Jammer Excision in Spread Spectrum Communications via Discrete Evolutionary Transform

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Abstract

In this paper, we propose time-frequency jammer excision techniques for direct sequence spread spectrum communications. One method is based on the estimation of the instantaneous frequency (IF) of each of the chirp jammer components using a combination of the discrete evolutionary and the Hough transforms. The second method is based in Wiener masking, and reduces the interference in a mean-square fashion. In the first method, the jammer is synthesized and subtracted from the baseband received signal, while in the second method a mean-square estimate of the message is obtained. The IF-based method applies equally well to multi-component chirp jammers with constant or time-varying amplitudes, and instantaneous frequencies not necessarily parametrically modeled. A statistical analysis of this method is developed based on the signal to interference and noise ratio. We will show that the Wiener masking method is a general method requiring the spectrum of the spreading function. The two methods are illustrated by simulations.

1 Introduction

Direct sequence spread spectrum (DSSS) communications offer advantages such a code division multiple access (CDMA), low probability of intercept, communication over channels affected by multi-path propagation, and robustness to intentional jamming or interference from other users [1]. This is achieved by spreading the message so that it ocuppies a bandwidth in excess of the minimum needed for transmission. Despreading at the receiver with a synchronized replica of the spreading function permits not only recovery of the message but reduction of interferences added in the transmission. But the performance of DSSS communication systems degrades as the power of the interferences increases, especially in the case of non-stationary jammers. Excision of the jamming signals from the received signal before despreading is known to enhance the interference robustness of the system. Due to ease in tracking jammers in the time-frequency domain, different time-frequency methods have been recently proposed for jamming excision [2, 3, 4, 5, 7, 6]. When transmitting a k^{th} data bit using DSSS, the received baseband signal is given by

$$r_k(n) = d_k p(n) + \sum_{q=1}^{Q} j_q^k(n) + \eta(n) \qquad 0 \leq n \leq (L-1),$$

where the data bit is d_k, $p(n)$ is a pseudo-noise signal of length L chips, the jamming signal has Q chirps $j_q^k(n)$, and $\eta(n)$ is white noise. These two signals are added during transmission. Possible excision approaches consist of projecting the received signal either onto the signal-plus-noise space and use time-varying filtering to excise, or onto the jamming subspace to synthesize and subtract the jamming signals. Likewise, the excision can be viewed as a non-stationary Wiener filtering problem where a mean-square estimator for the $dp(n)$ is sought. To deal with the excision and estimation we use the Discrete Evolutionary Transform (DET) [8] to represent the non-stationary received signal and its corresponding time-varying spectrum.

2 The Discrete Evolutionary Transform

The Discrete Evolutionary Transform (DET) [8] provides a representation for a non-stationary signal to which a time-dependent evolutionary spectrum is associated. A non-stationary signal, $x(n)$, can be represented by either of the following Wold-Cramer representations:

$$x(n) = \sum_{k=0}^{K-1} X(n, \omega_k) e^{j\omega_k n}, \quad (1)$$

which uses a sinusoidal basis, or a more general representation based on chirp basis

$$x(n) = \sum_{p=0}^{P-1} \sum_{k=0}^{K-1} X_p(n, \omega_k) e^{j(\omega_k n + \phi_p(n))}. \quad (2)$$

In these representations, $\omega_k = 2\pi k/K$ with K the number of frequency samples, P is the number of chirps and $\phi_p(n)$ can be considered a very general function of n. The functions $X(n, \omega_k)$ and $X_p(n, \omega_k)$ are the evolutionary kernels for the two representations. Expressing $X(n, \omega_k)$ and $X_p(n, \omega_k)$ in terms of $x(n)$ can be accomplished by considering a conventional representation for $x(n)$. In [8] we considered the Gabor and the Malvar wavelet, representations. The evolutionary kernels are given by

$$\begin{aligned} X(n, \omega_k) &= \sum_{\ell=0}^{N-1} x(\ell) W_k(n, \ell) e^{-j\omega_k \ell}, \quad (3) \\ X_p(n, \omega_k) &= \sum_{\ell=0}^{N-1} x_p(\ell) W_k(n, \ell) e^{-j(\omega_k \ell + \phi_p(\ell))}, \quad (4) \end{aligned}$$

where the window $W_k(n, \ell)$ is a time and frequency dependent window found from the expansion used. Once the windows are defined, one can compute the DET directly using equations (1) and (3), or (2) and (4). These equations can be seen as extensions of the Short-time Fourier transform. For the sinusoidal representation, it can be shown that $|X(n, \omega_k)|^2$ is a time-frequency energy density, and as such the evolutionary spectrum of $x(n)$ is given by $S(n, \omega_k) = |X(n, \omega_k)|^2$. Likewise, for the chirp expansion, the evolutionary spectrum is given by $S(n, \omega_k) = \left| \sum_{p=0}^{P-1} X_p(n, \omega_k - \omega_p(n)) \right|^2$.

3 Jammer Excision via Projection and Synthesis

We attempt to synthesize the jammer by finding estimates of the instantaneous frequencies (IFs) of each of the jammer components, and then estimating their amplitudes by linear filtering or singular value decomposition. The synthesized jammer is subtracted from the received signal. We have shown [7] that a combination of the discrete evolutionary and the Hough transforms can be efficiently used to find initial piecewise-linear estimates of the instantaneous frequencies of multi-component signals, and then recursively corrected using the DET representation of the signal. This provides a great advantage not shared by other IF estimation methods, using only spectral information. When using the the Malvar-based DET, the signal is partitioned into components represented by sinusoids or chirps. The proposed discrete evolutionary Hough (DEH) transform tracks the instantaneous frequencies of sinusoids or chirps and approximates them linearly, and indicates the number of components present locally – for each of which we obtain sequentially a linear IF estimate.

The Hough transform maps an image $I(x, y)$ into a parametric space (θ, ρ) to infer the presence of lines or curves by means of clusterings in the parameter space. The application of the DEH transform is simplified by consider its application to segments of the received signal $r(n)\mathrm{w}_i(n)$, and obtaining a linear approximation for each of the IFs of the jammer components. The following is the definition of the local DEH transform for $r(n)\mathrm{w}_i(n)$:

$$\mathrm{DEHT}(\theta, \rho, i) = \sum_{n,k} S(n, \omega_k) \mathrm{w}_i(n) \delta(\rho - n\cos\theta - \omega_k \sin\theta).$$

This transform tracks lines in the windowed evolutionary spectrum $S(n, \omega_k)\mathrm{w}_i(n)$, by means of clusters created in the parameter space (θ, ρ). The number of clusters corresponds to the number of lines detected. Unlike the Wigner-Hough transform [2], the DEH transform does not assume a parametric model for the IFs, and does not have the problem of cross terms introduced by the Wigner distribution.

The initial estimates can be improved by using the DET representation of the jammer. Consider the windowed received signal

$$\begin{aligned} x_{\mathrm{w}_i}(n) &= r(n)\mathrm{w}_i(n) \\ &= \sum_{p=1}^{Q_i} A_{ip}(n) e^{j\phi_{ip}(n)} + \eta_i(n) + dp_i(n), \end{aligned}$$

where the DET representation of the Q_i jammers present in this window is given, and $\eta_i(n)$ and $dp_i(n)$ are the windowed noise and DS signals. To improve the estimate $\hat{\phi}_{iq}(n)$ (the instantaneous phase of the q^{th} jammer component in the i^{th} window) we use it to dechirp $x_{\mathrm{w}_i}(n)$:

$$\begin{aligned} y_{iq}(n) &= x_{\mathrm{w}_i}(n) e^{-j\hat{\phi}_{iq}(n)} \\ &= A_{iq}(n) e^{j\tilde{\phi}_{iq}(n)} + \sum_{p \neq q} A_{ip}(n) e^{j\tilde{\phi}^p_{iq}(n)} \\ &\quad + (\eta_i(n) + dp_i(n)) e^{-j\hat{\phi}_{iq}(n)}, \end{aligned}$$

where $\tilde{\phi}_{iq}(n) = \phi_{iq}(n) - \hat{\phi}_{iq}(n)$ and $\tilde{\phi}^p_{iq}(n) = \phi_{ip}(n) - \hat{\phi}_{iq}(n)$. The first term above corresponds to a lowpass signal, thus if we pass $y_{iq}(n)$ through a narrow-band low-pass filter we obtain an analytic signal

$$z_{iq}(n) = [A_{iq}(n) + \varepsilon_{iq}(n)] e^{j\tilde{\phi}_{iq}(n)},$$

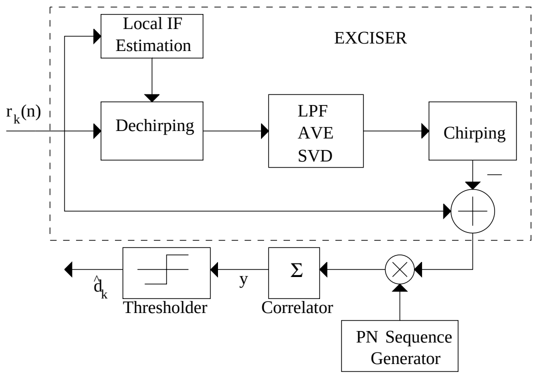

Figure 1. Block diagram of the exciser

where $\varepsilon_{iq}(n)$ is the effect of other jammers, as well as the windowed noise and DS signals, and $\tilde{\phi}_{iq}(n)$ is the instantaneous phase of the analytic signal $z_{iq}(n)$. The above indicates we can use a new estimator

$$\hat{\phi}^{n}_{iq}(n) = \hat{\phi}_{iq}(n) + \tilde{\phi}_{iq}(n). \tag{5}$$

The above process is repeated until the difference between the old and the new estimates is insignificant.

Figure 1 depicts the proposed exciser. Dechirping the windowed received signal using one of the estimated IFs gives us a low-frequency stationary signal –corresponding to the desired jammer component– along with other non-stationary components corresponding to the other jammer components, the noise and the DS signal. To separate the low-frequency stationary signal from the others we consider three different methods: arithmetic averaging (AVE), low-pass filtering (LPF) and singular value decomposition (SVD). This provides estimates of the amplitudes of the jammer components. Chirping back, with the same IF used to dechirp before, the resulting signal gives a synthesized jammer component which we subtract from the received signal. We have observed in simulations that the arithmetic averager performs consistently better in the cases of constant or slowly varying amplitudes of the jammer components, while the low-pass filtering and the singular value decomposition methods do better for wider windows or in global processing.

3.1 Statistical Performance Analysis

At the receiver, after the jammer is excised from the received baseband signal, the resulting signal is despreaded and correlated. The decision variable y used to determine, after thresholding, whether the sent bit was 1 or -1 is

$$y = dL + \sum_{n=0}^{L-1} \eta(n)p(n) + \sum_{n=0}^{L-1} \left(\sum_{i=0}^{I-1} \sum_{q=1}^{Q_i} \tilde{j}_{iq}(n) \mathrm{w}_i(n) \right) p(n), \tag{6}$$

where $\tilde{j}_{iq}(n)$ is the difference between the actual jammer and the synthesized one. This decision variable is for a bit d, of length L chips and partitioned into I segments, each having Q_i jammer components. To measure the effect of the jammer interference and the channel noise in the transmission, we consider the receiver signal to interference and noise ratio (SINR) given by

$$SINR = \frac{E^2\{y\}}{\sigma_y^2}. \tag{7}$$

Assuming the white noise and the pseudo-noise are zero mean, and uncorrelated, it can be shown that $E[y] = dL$ and the variance $\sigma_y^2 = \sigma_\eta^2 L + \rho$, where the first term is the contributions of the channel noise, while

$$\rho = \sum_{n=0}^{L-1} \sum_{i=0}^{I-1} E\left\{ \left| \sum_{q=1}^{Q_i} \tilde{j}_{iq}(n) \right|^2 \mathrm{w}_i(n) \right\} \tag{8}$$

is due to the residual jammer. Thus, we have Eq. (7) becomes:

$$SINR = \frac{L}{\sigma_\eta^2 + \rho/L}. \tag{9}$$

When $(\rho = 0)$, either because no jammers are present or because they were excised completely, we obtain the upper bound of the SINR. The lower bound corresponds to when no excision is performed, and ρ/L equals the total power of the jamming signal.

To compare our results with those from [9], we consider the special case of a single component jammer with a constant amplitude a. The arithmetic average exciser gives as estimate of the amplitude of the jammer:

$$\bar{A}_{i1} = \frac{a}{N} \sum_{m=0}^{L-1} \mathrm{w}_i(m) e^{-j\tilde{\phi}_{i1}(m)},$$

and it can be shown that

$$\rho = a^2 L \left(1 - \frac{1}{N}\right)(1 - e^{-\sigma_1^2}),$$

where σ_1^2 is the variance of the phase error. Thus, the SINR for the arithmetic averager exciser when there is a single jammer with constant amplitude is then given by

$$SINR_a = \frac{L}{\sigma_\eta^2 + a^2(1 - \frac{1}{N})(1 - e^{-\sigma_1^2})}. \tag{10}$$

Amin's projection method gives [9]

$$SINR_p = \frac{L(1 - \frac{1}{N})}{\sigma_\eta^2 + \frac{2}{N} + a^2(1 - e^{-\sigma_1^2})}. \tag{11}$$

It can also be shown that $SINR_a > SINR_p$. As we will see in the simulations, there is hardly any difference between these two values.

4 Jammer Excision via Wiener Masking

The above method assumes the TF spectrum clealy displays the jammer. When the JSR is low, or the jammer is not composed of chirps the above method fails. However for each bit, the information about the spreading sequence does not change and so we can compute *a priori* its evolutionary spectrum, we will see that this spectrum and the spectrum of the received baseband signal $r(n)$ can be used to obtain a mean-square estimate for the DS signal. This is a special case of the non-stationary Wiener filtering [10] that consists in obtaining a linear time–varying estimator for a signal $x(n)$ embedded in a non-stationary interference $\psi(n)$. The data is thus given by

$$y(n) = x(n) + \psi(n).$$

The filtering estimate can be found by minimizing a mean-square error

$$\varepsilon(n) = E|x(n) - \hat{x}(n)|^2, \tag{12}$$

where $\hat{x}(n)$ is the output of a linear time-varying filter or mask. The masking estimator has the Wold-Cramer representation

$$\hat{x}(n) = \int_{-\pi}^{\pi} Y(n,\omega)B(n,\omega)e^{j\omega n}dZ_y(\omega), \tag{13}$$

where $Y(n,\omega)$ is the evolutionary kernel of $y(n)$, and $B(n,\omega)$ is a masking function. The minimization of $\varepsilon(n)$ requires, according to the orthogonality principle, that

$$E\left[x(n) - \hat{x}(n)\right]\hat{x}^*(n) = 0$$

which can be shown to be equivalent to

$$\int_{-\pi}^{\pi}\left[\frac{S_x(n,\omega)}{Y^*(n,\omega)} - G(n,\omega)\right]G^*(n,\omega)d\omega = 0, \tag{14}$$

where $G(n,\omega) = Y(n,\omega)B(n,\omega)$. To minimize the above equation we let

$$G(n,\omega) = Y(n,\omega)B(n,\omega) = \frac{S_x(n,\omega)}{Y^*(n,\omega)}, \tag{15}$$

so that the mask is given by

$$B(n,\omega) = \frac{S_x(n,\omega)}{S_y(n,\omega)} \tag{16}$$

or the ratio of the evolutionary spectra of $x(n)$ to that of the data $y(n)$. This result is analogous to the non-causal stationary Wiener filter. The optimal estimator and the minimum mean square error are found to be

$$\begin{aligned} \hat{x}(n) &= \int_{-\pi}^{\pi}\frac{S_x(n,\omega)}{Y^*(n,\omega)}dZ_y(\omega), \\ \varepsilon_{\text{min}}(n) &= \int_{-\pi}^{\pi}\frac{S_x(n,\omega)S_\psi(n,\omega)}{S_y(n,\omega)}d\omega. \end{aligned} \tag{17}$$

When applying the above procedure to the estimation of the message bit, the data is given by $r(n)$, which consists of the desired signal $dp(n)$ and the interference is $j(n) + \eta(n)$. The Wiener masking, using a DET implementation, is given by the ratio of the spectrum of $dp(n)$ and that of $r(n)$. Notice the evolutionary spectrum of $dp(n)$ is the same independent of d, and that the spectrum of the received signal is available for every bit transmitted. Finally, we obtain the estimated message signal as the inverse discrete evolutionary transform of the kernel $R(n,\omega)B(n,\omega)$. The above is only possible because of the connection between the evolutionary kernel and the signal, and note there is no condition imposed on the form of the jammer, as long as its DET can be computed. Thus these results apply to a large class of jammers. Moreover, in theory this procedure is valid for any value of the jammer to signal ratio.

5 Simulations

IF Estimation. Consider a jammer composed of a linear and a sinusoidal FM components, and embedded in Gaussian noise (SNR 5.2 dB). Figure 2 shows the initial local IF linear and the corrected estimates.

Projection and Synthesis. We simulate the DSSS signals for a constant jammer to signal ratio (JSR), and perform 10^4 Monte Carlo trials for each SNR. Averaging the bit errors we obtain the corresponding bit error rate (BER). In the SINR simulations, we perform 100 Monte Carlo trials at each SNR to obtain the jamming error ρ for the AVE exciser and Amin's projection method, and the variance of the noise, to compute the SINR with the formulas obtained before. The results are shown in Figs. 3 and 4.

Wiener Masking. We perform 10^4 Monte Carlo trials at each SNR to compute the BER when using the Wiener masking approach. The jammer is composed of arbitrary sinusoids and chirps, with an JSR of 35(dB). The results indicate that the masking Wiener works very well for the case of a jammer whose composition is not known. The evolutionary spectrum of the pseudo noise sequence is known. The results are shown in Fig. 5.

6 Conclusions

In this paper, we propose two methods to excise jammers in DSSS: one that uses the DET and the Hough transform to synthesize the jammer and excise it, and the other based in a Wiener mask to estimate the message signal. The Wiener masking method is more general, but requires the spreading sequence. On the other hand, the synthesis method takes advantage of the nature of the jammer to synthesize it. Both methods show very good performance.

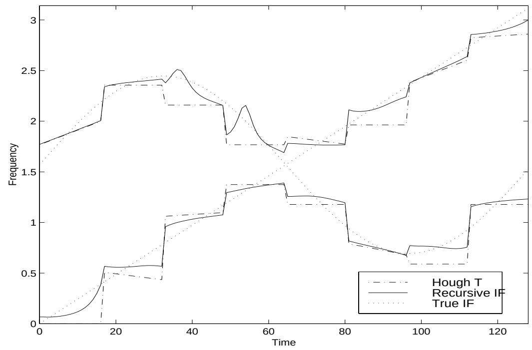

Figure 2. DEHT (dash-dot) and recursively corrected IF estimates (solid)

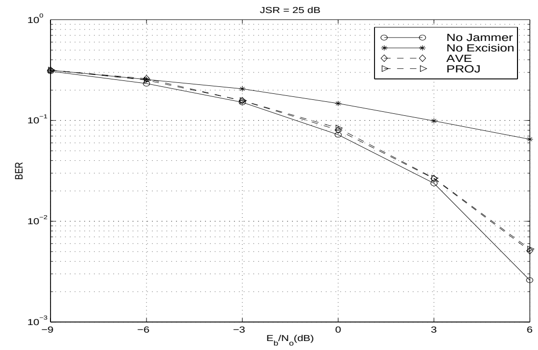

Figure 3. BERs vs SNRs: Excision using AVE and Amin's projection for mono-component Gaussian amplitude linear FM jammer (JSR 25 dB)

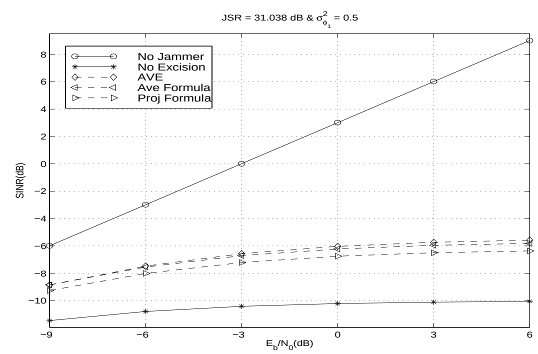

Figure 4. SINR vs SNRs for a mono-component, constant amplitude linear FM jammer (JSR 31 dB) and $\sigma_1^2 = 0.5$, excision using AVE and Amin's projection

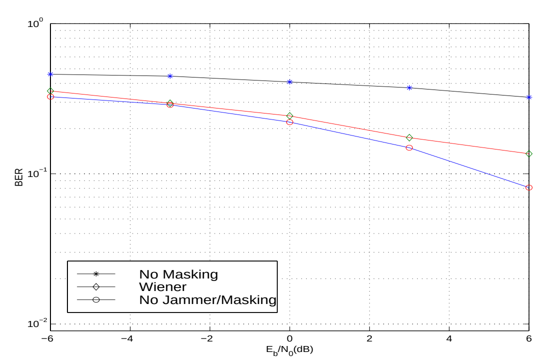

Figure 5. BER for an arbitrary jammer (JSR 35 dB) using Wiener masking

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