INSTANTANEOUS FREQUENCY ESTIMATION USING DISCRETE EVOLUTIONARY TRANSFORM FOR JAMMER EXCISION

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ABSTRACT

In this paper, we propose a method –based on the discrete evolutionary transform (DET)– to estimate the instantaneous frequency of a signal embedded in noise or noise-like signals. The DET provides a representation for non-stationary signals and a time-frequency kernel that permit us to obtain the time-dependent spectrum of the signal. We will show the instantaneous phase and the corresponding instantaneous frequency (IF) can also be computed from the evolutionary kernel. Estimation of instantaneous frequency is of general interest in time-frequency analysis, and of special interest in the excision of jammers in direct sequence spread spectrum. Implementation of the IF estimation is done by masking and a recursive non-linear correction procedure. The proposed estimation is valid for monocomponent as well as multicomponent signals in the noiseless and noisy situations. Its application to jammer excision in direct sequence spread spectrum communication is considered as an important application. The estimation procedure is illustrated with several examples.

1. INTRODUCTION

Although time-frequency analysis methods [1] typically consider the spectral representation of non-stationary signals, it is of interest to have signal representations to which a time-dependent spectra can be associated. Recently, we proposed the Discrete Evolutionary Transform (DET) [3] that provides a signal representation from which a kernel is obtained to compute the evolutionary spectrum. In many applications, instantaneous phase as well as instantaneous frequency need to be computed. For instance, in the excision of jammers in direct sequence spread spectrum (DSSS) [6, 7, 8], the instantaneous frequency is needed in the synthesis of the jammers. Existing IF estimation procedures are computationally expensive [7, 8] or deal with monocomponent signals. We will show that the DET permits the computation of the instantaneous phase and the instantaneous frequency from the evolutionary kernel. Masking makes it possible to obtain the IF of each component in a multicomponent signal embedded in noise or noise-like signals (as is the case in DSSS where the message and the channel noise are both wide-band). Masking serves as a denoiser. Our estimator uses the peaks of the evolutionary spectrum to obtain an initial estimate which is then recursively corrected by means of dechirping, linear and non-linear filtering. Masking, and recursive correction provide excellent results in estimating the IF of monocomponent signals, but for the case of multicomponent signals we need to develop a segmentation procedure that separates the spectra of the different components so that each can be dealt separately.

The synthesis of multicomponent chirp jammers is of practical application in the jammer excision in direct sequence spread spectrum. Although DSSS is robust to interferences, wide-band jammers can seriously affect its performance. Subtracting the synthesized jammer from the received signal provides a very efficient way to improve the robustness of DSSS to wide-band jamming. In such cases, the IF of each of the components of the jammer is needed. Many of the proposed methods based on time-frequency are computational expensive and depend on an a-priori parametric representation for the IF. The proposed estimation depends on the DET and does not require parametric characterizations.

2. THE DISCRETE EVOLUTIONARY TRANSFORM

Given a non-stationary signal, $x(n), 0 \leq n \leq N-1$, a discrete Wold-Cramer representation [2] for it is given by

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

where $\omega_k = 2\pi k/K$, K is the number of frequency samples, and $X(n,\omega_k)$ is an evolutionary kernel. To obtain a

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more general representation, one can replace the sinusoidal basis by a chirp basis to obtain a chirp representation:

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

where the chirps $\{e^{j(\omega_k n + \phi_p(n))}\}$ cover the time-frequency plane and $\phi_p(n)$ can be considered very general functions of n. The chirp representation provides a more parsimonious representation, but it requires we estimate the IF of each component.

The discrete evolutionary transformation (DET) is obtained by expressing the kernels $X(n,\omega_k)$ and $X_p(n,\omega_k)$ in terms of the signal. This is done by using conventional representations such as the Gabor and the Malvar transforms. Thus, for the sinusoidal representation in (1) the inverse DET that provides the evolutionary kernel $X(n,\omega_k)$, $0 \leq k \leq K-1$, is given by

$$X(n,\omega_k) = \sum_{\ell=0}^{N-1} x(\ell) \mathrm{W}_k(n,\ell) e^{-j\omega_k \ell}, \tag{3}$$

where $\mathrm{W}_k(n,\ell)$ is a time and frequency dependent window. Similarly the inverse chirp DET can be obtained. The DET can be seen as a generalization of the short-time Fourier transform, where the windows are constant, The windows $\mathrm{W}_k(n,\ell)$ can be obtained from either the Gabor representation that uses non-orthogonal bases, or the Malvar wavelet representation that uses orthogonal bases. Details of how the windows can be obtained for the Gabor and Malvar representations are given in [3].

Estimation of instantaneous frequency is a complex and not well understood task [9, 10]. Conventionally, the IF of a mono-component signal is obtained from its time–frequency distribution function as the average of frequencies present in the signal at a given time. For a multi-component signal such a computation of the IF does not have the same significance. Furthermore, the usual definition of the IF being the derivative of the phase of the corresponding analytical signal fails (or does not approach our intuition) in the case of multi-component signals. The DET can be used to obtain a general definition of IF by considering the signal $x(n)$ a sum of analytic functions with time-dependent magnitudes and phases, that is

$$x(n) = \sum_k |X(n,\omega_k)| e^{j\Psi(n,\omega_k)},$$

where $\Psi(n,\omega_k) = \mathrm{Arg}[X(n,\omega_k)] + \omega_k n$. Computing $\Psi(n,\omega_k)$ only where $|X(n,\omega_k)|$ is significant, a general instantaneous frequency function is defined as:

$$\mathrm{IF}(n,\omega_k) = \Psi(n,\omega_k) - \Psi(n-1,\omega_k). \tag{4}$$

This can be accomplished by determining the instantaneous phase at the peaks of the spectra. On the other hand, as we will see, decomposing the signal into its components $|X(n,\omega_k)|e^{j\Psi(n,\omega_k)}$ these are analytic functions that will also provide the instantaneous frequency.

In the direct sequence spread spectrum jamming problem, one is interested in estimating the multicomponent chirp jammers $j(n)$ present in the received signal

$$r_k(n) = d_k p(n) + j(n) + \eta(n)$$

where d_k is the message bit, $p(n)$ is a pseudonoise code, and $\eta(n)$ is white Gaussian noise. The jammer synthesis requires its amplitude and IF. In the next section we consider estimation of the IF of the jammers embedded in noise and a noise-like message.

3. RECURSIVE IF ESTIMATION

Let us consider a multi-component non-stationary signal embedded in noise. Estimation of the signal IF is complicated by the noise and the multicomponent nature of the signal. We need thus to denoise the signal and to separate the different components. The estimation is especially difficult at regions in the TF-plane where there is overlap of the spectra of the signal components. The basic approach consists in denoising by masking the signal evolutionary spectrum, and to segment the masking function into non-overlapping masks used to obtain the corresponding analytic signal for each of the segments by means of the inverse DET. Although, depending on the SNR, the estimated IF obtained with the DET in general is good, it can be improved by means of a recursive correction. The correction is based on dechirping, linear and non-linear filtering.

3.1. Masking

Masking the evolutionary kernel provides a way to decompose the signal into components, and thus to delete the noise components. Masking $X(n,w_k)$ provides different components that add up to the signal $x(n)$, as can be easily seen from:

$$\begin{aligned} x(n) &= \sum_i \sum_k X(n,w_k) M_i(n,k) e^{jw_k n} \\ &= \sum_i x_i(n) \end{aligned}$$

where the mask function $M_i(n,k)$ values are either 1 or 0 and $\bigcup_i M_i(n,k)$ coincides with the time-frequency support of $X(n,w_k)$. The analytic signal components $\{x_i(n)\}$ are computed as the inverse DET of $X(n,w_k)M_i(n,w_k)$. If the $x(n)$ is embedded in noise, we want to ignore the components corresponding to mostly noise. This can be accomplished by defining the masks according to a threshold in the spectrum that would include the significant signal components. It can also be done by considering the masking implementation of the evolutionary Wiener filtering [11].

The masking function separates the spectrum into regions of single spectrum (additional noise might be present in these regions). The analytic signal corresponding to each of these spectra, or $\{x_i(n)\}$, are then processed using DET to estimate their corresponding IFs.

3.2. Recursive Correction

Although masking serves as a denoiser, some of the noise leaks into the analytic signals $x_i(n)$. We can thus think of the analytic signals as

$$x_i(n) = A_i(n)e^{j\phi_i(n)} + \eta_i(n).$$

Dechirping $x_i(n)$ using the estimated IF, gives

$$x_i(n)e^{-j\hat{\phi}_i(n)} = A_i(n)e^{j(\phi_i(n)-\hat{\phi}_i(n))} + \eta_i(n)e^{-j\hat{\phi}_i(n)}$$

Passing the dechirped signal through a narrow-band low-pass filter gets rid of the noise and keeps most of the desired signal. If the filter output is $\tilde{A}_i(n)e^{j\tilde{\phi}_i(n)}$ we can then obtain a new phase estimator as

$$\hat{\phi}_{new}(n) = \hat{\phi}_i(n) + \tilde{\phi}_i(n)$$

Repeating the procedure, we recursively improve the phase estimate. Notice that if $\tilde{\phi}_{new}(n) = \phi_i(n) - \hat{\phi}_i(n)$, then $\hat{\phi}_{new}(n) = \phi_i(n)$. The recursion is stopped when $\tilde{\phi}_i(n)$ is sufficiently small. The final estimate may have outliers that can be efficiently deleted by median filtering.

4. EXAMPLES

As a first example, consider the estimation of the IF of two chirps without any added noise. The top part of Fig. 1 shows the evolutionary spectrum using the Gabor derived windows with the superposed IF estimate obtained from the DET; the lower part of the figure shows the comparison with the exact IF. In Fig. 2, we show the corrected IF estimate, again superposed on on the evolutionary spectrum and comparing it with the exact IF. The evolutionary spectrum is plotted in a logarithmic scale.

In Fig. 3, we display the results of estimating the IF of the signal used above but now with white Gaussian noise added (SNR 6.5 dB). The top figure shows the masks superposed over the spectrum (in logarithmic scale). The lower figures correspond to the comparison of the exact IF with the one obtained from the DET directly and from the correcting algorithm. The estimated IF appear noisy but are close to the exact IF.

In Fig. 4 we consider the case of a jammer composed of three chirps (with partially overlapping spectra) that has been added to the DSSS message (JSR=24.7dB) and Gaussian noise (SNR=11.3dB). The top pannel shows the spectrum in logarithmic scale with the masks superposed, and the lower pannel displays the estimated IFs superposed on the spectrum. The original jammer and the synthesized jammer are shown in Fig. 5, the two differ by a constant but have similar shape.

5. CONCLUSIONS

In this paper we show that the discrete evolutionary transform can provide not only the spectral characteristics of a signal, but also its instantaneous phase from which its instantaneous frequency can be computed. Estimation of IF of signals embedded in noise is of interest in applications such as jamming excision in direct sequence spread spectrum. We consider the case of jammers composed of several chirps with different rates. Segmenting the spectrum by means of masks, permits us to obtain analytic components from which we can find their IFs. Although DET provides very good estimates, these can be improved by a recursive correcting algorithm and a median filter. Application of our procedure to the jamming problem in DSSS shows very good results compared with the present techniques that are available for IF estimation. Most of these techniques are computationally expensive, depend on models of the IF or do not consider multi-component signals.

6. REFERENCES

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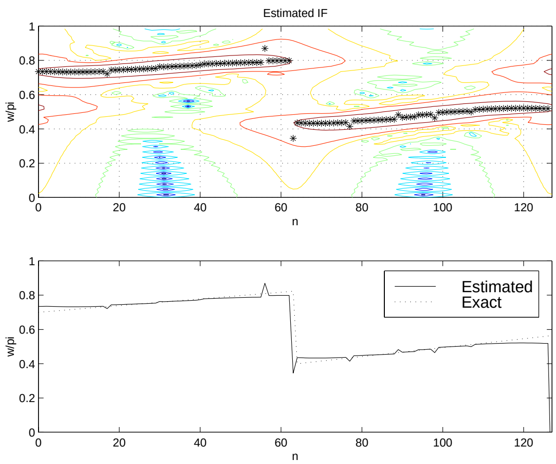

Figure 1: IF estimate using DET – Noiseless case.

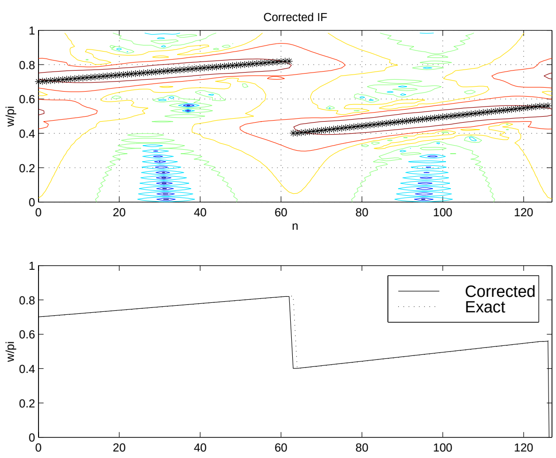

Figure 2: Corrected IF estimate – Noiseless case.

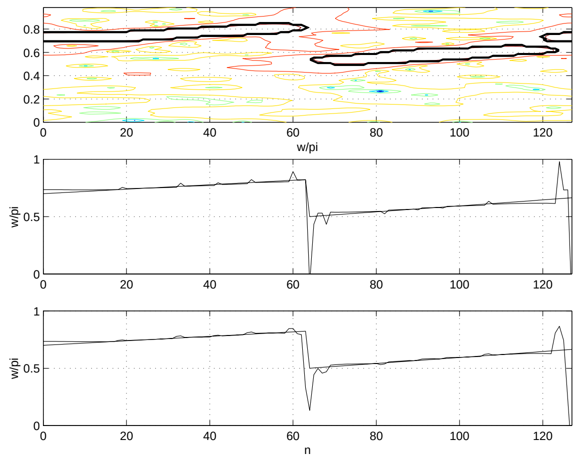

Figure 3: Spectrum, DET estimate, corrected estimate – Noisy case.

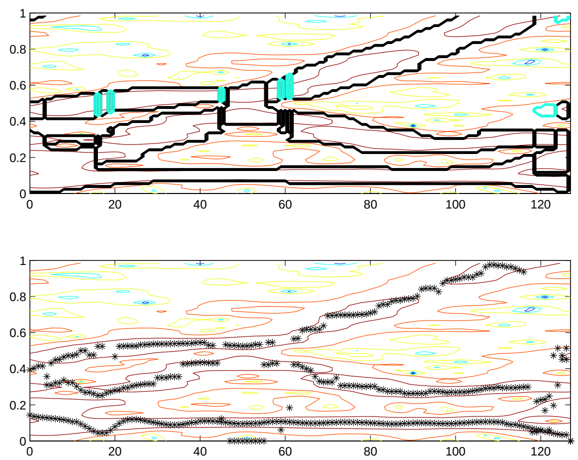

Figure 4: Evolutionary spectrum with superposed masks; IF estimates superpossed on spectrum.

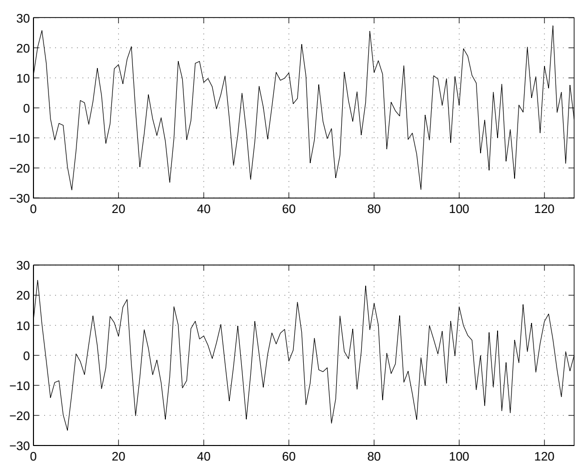

Figure 5: Original jammer (upper) compared with synthesized jammer.