bk'} with {bk}, and expressing the number of erroneous estimates as a percentage of the total number of message symbols yields the bit error rate.
- *Chip error rate.* We define the chip error as

$$\mathbf{sign}[p_k(n)\hat{w}_k(n)] \neq \mathbf{sign}[p_k(n)w_k(n)],$$
$$\text{for } n \in \{0,\ldots,L-1\} \text{ and } k \in \{1,2,\ldots\}.$$

4.2. BER performance

To measure the performance of the DSSS system using the new interference excision algorithm developed in this paper, we evaluated the BER results for the following three interference scenarios, where we assumed the presence of

- a single-component linear chirp,
- a single-component quadratic chirp,
- a multi component interference with linear and quadratic chirps.

The interferences were measured with JSR values in the range of 0 to 50 dB at 10 dB steps. We assumed the SNR to be 10 dB in each case. We suppressed the interference before despreading, using the proposed interference excision algorithm. We observed zero bit errors in all cases after the excision of single-component and multi component interferences. We repeated the same process for different SNR values in the range of −10 dB to 10 dB, and also recorded zero bit errors.

4.3. Chip error rate performance

We evaluated the DSSS system by calculating the percentage of chips received in error at various SNR values. Figures 4and 5 show the simulation results for calculating the chip error rates for the JSR values 40 dB and 5 dB, respectively. Figure 4 shows the percentage of chips in error before and after the excision of single and multi component interferences. The JSR value of 40 dB is used because at this JSR level with no interference excision, the system BER is approximately 50 percent indicating that the system cannot suppress any part of the interference. It is observed that the excision of a single interference results in less chip error rate than the excision of a multi component interference. This is a result of the excision of a multi component interference introducing more noise than the excision of single-component interference at the same power level. When the estimates of the interferences are excised from the SS signal, part of the SS signal in the vicinity of the interference localization is also suppressed. Therefore, multi component interferences are likely to introduce more residual noise.

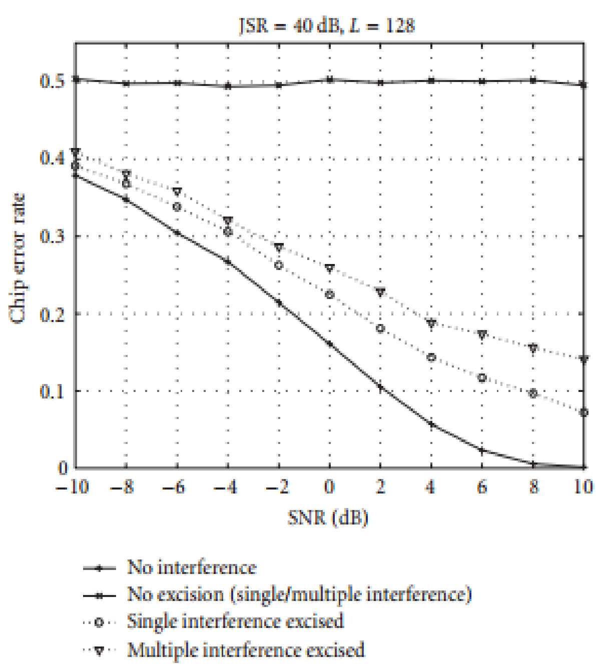

Figure 4: Chip error rate versus SNR for JSR = 40 dB.

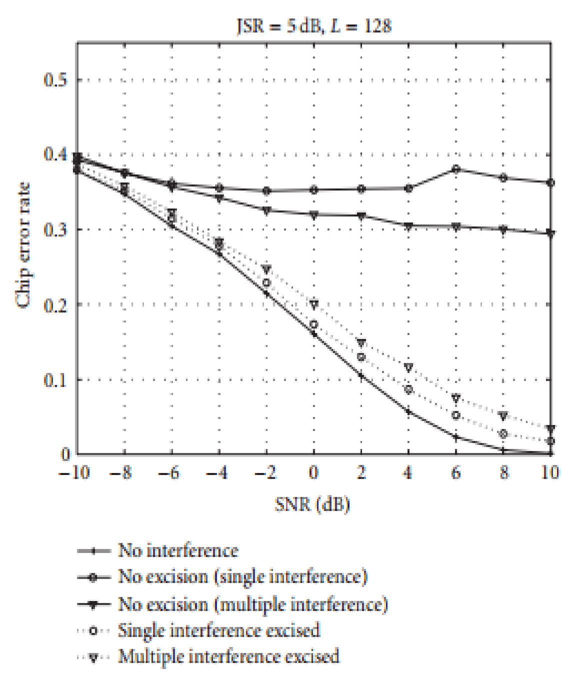

Figure 5: Chip error rate versus SNR for JSR = 5 dB.

Figure 5 shows the results for the same experimental setup at JSR = 5 dB. JSR value of 5 dB is used since the system can suppress the interference partly without interference excision prior to despreading.

V CONCLUSIONS

In this paper, we proposed a new interference excision algorithm and evaluated its performance in terms of the BER and chip error rates. The most striking observation resulting from the simulation studies is that there were no bit errors after the excision of single and multi component interferences at all JSR levels tested, that is, JSR $\leq$ 50dB. Under similar test conditions, the algorithms developed in earlier studies reported bit errors with the notable exception of [12].

This highly desirable characteristic is the result of the following three factors.

(1) The model of the interference uses Gaussian functions, which provide optimal TF resolution within the limits of the uncertainty principle.

(2) The MP TFD uses WVD, which also localizes the components well and provides a high TF resolution. The modeling of the interferences as a linear combination of basis functions eliminated the cross-terms in the construction of the TFD for multi component interferences. Lack of cross-terms prevents undesired peaks in the HRT space, which may lead to incorrect parameter estimates.

(3) The HRT algorithm acts as an adaptive thresholding mechanism successfully determining the functions that model the interference

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