

Adaptive Time-Varying Cancellation of Wideband Interferences in Spread-Spectrum Communications Based on Time–Frequency Distributions

Sergio Barbarossa, *Member, IEEE*, and Anna Scaglione, *Student Member, IEEE*

Abstract—The aim of this paper is to propose an adaptive method for suppressing wideband interferences in spread spectrum (SS) communications. The proposed method is based on the time–frequency representation of the received signal from which the parameters of an adaptive time-varying interference excision filter are estimated. The approach is based on the generalized Wigner–Hough transform as an effective way to estimate the instantaneous frequency of parametric signals embedded in noise. The performance of the proposed approach is evaluated in the presence of linear and sinusoidal FM interferences plus white Gaussian noise in terms of SNR improvement factor and bit error rate (BER).

Index Terms—Interference suppression, spread spectrum communication, time-varying filters.

I. INTRODUCTION

SPREAD spectrum (SS) communications use signals whose bandwidth is much wider than the information bandwidth. The spreading can be achieved in different ways, e.g., using direct sequence (DS) or frequency-hopping (FH) techniques [18], [20]. In this work, we will concentrate on DS systems. Spread spectrum techniques offer a number of important advantages, such as code division multiple access (CDMA), low probability of intercept (LPI), communications over channels affected by multipath propagation, and resistance to intentional jamming [18], [20]. As far as the immunity to interferences is concerned, SS systems are implicitly able to provide a certain degree of protection against intentional or nonintentional interferences thanks to the despreading gain. However, in some cases, the interference might be much stronger than the useful signal, e.g., when the interfering stations are much closer to the receiver than the useful transmitting station, they use much more transmission power, or the useful signal is affected by fading, etc. In such cases, the gain due to the coding might be insufficient to decode the useful signal reliably. Therefore, many efforts have been addressed to study adaptive interference cancellation techniques to improve the interference immunity of SS systems.

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The authors are with the Department of Information and Communication, University of Rome “La Sapienza,” Rome, Italy (e-mail: sergio@infocom.ing.uniroma1.it; annas@infocom.ing.uniroma1.it).

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Several works deal with the suppression of narrowband interferences [13], [18], [19], [25]. Indeed, SS systems offer a good interference rejection capability for narrowband interferences. In fact, an SS sequence is not easily predictable because it appears to be noise-like (unless the code is known, of course). Conversely, if the interference is a predictable process, it can be predicted from the observation and then canceled (see, for example, [16] or [25] and the references therein). The situation is more complicated in the presence of wideband interferences. Two models have been considered for wideband interferences: white noise [20] and linear FM signals (chirp signals) [1], [2], [8], [11]. From the jammer point of view, the choice between these two categories of signals depends on different requirements or constraints. White noise signals are impossible to predict and then cancel, and the only gain against them for an SS system comes from the despreading. Conversely, constant modulus signals, like LFM or sinusoidal frequency modulation (SFM) signals, may be preferred because they allow for the maximization of the average transmitted energy for a given transmitter peak power.

In [11], an adaptive filter was used to track and cancel chirp-like interferences in SS systems. Preliminary works on the cancellation of chirp interferences using adaptive filters were presented in [8] and [24]. In particular, Glisic *et al.* found out that the performance of the adaptive canceler degrades as the chirp sweep rate increases [11]. Quite recently, Amin proposed a novel approach for suppressing chirp-like interferences in SS communications based on the time–frequency representations of the observed signal [1], [2]. The method proposed in [2] consists of evaluating the Wigner–Ville distribution (WVD) or a related time–frequency distribution (TFD) belonging to the generalized Cohen’s class [9] of the observed signal and estimating the parameters of the interfering signal from the WVD. Once the parameters have been estimated, an adaptive time-varying filter can be set up to suppress the interference. Once again, the method exploits the property that SS signals are difficult to track, even in the time–frequency domain, whereas a large class of interferences, like, for example, constant modulus signals, can be tracked and then canceled, working in the time-frequency domain. A parallel approach based on time-scale or multiresolution representations was proposed by Tazebay and Akansu [21]–[23]. The multiresolution-based method is linear, whereas Amin’s method is nonlinear. However, it is known that for particular classes of signals, e.g., chirp signals, the analysis based on

the generalized Cohen's class time–frequency distributions has superior performance, in terms of time–frequency localization, with respect to linear methods [9]. The price paid for using nonlinear TFD's is the appearance of undesired cross terms in the presence of multicomponent signals and the threshold effect such that if the SNR is not sufficiently high, the method is not reliable because of noise-masking effects. However, there exist several nonlinear TFD's that provide very low cross terms (the so-called reduced interference distributions (RID's) [9]), and in applications such as SS systems, if the power of the interference is low, it is not even necessary to use an adaptive canceler because the gain achievable by despreading is sufficient to combat the interference. Therefore, in such a case, the use of TFD's is appropriate. For this reason, we will follow the TFD-based approach.

One of the problems related to the method proposed in [2] is that if the signal-to-interference ratio (SIR) is high, the estimation of the interference parameters might fail, and the suppression filter could track the useful signal, instead of the interference, with obvious shortcomings. In this work, we propose an extension of the method proposed in [2] using the so-called Wigner–Hough transform (WHT) [5]. The method assumes that i) the interference has constant amplitude (or is the sum of constant amplitude signals) and that ii) the instantaneous frequency assumes a known parametric form (but the parameters are not known *a priori*). The number of interfering terms does not need to be known *a priori*, but it can be estimated from the data. The WHT-based estimation method was initially proposed in [5] for the analysis of multicomponent linear frequency modulation (chirp) signals and then generalized to the case of signals having a generic parametric instantaneous frequency modulation law (mono or multicomponent) in [6].

The main advantage of the proposed algorithm, with respect to [2], is a consistent improvement of the interference suppression capabilities at low interference-to-signal plus noise ratios. The proposed method is also able to deal with multicomponent (mc) interferences, and the integration in the time–frequency domain operated by the WHT helps to reduce the cross terms. The main disadvantage of our approach is that it is not robust against mismatching between the observed signal and the model, but this is a problem shared by all model-based approaches.

The paper is organized as follows. In Section II, we recall the Wigner–Hough transform and apply it to the estimate of the interference parameters; in Section III, we propose optimal and suboptimal schemes for detecting SS signals superimposed to linear or sinusoidal FM interferences plus noise; in Section IV, we provide the performance of the proposed approach expressed in terms of improvement of the signal-to-disturbance ratio and bit error rate (BER).

II. ESTIMATION OF INTERFERENCE PARAMETERS USING A TIME–FREQUENCY APPROACH

The observed signal is assumed to have the form

$$x(t) = \sqrt{P_s}Ac(t) + \sum_{k=1}^K \sqrt{P_{I_k}}d_k(t) + w(t) \quad (1)$$

where

P_s	signal power;
$A = \pm 1$	transmitted symbol (we assume BPSK modulation);
$d(t)$	interfering signal;
$w(t)$	complex additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_w^2 = 2\sigma_n^2$, where σ_n^2 is the variance of the in-phase and quadrature noise components;
$c(t)$	maximum-length sequence (MLS) [17] whose entries belong to the binary alphabet $\{-1, 1\}$.

We will assume perfect synchronism on the receiver and that the duration of the observation is equal to one codeword, whose length is forced to be $L = 2^m - 1$, where m is the length of the shift register used to generate the code.

We assume that each interference signal belongs to the class of constant amplitude signals, i.e.,

$$d_k(t) = e^{j\phi(t, \theta_k)} \quad (2)$$

in (1), and the instantaneous phase is expressed in a parametric form [the parameters are the entries of vector θ_k in (2)]. Constant modulus signals are commonly used whenever the interferer wants to maximize the power of the transmitted signal and then uses a signal with a constant amplitude $\sqrt{P_{I_k}}$ equal to the peak value. This class of signals is particularly useful to generate wideband signals while still retaining the power efficiency property. Other classes of wideband interference signals, e.g., noise-like signals, are also used, but they inevitably entail a waste of power because of the amplitude modulation.

Two classes of parametric expressions will be considered as representatives of typical applications, e.g., linear frequency modulation (FM) signals, where

$$\phi(t, \theta_k) = 2\pi f_k t + \pi g_k t^2 \quad \text{and} \quad \theta_k := (f_k, g_k) \quad (3)$$

or sinusoidal FM signals, where

$$\phi(t, \theta_k) = \beta_k \sin(2\pi f_k t + \alpha_k) \quad \text{and} \quad \theta_k := (\beta_k, f_k, \alpha_k). \quad (4)$$

The approach proposed in [1] for the estimation of the interference instantaneous frequency based on time–frequency distributions (TFD's), belonging to the generalized Cohen's class, is appropriate if the interference power is considerably greater than the noise power and the spread spectrum signal power added together. In fact, such TFD's are bilinear operators applied to the input signal, and as such, they exhibit the common problems when dealing with nonlinear transformations, that is, weak signals are “captured” from stronger signals, and the method works properly only if the input signal-to-noise ratio (SNR) is above a certain threshold, but the performance degrades considerably as the input SNR goes below the threshold. TFD's are particularly useful for analyzing signals whose energy is well concentrated along the curve of the IF in the time–frequency plane. This property is true for constant amplitude signals (in such a case, the instantaneous bandwidth [9] is zero), as in the application considered in this work, but the same property does not hold,

for example, for the noise whose energy is spread all over the time–frequency domain. Therefore, it is desirable to use TFD’s for discriminating constant-amplitude signals from the noise, but on the other hand, we should try to minimize the undesired effects related to using a nonlinear transformation. Possible ways to improve the performance of time–frequency based approaches in the analysis of constant amplitude signals embedded in additive white Gaussian noise (AWGN) were proposed in [5] and [15] for linear FM signals, in [7] and [14] for polynomial-phase signals, and in [6] for the more general class of instantaneous frequency laws expressed in a parametric form. Examples of sinusoidal and hyperbolic FM signals were considered in [6]. The improvement was achieved by exploiting the *a priori* knowledge of the parametric instantaneous frequency. The methods proposed in [5]–[7] conjugate time–frequency approaches, which are, in general, nonparametric with parametric estimation methods based on the time–frequency representations. In particular, the methods proposed in [6] and [7] are based on the integration of the TFD over parametric curves having the same form as the signal’s instantaneous frequency. The overall transformation is a mapping from the time domain onto the signal parameter space domain and is based on two main steps: 1) mapping onto the time–frequency plane using some TFD (e.g., Wigner–Ville distribution, etc.) and 2) pattern recognition applied to TFD to recognize the signal “signature” expressed through its instantaneous frequency curve. The tool used for pattern recognition is the generalized Hough transform (HT) [4] for its capability of detecting arbitrary shapes. The method was named Wigner–Hough transformation (WHT) [5]. Given a signal $x(t)$, its WHT is defined as

$$\text{WHT}_x(\theta_k) = \int_{-\infty}^{\infty} W_x(t, f(t; \theta_k)) dt \quad (5)$$

where $W_x(t, f)$ denotes the Wigner–Ville distribution of $x(t)$

$$W_x(t, f) = \int_{-\infty}^{\infty} x(t + \tau/2)x^*(t - \tau/2)e^{-j2\pi f\tau} d\tau \quad (6)$$

and $f(t; \theta_k)$ is the interference instantaneous frequency

$$f(t; \theta_k) = \frac{1}{2\pi} \frac{d\phi(t; \theta_k)}{dt}. \quad (7)$$

For example, when dealing with linear FM signals, each signal component gives rise to energy concentrations along straight lines in the time–frequency plane of [see (3)] $f(t; \theta_k) = f_k + g_k t$. The integration over all possible lines, which is obtainable by applying a Hough or, equivalently, a Radon transform to the WVD, gives rise to peaks in the final parameter space; each peak corresponds to one linear FM signal, whose modulation parameters (f_k and g_k) are the coordinates of the peak. The method was initially suggested by Kay *et al.* [12] and was extended to the multicomponent case in [5], where it was also proved that the method provides estimation variance tending to the Cramér–Rao lower bound (CRLB) as the input SNR increases. Furthermore, the SNR threshold was shown to be moderate (around 0 dB).

In this paper, we will extend the approach proposed in [5] and [6] to the analysis of constant amplitude signals (the

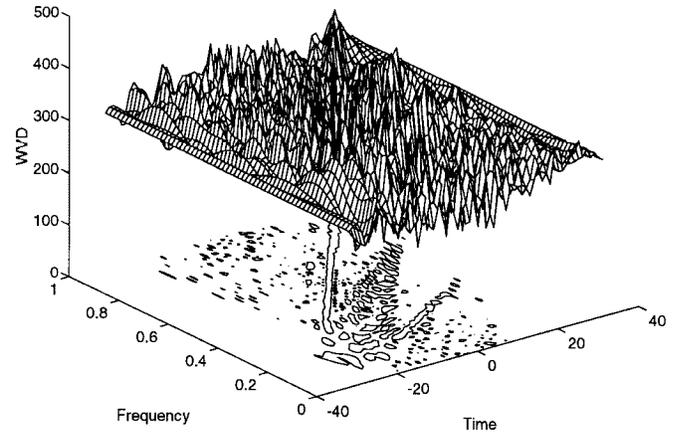


Fig. 1. WVD of SS signal plus two linear FM interferences plus noise.

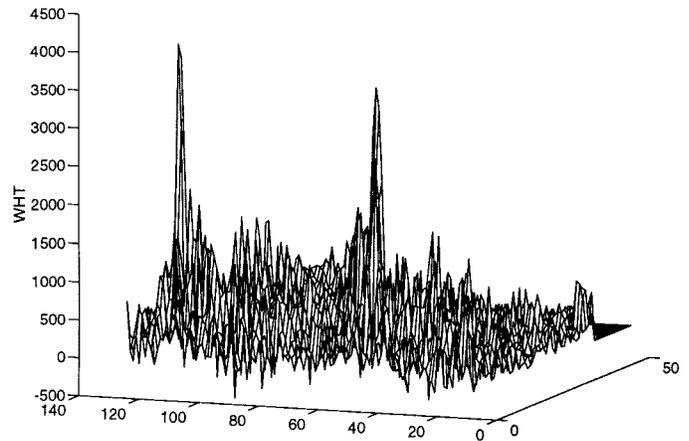


Fig. 2. WHT of the same signal as Fig. 1.

interferences) added to an SS signal plus AWGN. The estimate of the interference parameters will then be used in the ensuing section to set up a proper time-varying excision filter. We now show some examples of application of the WHT-based method to linear and sinusoidal FM interferences.

A. Linear FM Interference

Fig. 1 shows the WVD of the sum of two linear FM interferences added to a SS signal plus noise. The number of samples is 63 and is equal to the number of chips in a MLS codeword; the power ratio between each interference and the SS signal is 3 dB, and the signal-to-noise ratio (SNR) is also 3 dB. Due to the low interference-to-signal ratio, the WVD is not very meaningful (the two interferences are barely visible). In particular, the cross terms due to the interactions among all contributions are not negligible. Conversely, the WHT of the same signal, shown in Fig. 2, shows two evident peaks, witnessing the presence of the two interferences.

B. Sinusoidal FM Interference

In the case of sinusoidal interferences, if we apply the WVD directly to the signal, the result does not show the presence of a sinusoidal modulation due to the so-called *inner interference*, which is a further inconvenient due to the nonlinearity of the transformation [10]. To improve the readability of the WVD,

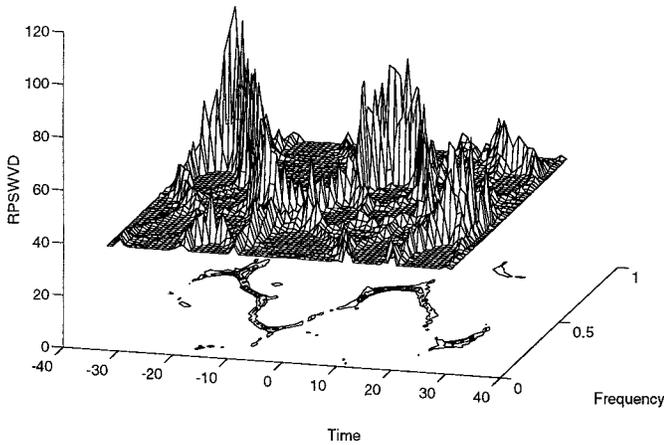


Fig. 3. RSPWVD of SS signal plus sinusoidal FM interference plus noise.

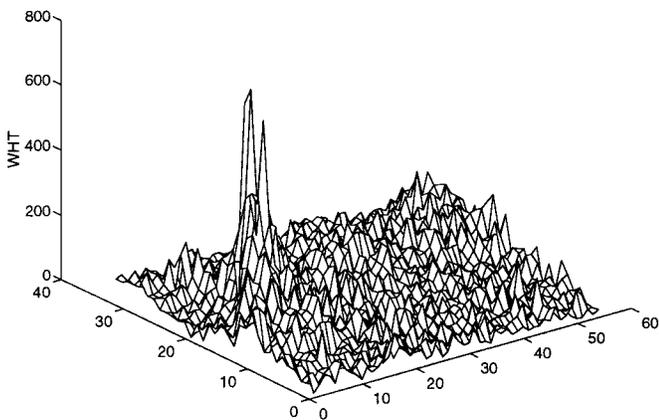


Fig. 4. WHT of the same signal as Fig. 3.

we computed the so-called *reassigned smoothed pseudo* WVD (RSPWVD), which has the advantage of reducing the cross terms while still retaining good localization properties [3]. The RSPWVD is sketched in Fig. 3. In this case, we can also use the generalized Hough transform to improve the estimation of the sinusoidal FM parameters. The corresponding WHT is reported in Fig. 4. The power ratios are the same as in Fig. 1. Even in this case, we can clearly see a peak corresponding to the interference.

III. ADAPTIVE TIME-VARYING INTERFERENCE EXCISION FILTER

After having estimated the instantaneous frequency of the interference, we can set up the adaptive time-varying (ATV) filter shown in Fig. 5. The excision filter shown in the figure is aimed to the cancellation of one interference; in the case of more than one interfering term, the overall excision filter can be obtained cascading a corresponding number of excision filters, where each one is driven by the estimates of the relative interference parameters, as obtained with the WHT-based method.

The instantaneous phase $\phi(t; \theta_k)$ of the k th interference is recovered, up to a constant term, integrating the estimated instantaneous frequency using the WHT-based method described in the previous section. We will initially assume an error-free estimation, and then, we will add some considerations about

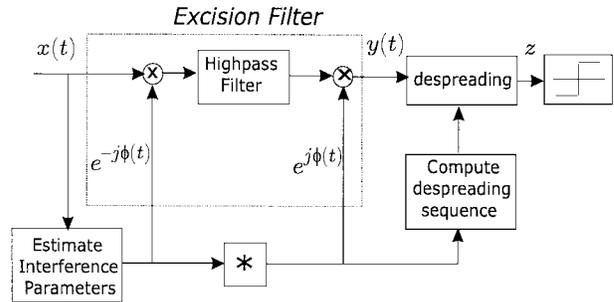


Fig. 5. Adaptive time-varying excision filter.

the limit of the validity of such an assumption, in terms of SNR, and on the effect of small estimation errors.

The input signal is given by (1). After multiplication by $e^{-j\phi(t; \hat{\theta}_k)}$, if $\hat{\theta}_k = \theta_k$, the interference term is constant; therefore, the ensuing highpass filter is able to cancel the interference. The overall ATV filter shown in Fig. 5 puts a notch in the time–frequency domain, whose position varies as a function of time according to the instantaneous frequency. In the following, we will express the relationship between the ATV filter input and output signals in matrix form. We will consider, for simplicity of notation, the case of the single zero highpass filter, i.e., a filter whose output is equal to the difference between successive samples of the input, but we will then evaluate the performance using higher order highpass filters.

If the estimation of the instantaneous frequency is correct, that is, $\hat{\theta}_k = \theta_k$, the highpass filter completely suppresses the interference, and the output is simply equal to [we use $\phi(t) = \phi(t; \hat{\theta}_k)$ so that we will not overcrowd the formula unnecessarily]

$$\begin{aligned} y(t) &= \left[\left(s(t)e^{-j\phi(t)} - s(t-T)e^{-j\phi(t-T)} \right) \right. \\ &\quad \left. + \left(w(t)e^{-j\phi(t)} - w(t-T)e^{-j\phi(t-T)} \right) \right] e^{j\phi(t)} \\ &= s(t) - s(t-T)e^{j\Delta\phi(t)} + w(t) - w(t-T)e^{j\Delta\phi(t)} \quad (8) \end{aligned}$$

where $\Delta\phi(t) = \phi(t) - \phi(t-T)$, $s(t) := \sqrt{P_s}Ac(t)$, and $c(t)$ contains exactly one codeword (we assume perfect synchronism at the receiver). The decision about the transmitted symbol is taken after a proper despreading of the SS signal.

We introduce the following vector notation to indicate the samples of the observed signal and the filter coefficients (a unitary sampling rate is assumed hereafter):

$$\begin{aligned} \mathbf{c} &:= (c(1), \dots, c(L))^T \\ \mathbf{w} &:= (w(1), \dots, w(L))^T \\ \mathbf{d} &:= (e^{j\phi(1)}, \dots, e^{j\phi(L)})^T \\ \mathbf{F} &= \begin{pmatrix} -e^{-j\phi(1)} & e^{-j\phi(2)} & 0 & \dots & 0 \\ 0 & -e^{-j\phi(2)} & e^{-j\phi(3)} & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \dots & -e^{-j\phi(L-1)} & e^{-j\phi(L)} \end{pmatrix} \quad (9) \end{aligned}$$

$$\Phi = \text{diag} \{ e^{j\phi(2)}, e^{j\phi(3)}, \dots, e^{j\phi(L)} \} \quad (10)$$

where $\mathbf{F} \in \mathbf{C}^{L-1 \times L}$, and $\Phi \in \mathbf{C}^{L-1 \times L-1}$. The noise vector \mathbf{w} is assumed to have zero mean and a diagonal covariance matrix $\sigma_w^2 \mathbf{I}$.

In the following, we will consider the presence of one interference, e.g., $K = 1$ in (1), but the method can be extended to the general case by cascading as many excision filters as the number of interferences, where each filter is driven by the corresponding estimates of the interference parameters. In fact, the WHT is able to estimate the parameters of multicomponent signals (see, e.g., Fig. 2).

The input sequence can then be written as

$$\mathbf{x} = \sqrt{P_s} \mathbf{A} \mathbf{c} + \sqrt{P_I} \mathbf{d} + \mathbf{w} \quad (11)$$

whereas the sequence at the output of the ATV filter is

$$\mathbf{y} = \Phi \mathbf{F} \mathbf{x}. \quad (12)$$

The output corresponding to the interference is clearly zero, whereas the outputs corresponding to the input signal and noise are

$$\mathbf{y}_s = \sqrt{P_s} \mathbf{A} \Phi \mathbf{F} \mathbf{c} \quad \text{and} \quad \mathbf{y}_n = \Phi \mathbf{F} \mathbf{w} \quad (13)$$

respectively. The ATV filter introduces a certain correlation of the noise samples and produces a delayed and phase-shifted replica of the SS signal [see (8)]. The output noise covariance matrix is

$$\mathbf{R} = E\{\Phi \mathbf{F} \mathbf{w} \mathbf{w}^H \mathbf{F}^H \Phi^H\} = \sigma_w^2 \Phi \mathbf{F} \mathbf{F}^H \Phi^H. \quad (14)$$

Indicating by \mathbf{h} the vector containing the coefficients (conjugated) of the despreading filter, the overall output is

$$z = \mathbf{h}^H \mathbf{y} = \mathbf{h}^H \mathbf{y}_s + \mathbf{h}^H \mathbf{y}_n = z_s + z_n. \quad (15)$$

The output SNR is then

$$\text{SNR}_{\text{out}} = \frac{|z_s|^2}{E\{|z_n|^2\}} = \frac{|\mathbf{h}^H \mathbf{y}_s|^2}{|\mathbf{h}^H \mathbf{R} \mathbf{h}|^2}. \quad (16)$$

The vector \mathbf{h} can be simply put equal to the codeword \mathbf{c} , or it can be optimized. We consider two possible choices for \mathbf{h} .

A. Suboptimal Despreading Filter: $\mathbf{h}_{\text{sub}} = \mathbf{c}$

The choice $\mathbf{h} = \mathbf{c}$ is commonly adopted for its simplicity, but it is a suboptimal solution because it does not take into account neither the noise correlation nor the modifications on the useful signal introduced by the ATV filter.

B. Optimal Despreading Filter: $\mathbf{h}_{\text{opt}} = \mathbf{R}^{-1} \Phi \mathbf{F} \mathbf{c}$

The optimal decoding takes into account the modification of the useful signal and the noise correlation due to the ATV filter. The optimality criterion assumed for the choice of the optimal despreading filter is the maximization of the improvement factor (IF), which is defined as the ratio between the output and the input SNR's

$$\text{IF} = \frac{\text{SNR}_{\text{out}}}{\text{SNR}_{\text{in}}}. \quad (17)$$

The input SNR_{in} is

$$\text{SNR}_{\text{in}} = \frac{P_s}{\sigma_w^2}. \quad (18)$$

The output SNR is given by (16) and, considering (18), the vector \mathbf{h} that maximizes the IF is

$$\mathbf{h}_{\text{opt}} = \mathbf{R}^{-1} \Phi \mathbf{F} \mathbf{c}. \quad (19)$$

and using (16), the maximum output SNR is

$$(\text{SNR}_{\text{out}})_{\text{max}} = \frac{P_s}{\sigma_w^2} \mathbf{c}^H \mathbf{F}^H (\mathbf{F} \mathbf{F}^H)^{-1} \mathbf{F} \mathbf{c}. \quad (20)$$

As a consequence, the maximum IF is

$$\text{IF}_{\text{max}} = \mathbf{c}^H \mathbf{F}^H (\mathbf{F} \mathbf{F}^H)^{-1} \mathbf{F} \mathbf{c}. \quad (21)$$

Remark: Had we chosen matrices \mathbf{F} and Φ as

$$\mathbf{F} = \begin{pmatrix} e^{-j\phi(1)} & 0 & 0 & \dots & 0 \\ -e^{-j\phi(1)} & e^{-j\phi(2)} & 0 & \dots & 0 \\ 0 & -e^{-j\phi(2)} & e^{-j\phi(3)} & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \dots & -e^{-j\phi(L-1)} & e^{-j\phi(L)} \end{pmatrix} \quad (22)$$

$$\Phi = \text{diag}\{e^{j\phi(1)}, e^{j\phi(2)}, \dots, e^{j\phi(L)}\} \quad (23)$$

the matrix \mathbf{F} would have been invertible (in this case, \mathbf{F} is a $L \times L$ matrix), and then, according to (21), the IF_{max} would have been equal to $\mathbf{c}^H \mathbf{c} = L$, which is the maximum possible gain. However, with such a choice, we would have a residual interference at the output of the ATV filter due to the filter transient (e.g., the first output sample would contain a nonzero interference contribution), whereas, according to our choice, the interference is completely canceled.

The performance of both optimal and suboptimal decoding filters are evaluated in the ensuing section.

IV. PERFORMANCE

The performance is expressed in terms of improvement factor and BER. Two interference classes, i.e., linear and sinusoidal FM signals, will be considered.

A. Improvement Factor

The IF depends on the interference parameters. To analyze such a dependency, in Figs. 6 and 7, we show the IF corresponding to linear (3) and sinusoidal (4) FM interferences, respectively. The highpass filter used in the ATV filter is a single-zero filter with impulse response $[1, -1]$. Fig. 6 shows the IF as a function of the chirp parameters (f_k, g_k), e.g., mean frequency and sweep rate (both parameters are normalized with respect to the sampling rate). The upper surface reports the IF obtained with the optimal despreading filter (e.g., $\mathbf{h} = \mathbf{R}^{-1} \Phi \mathbf{F} \mathbf{c}$), whereas the lower surface refers to the suboptimal despreading filter whose coefficients are simply equal to the codeword (e.g., $\mathbf{h} = \mathbf{c}$), which is a common

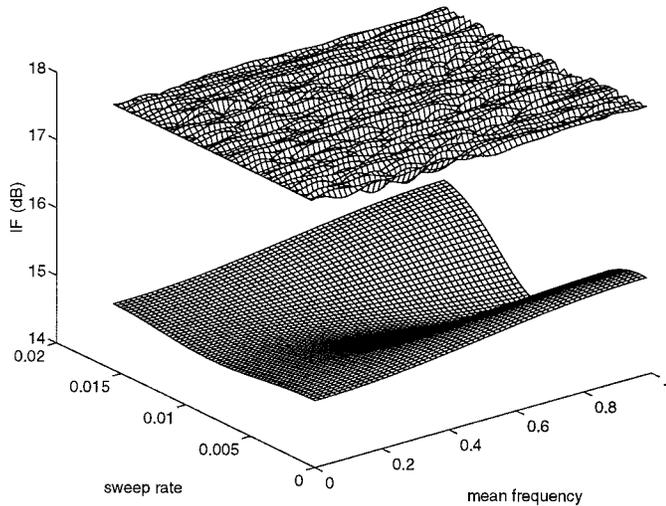


Fig. 6. IF_{opt} (upper surface) and IF_{sub} (lower surface) (in decibels) versus mean frequency and sweep rate in case of a linear FM interference.

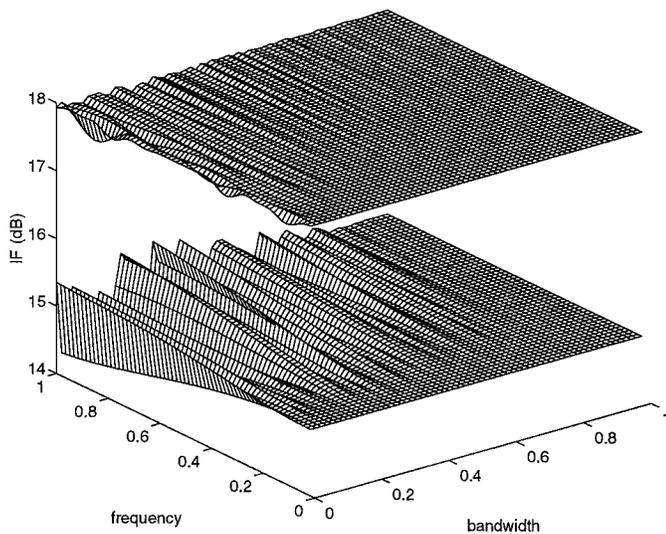


Fig. 7. IF_{opt} (upper surface) and IF_{sub} (lower surface) (in decibels) versus mean frequency and relative bandwidth in case of a sinusoidal FM interference.

assumption (see, for example, [1]). Similarly, Fig. 7 reports the results corresponding to a sinusoidal FM interference.

The length of the observed sequence is $L = 63$ in both cases; therefore, the theoretical limit for the IF is 63, or about 18 dB. To extract a single performance parameter and analyze the effect of the code length L , we computed the average loss between the suboptimal scheme and the optimal scheme proposed above averaged over all values of the interference parameters. The results are shown in Tables I and II, referring to linear and sinusoidal FM interferences, respectively. Each table shows the loss between the suboptimal and the optimal despreading filters (left column) and the loss between the optimal scheme and the theoretical maximum gain, i.e., $IF_{max} = L$ (right column), for three filter orders, i.e., $Q = 1, 2$, and 4. We considered three kinds of highpass filters, i.e., first-, second-, and fourth-order filters, having a single, double, or quadruple zero in $z = 1$, respectively, to

TABLE I
AVERAGE LOSSES BETWEEN SUBOPTIMAL AND OPTIMAL SCHEMES (LEFT COLUMN) AND BETWEEN OPTIMAL SCHEME AND THEORETICAL LIMITS (IN DECIBELS) (RIGHT COLUMN) FOR LFM INTERFERENCES

L	$Q=1$		$Q=2$		$Q=4$	
7	2.83	0.67	1.52	1.46	2.30	3.68
15	2.93	0.3	1.67	0.62	2.83	1.35
31	2.99	0.14	1.75	0.29	2.86	0.60
63	2.99	0.07	1.75	0.14	2.87	0.20

TABLE II
AVERAGE LOSSES BETWEEN SUBOPTIMAL AND OPTIMAL SCHEMES (LEFT COLUMN) AND BETWEEN OPTIMAL SCHEME AND THEORETICAL LIMITS (IN DECIBELS) (RIGHT COLUMN) FOR SINUSOIDAL FM INTERFERENCES

L	$Q=1$		$Q=2$		$Q=4$	
7	2.83	0.67	1.42	0.42	3.57	7.25
15	2.93	0.3	2.28	0.20	3.51	1.00
31	2.99	0.14	2.00	0.09	3.13	0.45
63	2.99	0.07	1.78	0.09		

evaluate the effect of the notch width on the performance. The filters with $Q = 1$ and 4 have a linear phase, and this property affects the system performance, as will be shown next. Linear-phase excision filters were also suggested in [2]. From the results shown in both tables, we have the following remarks: i) The minimum loss of the scheme using the optimal despreading, with respect to the theoretical limit, is achieved with the lowest order filter, and ii) the best performance for the scheme using the suboptimal despreading is obtained with $Q = 2$, i.e., with a linear-phase filter, but with a notch that is not so wide, as in the case of $Q = 4$, to also suppress a considerable portion of the useful signal.

The losses for linear or sinusoidal FM interferences are similar (the sinusoidal FM case shows a slightly smaller loss with respect to the linear FM case). The loss of the suboptimal despreading filter with respect to the optimal one can be intuitively explained by noticing that the excision filter produces an output noise having twice the variance of the input noise. The consequent loss in SNR is completely recovered using the optimal despreading filter, whereas it is not using the suboptimal scheme. The suboptimal scheme recovers some of its losses with a linear phase, i.e., a symmetric, highpass filter, because the second portion of the impulse response acts like a filter matched to the signal that is filtered by the first portion of the impulse response.

B. Bit Error Rate

Assuming that the estimation of the interference parameters is correct, the output of the ATV filter contains only signal and noise. Transmitting a BPSK signal and considering a Gaussian noise, we can express the error probability (BER) in a closed form. The overall system shown in Fig. 5 is linear and can be described by the equivalent weighting vector

$$\mathbf{q} = (\Phi \mathbf{F})^H \mathbf{h} \quad (24)$$

where \mathbf{h} may be equal to the optimal vector \mathbf{h}_{opt} or to the suboptimal vector \mathbf{h}_{sub} . Assuming (11) as input, with $K = 1$, the filter output is simply

$$\mathbf{q}^H \mathbf{x} = A \sqrt{P_s} \mathbf{q}^H \mathbf{c} + \mathbf{q}^H \mathbf{w}. \quad (25)$$

The decision is made by comparing the real part of the filter output with a zero threshold.¹ The filter output due to the signal is

$$z_s = A\sqrt{P_s}\mathbf{q}^H\mathbf{c} \quad (26)$$

and the output noise

$$z_n = \mathbf{q}^H\mathbf{w} \quad (27)$$

is Gaussian with zero mean and variance

$$\sigma_z^2 = \sigma_w^2\mathbf{q}^H\mathbf{q}. \quad (28)$$

Therefore, in the BPSK case, using (18), the error probability, using (24), is

$$P_e = Q\left(\sqrt{\text{SNR}_{\text{in}}}\frac{\Re(\mathbf{q}^H\mathbf{c})}{\sqrt{\mathbf{q}^H\mathbf{q}}}\right) \quad (29)$$

where

$$Q(x) := \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} e^{-u^2/2} du. \quad (30)$$

Although we have assumed a perfect interference cancellation, the error probability depends on the interference parameters because the excision filter coefficients depend on the interference parameters, and then, SS signal and noise are consequently modified. We should then average the error probability over all the interference parameters. To reduce the computational time and make a conservative estimate, we selected the interference parameters that produce the minimum IF (worst case) and then computed the corresponding error probability (maximum error probability).

Since the excision filter inevitably introduces a mismatch in the receiver and the despreading alone provides, in any case, a certain amount of interference immunity, it is important to compare the error probabilities obtainable with the proposed scheme and with a conventional scheme that does not use any filtering but demands all the interference immunity to the despreading operation, e.g., $\mathbf{q} = \mathbf{c}$ instead of (24). In the latter case, in the presence of the interference, the output corresponding to (11) is

$$\begin{aligned} \mathbf{q}^H\mathbf{x} &= \mathbf{c}^T(A\sqrt{P_s}\mathbf{c} + \sqrt{P_I}\mathbf{d} + \mathbf{w}) \\ &= A\sqrt{P_s}L + \sqrt{P_I}\mathbf{c}^T\mathbf{d} + \mathbf{c}^T\mathbf{w}. \end{aligned} \quad (31)$$

Therefore, in the absence of noise, taking the real part as in the previous case, we have

$$\sqrt{P_s}L + \sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d}) \quad \text{or} \quad -\sqrt{P_s}L + \sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d}) \quad (32)$$

¹Indeed, the output signal is complex. We decided to take the real part because the imaginary part of the useful signal component, due to the mismatching introduced by the excision filter, is much smaller than the real part; in this way, we maintain the linearity of the filter and avoid any unnecessary addition of noise.

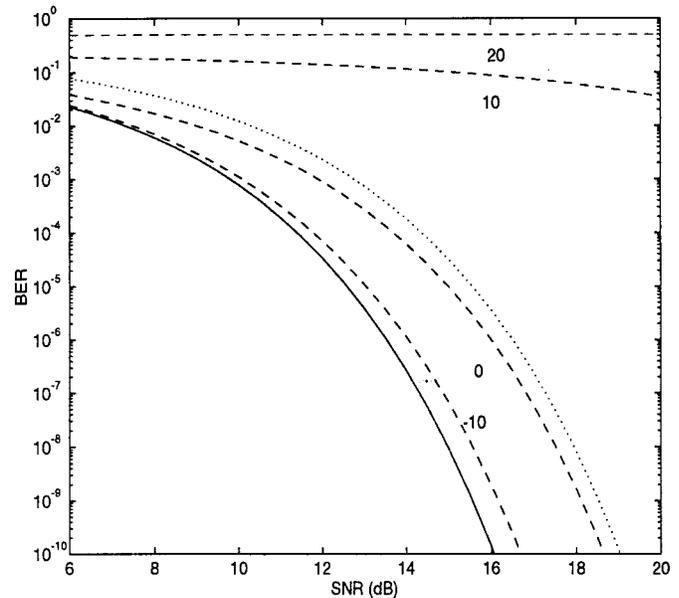


Fig. 8. BER for linear FM interference versus $\text{SNR}_{\text{in}}L$.

depending on the transmitted symbol A . The noise variance is

$$\sigma_z^2 = \sigma_w^2\mathbf{c}^T\mathbf{c} = \sigma_w^2L. \quad (33)$$

Hence, the error probability is

$$\begin{aligned} P_e &= \frac{1}{2}Q\left(\frac{\sqrt{P_s}L + \sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d})}{\sigma_w\sqrt{L}}\right) \\ &\quad + \frac{1}{2}Q\left(\frac{\sqrt{P_s}L - \sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d})}{\sigma_w\sqrt{L}}\right) \\ &= \frac{1}{2}Q\left(\sqrt{\frac{P_sL}{\sigma_w^2}}\left(1 + \frac{\sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d})}{\sqrt{P_s}L}\right)\right) \\ &\quad + \frac{1}{2}Q\left(\sqrt{\frac{P_sL}{\sigma_w^2}}\left(1 - \frac{\sqrt{P_I}\Re(\mathbf{c}^T\mathbf{d})}{\sqrt{P_s}L}\right)\right). \end{aligned} \quad (34)$$

Therefore, defining the interference-to-signal ratio (ISR) as

$$\text{ISR} = \frac{P_I}{P_s} \quad (35)$$

we can express the BER as

$$\begin{aligned} P_e &= \frac{1}{2}Q\left(\sqrt{\text{SNR}_{\text{in}}L}\left(1 + \sqrt{\text{ISR}}\frac{\Re(\mathbf{c}^T\mathbf{d})}{L}\right)\right) \\ &\quad + \frac{1}{2}Q\left(\sqrt{\text{SNR}_{\text{in}}L}\left(1 - \sqrt{\text{ISR}}\frac{\Re(\mathbf{c}^T\mathbf{d})}{L}\right)\right). \end{aligned} \quad (36)$$

The BER has been computed for both linear and sinusoidal FM interferences. In particular, Figs. 8 and 9 report the error probabilities for the linear FM and the sinusoidal FM cases, respectively.

In particular, the solid line shows the BER obtained using the excision filter and the optimal despreading filter; the dotted line shows the BER obtained using the excision filter and

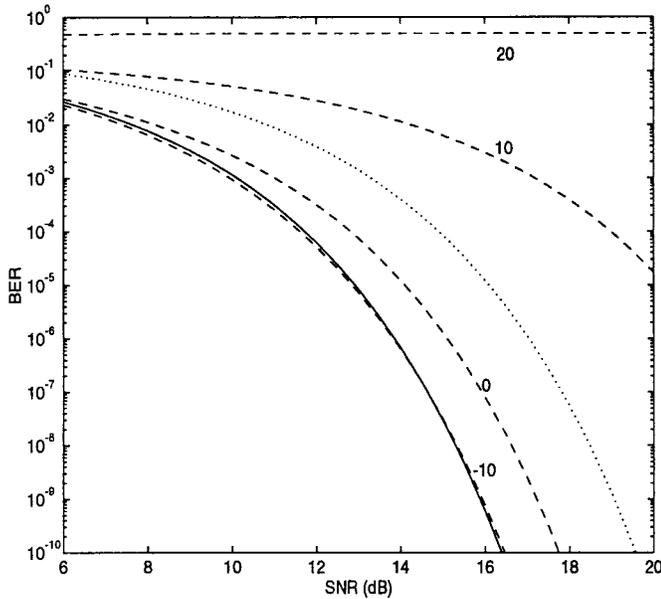


Fig. 9. BER for sinusoidal FM interference versus $\text{SNR}_{\text{in}} L$.

the suboptimal despreading filter; the dashed lines show the BER obtainable with the simple scheme that does not use any excision filter [the labels on each curve indicate the interference-to-signal ratio (ISR) in decibels]. To make a conservative comparison, in all cases, the interference parameters are the ones that lead to the minimum IF for the optimal scheme (worst-case analysis). We can observe that in both cases, i.e., linear or sinusoidal FM, the proposed scheme provides a consistent gain with respect to the simpler schemes, especially at high ISR's. The gain is moderate only at low ISR, which suggests that we could decide to not use the excision filter, thus avoiding any unnecessary complication in the receiver.

C. Effect of Estimation Errors

All previous analysis assumes perfect estimation of the interference parameters. Of course, the estimation is affected by an error depending on the interference-to-signal plus noise ratio (ISNR). In [5], it was shown that the estimates of linear FM signal parameters obtained using the WHT, in the presence of additive white Gaussian noise, are unbiased, at least for high ISNR, and the variances on the estimates of the chirp parameters f and g are approximately, for $L \gg 1$ and $\text{ISNR} \gg 1$ (the only difference between these formulas and the ones given in [5] is that the SNR is here replaced by the ISNR)

$$\sigma_f^2 \approx \frac{24}{\pi^2 L^3} \frac{1}{\text{ISNR}} \quad (37)$$

and

$$\sigma_g^2 \approx \frac{90}{\pi^2 L^5} \frac{1}{\text{ISNR}} \quad (38)$$

respectively.

If we model the SS signal as white noise itself, independent of the receiver noise, we can use the results of [5] to get expected values and variances of the errors in the case of linear

FM interferences. Indeed, the results obtained in [5] assumed the presence of Gaussian noise and, in the present case, we cannot assume that the SS sequence is Gaussian (the alphabet is binary). However, at high ISNR, the results are similar.²

It is important to evaluate which is the maximum tolerable error that still allows an effective interference rejection. Given a sequence of L samples, the maximum errors in the estimate of mean frequency and sweep rate are $1/L$ and $1/L^2$, respectively (due to resolution limits consequent to observing the data within a finite length interval, an error smaller than these limits cannot be appreciated). Imposing the constraints

$$\sigma_f < \frac{1}{L} \quad \text{and} \quad \sigma_g < \frac{1}{L^2} \quad (39)$$

we arrive at

$$\text{ISNR} > \frac{24}{\pi^2 L} \quad \text{and} \quad \text{ISNR} > \frac{90}{\pi^2 L} \quad (40)$$

respectively. Clearly, the second condition is then the one to be considered. It is important to not forget that (37) and (38) are only approximately valid for high ISNR (a better approximation is given in [5]). From the analysis of the threshold effect (see [5]), the previous conditions should be considered valid only for ISNR that not below a few decibels.

As a consequence, we can see that the error on the estimate of the interference parameters can be neglected even for ISNR not excessively large, provided that the code length is sufficiently high and that the input ISNR does not fall below the threshold. On the other hand, if the interference power is low, it is not necessary to use an excision filter because, in such cases, the simple despreading is sufficient to guarantee a certain interference rejection. We are currently studying the possibility to put a threshold on the WHT so that if an interference with sufficient power is detected, the excision filter is employed as described above; otherwise, the filter is simply bypassed.

V. CONCLUSION

In this paper, we have proposed a novel interference rejection scheme for wideband interferences. Assuming a parametric interference model, the method estimates the interference parameters using the generalized Wigner-Hough transform and uses an adaptive time-varying filter for the interference excision. The despreading filter coefficients are optimized in order to maximize the improvement factor, which is defined as the gain between input and output SNR's. We have shown that the proposed method provides advantages with respect to similar techniques that are still based on time-frequency distributions for the estimate of the interference parameters, e.g., [1], concerning the following aspects: 1) The method is able to reliably estimate the interference parameters at lower

²In computing the estimation variances, the Gaussianity assumption affects the computation of the higher order moments (second- and fourth-order moments appear in the variance expressions). Of course, higher order moments of Gaussian random variables and of binary random variables do not follow the same laws; therefore, the results obtained in [5] cannot be directly applied to the present case. However, at high ISNR, the main contribution to the variance is given by the second-order moments so that, in such a case, the hypothesis on the second-order moments is sufficient to provide a reliable result.

SNR, exploiting the signal model, and 2) the despreading filter is optimal and takes into account the presence of the excision filter. The method also works better than previous methods using adaptive (e.g., LMS) filters, which are less effective against wideband disturbances, especially for high sweep rates [11]. The performance of the method has been given in terms of improvement factor and bit error rate. Investigations are in progress to establish a rigorous criterion for thresholding the Wigner–Hough transform to avoid the excision filter at low interference-to-signals ratios, where the interference rejection provided by simple despreading is sufficient to recover the useful data.

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Sergio Barbarossa (M'88) received the M.Sc. and Ph.D. degrees in electrical engineering from the University of Rome "La Sapienza," Rome, Italy, in 1984 and 1988, respectively.

From 1984 to 1986, he was with Selenia as a Radar System Engineer. Since 1986, he has been with the Information and Communication Department of the University of Rome "La Sapienza," where he is an Associate Professor. In 1988, on leave from the University of Rome, he was a Research Engineer at the Environmental Research Institute of Michigan, Ann Arbor. During the spring of 1995 and the summer of 1997, he was a Visiting Faculty with the Department of Electrical Engineering at the University of Virginia, Charlottesville. His general interests are in the area of statistical signal processing with applications to radar and communications.

Dr. Barbarossa is a member of the IEEE Technical Committee on Signal Processing for Communications and is currently serving as an Associate Editor for the IEEE TRANSACTIONS ON SIGNAL PROCESSING.



Anna Scaglione (S'96) received the degree in electrical engineering from the University of Rome "La Sapienza," Rome, Italy, in 1995, where she is currently a Ph.D. student with the Information and Communication Department.

In 1997, she visited the University of Virginia, Charlottesville, as a Research Assistant. Her general interests lie in the areas of statistical signal processing and multirate filterbanks. Specific research areas of current interest include polynomial-phase signal modeling for SAR applications and demodulation of CPM signals, multirate filterbanks for CDMA, and equalization over frequency-selective channels.