TIME-FREQUENCY ANALYSIS OF MULTIPATH DOPPLER SIGNATURES OF MANEUVERING TARGETS

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ABSTRACT

Multipath signals arise in many active sensing modalities, such as radar and sonar. Moving targets cause Doppler effects that could vary for different paths. Target Doppler information corresponding to direct and non-direct paths is important for moving target localizations and classifications, particularly when narrowband signals are involved. This information, however, becomes difficult to reveal when dealing with nonlinear time-varying multi-component Doppler signals. In this paper, we introduce a new time-frequency analysis technique based on the local phase information to accurately extract complex Doppler signature of each signal arrival. This is achieved through short-time polynomial phase modeling of data segments. The global behavior is obtained by fusion of the phases across neighboring segments using the data phase continuity property. The offering of the proposed technique is demonstrated using synthetic data in an over-the-horizon radar platform.

Index Terms — *Time-frequency analysis, time-varying filter, signal representation, Doppler effect, over-the-horizon radar*

1. INTRODUCTION

In many sensing applications, such as over-the-horizon radar (OTHR), narrowband waveforms are employed because of the environment constraints. The signal returns from maneuvering targets have time-varying Doppler frequencies [1] which are difficult to analyze for a target with complex maneuverability. In this case, the unknown target motion profiles, in the presence of multipath propagation, limit the use of parametric models and invite the application of nonparametric estimation methods for multi-component signals.

In this paper, we consider the estimation of Doppler signature of maneuvering targets by utilizing the phase continuity of each Doppler component over time. OTHR is considered as the example case, though the proposed technique can be applied to other sensing modalities. A simple micro-multipath model of an OTHR is defined by three two-way paths [2]. As such, the received signal is composed of three nonlinear time-varying Doppler signatures which are closely separated. As discussed in [3], despite its arbitrary nonlinearity due to unknown target maneuvering, a Doppler modulation corresponding to each path has a continuous phase variation. This property could be exploited for accurate Doppler signature tracking. To do so, the local phase is analyzed using the warped third-order ambiguity function. The resulting components are merged through local correlation maximizations and yield a global time-frequency trajectory corresponding to the signal arrivals. In this paper, the estimation performance is further improved by utilizing the frequency warping technique that uses the nominal Doppler estimate to convert the global time-frequency content of the signal to a time-invariant signal through a warping operator. High resolution spectral analysis is then applied in the warped domain to estimate the closely spaced signal components.

The paper is structured as follows. Section 2 describes the proposed local phase based method for the tracking of Doppler signatures. Results based on synthetic data highlight and support the potential of the proposed method. In Section 3, the proposed method is compared with the Radial Gaussian Kernel (RGK). Section 4 concludes this paper.

2. LOCAL PHASE BASED TRACKING METHOD

A. Signal Model

Consider, for example, an OTHR signal received from a target, which makes a 180° turn in approximately 30 seconds

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to change its elevation and direction. Fig. 1 shows the spectrogram of the synthetic target data overlaid over measured OTHR clutter signals. Prewhitening processing [2] has been applied to the data mixture for clutter mitigation. The instantaneous frequency laws (IFLs) of the three multipath components are illustrated in this figure. The analytical signal is generally modeled by

$$x(t) = \sum_{i=1}^{3} A_i \exp(j\phi_i(t)) \quad (1)$$

where $\{A_i\}$ are the amplitudes associated with each path and are considered constant over the observation time, and $\{\phi_i\}$ represent the instantaneous phase laws of the components.

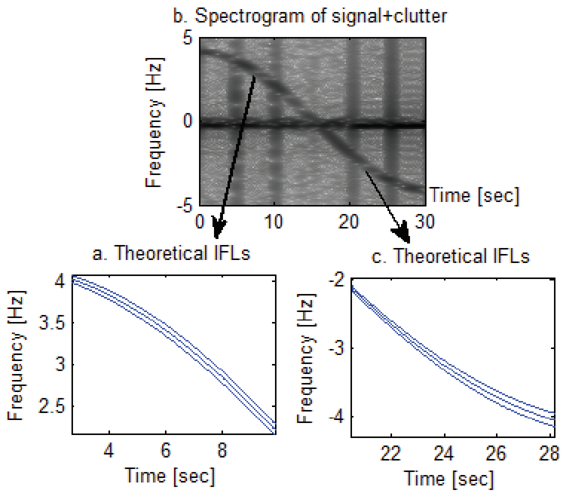


Figure 1. Time-varying Doppler signatures of a received signal (initial range = 2000 km, height of ionosphere layer H=350 km, initial target height $h(0)$=15 km, carrier frequency f_c=20 MHz).

To illustrate as an example of very challenging time-frequency analysis problems, the elevation velocity of the target is set to nonlinearly vary between –2.2 m/sec (descending) and 3.2 m/sec (ascending). As indicated in Fig. 1, the corresponding Doppler signatures of the three multipath components are very close (with a maximum separation of only 0.15 Hz), and they are corrupted by the clutter. In the spectrogram plotted in logarithmic scale, the multipath components are not identifiable and they cross the clutter in the spectral band defined around 0 Hz. The tracking of each multipath component in such a scenario is not an easy task, and calls for the application of time-varying high-resolution methods.

B. Coarse Doppler Signature Estimation

In this paper, we divide the data into segments, which are defined by half-overlapping time windows. The phase continuity across consecutive segments is exploited as follows. As illustrated in Fig.2, a third order polynomial phase modeling is applied locally on each segment. For each window position, the phase modeling is performed by the warped high-order ambiguity function (WHAF) of order 3 [4]. The IFL estimates obtained for two overlapped neighboring windows, $2i$ and $2i+1$, are plotted in Fig. 2. Due to the existence of multiple signal components and various clutter and noise sources, the WHAF may provide several estimates for each window (Fig. 2). Consider N_c estimates for each window, and denote the set of phase functions obtained from WHAF-based phase modeling applied in the ith window as:

$$D^{(i)} = \{\psi_k^{(i)}\}_{k=1,\dots,N_c};\ \psi_k^{(i)} = \sum_{i=1}^{3} a_{ki} t^i, \quad t \in [iT; (i+3/2)T] \quad (2)$$

where $\psi_k^{(i)}$ is the kth phase function of order 3 and T is the window size. As indicated in Fig. 2, the phase functions are just an approximate estimation of the true time-varying Doppler signature of the signal. They are used for the regrouping procedure provided by the second step of the methodology, i.e., *fusion of local phase information*. The phase functions (2) are used to build local filter functions, which extract the signal's samples corresponding to the time-frequency regions in the vicinity of the local functions.

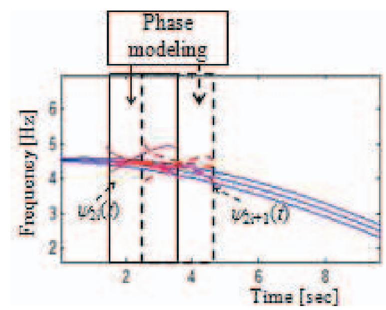


Figure 2. Short-time polynomial phase modeling with half over-lapped windows

Let us consider signal $x(t)$ at two analyzing windows $2i$ and $2i+1$ (see Fig. 2) and define $D^{(2i)} = \{\psi_k^{(2i)}\}_{k=1,\dots,Nc}$ and $D^{(2i+1)} = \{\psi_k^{(2i+1)}\}_{k=1,\dots,Nc}$ as the WHAF sets for these two windows. Time-varying filters $\{W_k^{(2i)}\}_{k=1,\dots,Nc}$ and $\{W_k^{(2i+1)}\}_{k=1,\dots,Nc}$ are constructed based on the WHAF sets to extract, from the analyzed signal $x(t)$, the corresponding signal's samples as

$$\begin{aligned} \{s_k^{(2i)}\} &= \{(W_k^{(2i)} x)(t)\}_{k=1,\dots,N_c} \\ \{s_k^{(2i+1)}\} &= \{(W_k^{(2i+1)} x)(t)\}_{k=1,\dots,N_c} \end{aligned} \quad (3)$$

Using these samples, we decide that the two phase functions, $\psi_m^{(2i)}$ and $\psi_n^{(2i+1)}$, will be connected (i.e., they belong to the same multipath component) if the correlation of the corresponding samples, $\{s_m^{(2i)}\}$ and $\{s_n^{(2i+1)}\}$, $m, n = 1,\dots, N_c$, is maximal for all pairs (m,n). After examining all segments of the signal, the time-frequency trajectory corresponding to the jth multipath component is determined by the entire phase set as

$$\phi_j(t) = \left[\psi_{k_1}^{(1)}, \psi_{k_2}^{(2)}, \ldots, \psi_{k_N}^{(N)}\right] \quad (4)$$

where N is the number of analyzing windows and k_i is the index of the phase function obtained from the ith window. The tracking result is illustrated in Fig. 3 for the synthetic signal considered in this paper. We observe that the tracking performance is accurate, and the estimated time-frequency trajectory fits the true Doppler signature of the signal.

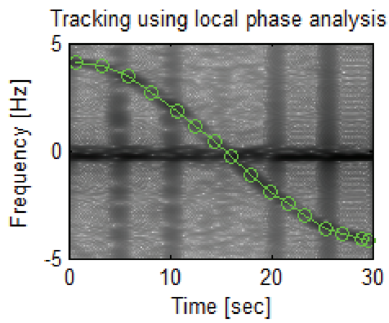


Figure 3. Tracking result provided by the local phase analysis

C. Time-Frequency Warping

The time-frequency trajectory $\phi_j(t)$ is used to design the following *warping operator* [4]:

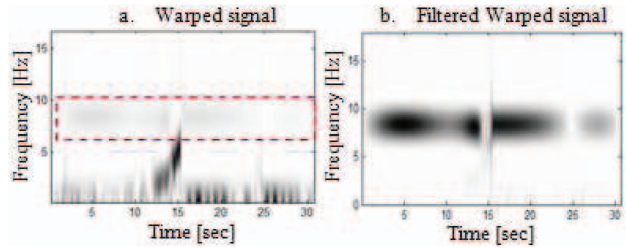
$$\left\{ \mathbf{W} \middle| x(t) \longrightarrow \mathbf{W}x(t) = \left|\frac{dw(t)}{dt}\right|^{1/2} x(w(t)) \right\} \quad (5)$$
$$w(t) = \phi_j^{-1}(t)$$

where $\phi_j^{-1}(t)$ is the inverse function of $\phi_j(t)$ that will attempt to stationnarize the time-frequency content of the signals. The aim of this operation is to transform the signal into a narrowband one so as to allow the use of short-time high-resolution spectral analysis for estimating the time-varying frequency variation of the multipath component.

Fig. 4(a) depicts the results of the warping operation that almost stationnarize the useful part of the signal, where its center frequency is aligned to 8.5 Hz that was the reference frequency used in the warping operation. Note that the majority of the clutter and noise is removed from this region. As a result, in the warped representation domain, the signal can be extracted by a simple bandpass filter

$$x_w(t) = \mathrm{W}x(t) * h(t) \quad (7)$$

where $h(t)$ is a bandpass filter whose passband is set to 7.5–10.5 Hz. The result of such operation is illustrated in Fig. 4(b) in the warped domain. We observe that the clutter is significantly reduced. We also observe that the three multipath components remain indistinguishable in the spectrogram because of the closely separated IFLs. One of the components, corresponding to the warping by the trajectory defined in Fig. 3, is a sinusoid while the other components have slowly time-varying (i.e., narrowband) time-frequency contents.



(a) (b)

Figure 4. Warped representation domain and the extraction of the useful signal

D. Signal Analysis Using Short-Time MUSIC

Because of the slow variation, it is possible to estimate the spectral content of each component by using short-time MUSIC method (windows of L=128 samples). This method consists of estimating the correlation matrix of the windowed filtered and warped signal $x_w^{(i)} = h_L(t - i \cdot L) \cdot x_w(t)$

$$R_{x_w^{(i)}} = \left\{ E\left[x_w^{(i)}, x_w^{(i)*}\right] \right\} \quad (6)$$

for i=1 and 2, where h_L is a rectangular window. For the correlation matrix estimated for each window, we obtain the three largest eigenvalues, knowing that we are looking for three time-frequency trajectories associated with the three propagation paths. These estimated eigenvalues constitute, for a given window, the frequencies of the components.

The estimated frequency results on the warped signal whose spectrogram is plotted in Fig. 4(b) are indicated in Fig. 5. The comparison of these results with the theoretical ones is depicted in Fig. 7.

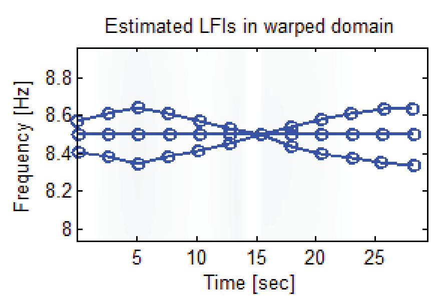


Figure 5. Short-time MUSIC applied on the warped signal

We remark that the component characterized by the IFL depicted in Fig. 3 is transformed, by the corresponding warping operator, into a sinusoid that is accurately estimated. The other components become narrowband, and their frequencies are also relatively well estimated. The next section is devoted to the comparison of the proposed method with one powerful data-dependent time-frequency method that is applied to OTHR.

3. COMPARISON TO RGK

The estimation of the IFLs of a multi-component signal, characterized by path-dependent Doppler signatures, can be performed by other techniques (e.g., [5], [6]). One of these techniques is through the tracking of the time-frequency distribution generated by the radial Gaussian kernel (RGK). This technique generates the time-frequency distribution by adaptively weighting the ambiguity domain with an RGK [5]. For the test signal considered, the corresponding RGK distribution is plotted in Fig. 6(a) and its peak value trajectory is traced in Fig. 6(b). While the components are not separated, the tracking procedure connects time-frequency points belonging to the different components, leading to a less accurate IFL estimation (compared with the proposed method, Fig. 3).

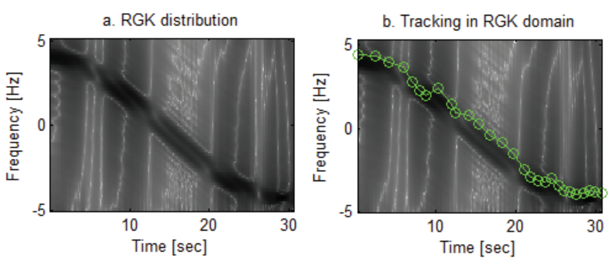


Figure 6. Tracking using the RGK-based distribution

In the context of the OTHR, the estimated IFLs of the arrivals are used to evaluate the target's trajectory. The differences of IFLs provide the information about the vertical motion [2]. Fig. 7 compares the IFL differences estimated by the RGK-based method and the proposed one. We also include the theoretical difference between IFLs, calculated from the curves plotted in Fig. 1.

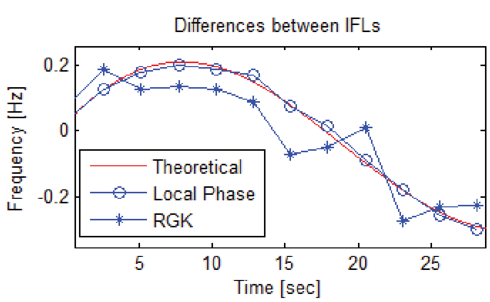


Figure 7. Estimation of differences between IFLs

For tracking of target elevation, only the differences between the IFLs are required. Using the fact that the warping operator conserves the time-frequency distances, the differences between the IFLs evaluated in the warped domain are the same with the one that could be obtained from the original domain. The main interest, however, is that the narrowband structure of the signal in warped domain allows the use of high-resolution spectral analysis. This enables improved estimation accuracy of the IFL differences. On the other hand, the tracking method based on the application of RGK fails when connecting successive Doppler estimates.

4. CONCLUSIONS

In this paper, we have introduced a new method for the tracking of complex signals characterized by nonlinear time-frequency components. The signal's model is inspired by the OTHR application in which a multipath Doppler dependent configuration arises due to maneuvering targets.

The key element of the proposed technique is the exploitation of phase coherence. By using the polynomial phase modeling of the third order, the local components are connected based on the fitting of the phase laws corresponding to consecutive data windows. The estimated IFL is used to design the warping operator that transforms the multi-component signal into a narrowband signal. In this context, it is important that the tracking preserves, in the warped domain, the spectral distances between the signal components for correct estimation of the differences between IFLs. This information, which is accurately provided by the proposed technique, is important for the estimation of the target's maneuvering behavior.

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