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Analysis of micro-Doppler signatures of vibration targets using EMD and SPWVD

Yan Wang [1,a], Xi Wu [b,1], Wenzao Li [a,b], Zhi Li [a], Yi Zhang [a,*], Jiliu Zhou [a]

[a] College of Computer Science, Sichuan University, Chengdu 610065, China
[b] College of Computer Science, Chengdu University of Information Technology, Chengdu 610065, China

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ABSTRACT

In the micro-Doppler signature analysis of vibration targets, the joint time–frequency methods can provide useful information for target detection, classification, and recognition. In this paper, we proposed a procedure which combines both Empirical Mode Decomposition (EMD) and Smoothed Pseudo Wigner-Ville Distribution (SPWVD) techniques for the micro-Doppler analysis. The Ensemble Empirical Mode Decomposition (EEMD) based method was also proposed to address the problem of mode mixing which may occur in EMD procedure. The simulation results showed that, compared with the traditional Cohen's class time–frequency method (SPWVD), the method we proposed achieved much better performance under three different conditions (severe noise, weak modulation and compound vibrations).

1. Introduction

When an electromagnetic signal is transmitted by the radar to a target, the signal interacts with the target and returns back to the radar. Changes in the properties of the returned signal reflect the characteristics of interest for the target. When the target moves with a constant velocity, the carrier frequency of the returned signal will be shifted. This is known as the Doppler effect and the frequency shift is determined by the wavelength and the radial velocity of the moving target [1]. In many cases, structures on the target may have rotations or vibrations in addition to target movement, such as the engine compressor and blade assemblies of a jet aircraft, the rotation of the aircraft propeller or the swinging arms of the pedestrian. Mechanical rotation or vibration of structures in a radar target may induce additional frequency modulation on the returned radar signal, which generates sidebands about the target's Doppler frequency, called the micro-Doppler effect [2]. Since the notion of micro-Doppler effect was originally introduced in coherent laser systems [3,4], lots of researches based on micro-Doppler effect have been presented [5–8], which demonstrate micro-Doppler frequencies accord with target micro-motion and the corresponding micro-Doppler features can be utilized to depict the micro-motion structures of the targets. The dynamic properties of the target signatures such as the speed of the target, the micro-amplitude, and the micro-vibration cycle can be determined by the micro-Doppler effect analysis, which can provide useful information for target detection, classification and recognition. Consequently, the extraction method of micro-Doppler signatures for the vibration targets is important in the radar system, and there has been increasing attention in this research field in recent years.

Until now, several micro-Doppler feature extraction algorithms have been proposed in the literatures. In [9], high-resolution joint time–frequency algorithms incorporated with order statistics and wavelet transforms are developed for micro-Doppler feature extraction, and in [10], the radar signal is parameterized into a set of chirplet functions, and the micro-Doppler signal is extracted by chirp-rate thresholding. Additionally, the Cohen's class time–frequency methods with potentially high resolution, such as the Wigner-Ville Distribution (WVD), Choi-William Distribution (CWD), smoothed pseudo Wigner-Ville distribution (SPWVD), are suitable for such nonlinear and non-stationary signals [11–15]. With a clear and accurate micro-Doppler plot in the joint time–frequency domain, we can estimate the vibrational parameters of the target. However, the difficulty with these methods is the severe cross terms as indicated by the existence of negative power

* Corresponding author.
[1] These authors contributed equally to this work.

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for some frequency ranges. In addition, when the returned signal is contaminated by noise or by backscattering from other reflectors, it becomes more difficult for Cohen's class methods to extract the micro-Doppler signatures.

To solve the problems of Cohen's class methods, another approach based on Empirical Mode Decomposition (EMD, which is included in the so-called Hilbert-Huang Transform (HHT)) [16] is introduced. For full-field optical technique used in vibration analysis called time averaged interferometry, a 2D EMD (Fast and Adaptive EMD) was used to enhance the Bessel fringes encoding the vibration amplitude [17]. In this study, we combine the EMD algorithm with SPWVD to elevate the micro-Doppler parameter estimation performance. The EMD process generates a set of components, called the intrinsic modes functions (IMF). Each IMF is a mono-component function respect to time. After EMD, the SPWVD is implemented on the IMFs which contain the important vibrational information, to estimate the signatures of the micro-Doppler signals. The implementation of EMD before SPWVD can address the problems of cross terms and other less effective performances brought by using the SPWVD directly. However, if the micro-Doppler signals contain more than one frequency vibrations, the EMD method has an annoying mode mixing problem caused by the signal intermittency, making the physical interpretation of each IMF component unclear [18]. To alleviate the mode mixing problem, we further propose an Ensemble Empirical Mode Decomposition (EEMD) based method. Then, SPWVD is implemented on the IMFs to obtain the micro-Doppler signatures of the vibration targets.

The rest of the paper is organized as follows: the micro-Doppler signal model is introduced in Section 2. In Section 3, the methodologies of the EMD, the EEMD based method, and the SPWVD are discussed respectively. Three different conditions are considered and investigated in the simulation experiments, and the experimental results are analyzed and discussed in Section 4. Finally, Section 5 presents discussion and conclusion.

2. Micro-Doppler signal model

The basic mathematic description of the micro-Doppler effect induced by vibrational motions is firstly discussed in this section. Rotation can be seen as a special case of vibration. In coherent radar, the variations in range cause a phase change in the returned signal from a target. A 360° phase change can be caused by a half-wavelength change in range. It is conceivable that the vibration of a reflecting surface may be measured with the phase change. Therefore, the Doppler frequency shift that represents the change of phase function with time can be used to detect vibrations of structures in a target. From the electromagnetic point of view, when a target has micro-motions like vibration or rotation, the radar backscattering is subject to modulations that constitute features in the signature. Victor C. Chen has developed a model for the micro-Doppler effect from the theory of the electromagnetic back-scattering field [4,19]. Using his model, the returned signal $s(t)$ from a vibrating point scatterer can be expressed as a sinusoidal modulated signal

$$s(t) = \rho \exp[j2\pi f_c t + j\beta \sin(2\pi f_v t)] \tag{1}$$

with $\beta = 4\pi D f_c$, where f_c and f_v represent the carrier frequency and the target vibrating frequency respectively, $\rho$is the reflectivity of the target which is in the range of 0–1 and D is the light of sight oscillation displacement between the target and the radar. If the target is vibrating along the projection of the radar light of sight direction, then D equals the value of the vibrating amplitude d_v[19]. As the micro-frequency of the signal is not affected by the parameterρ, it is assumed to be 1 in this paper, and this signal model is used to generate simulative signals in the experimental part.

In the time–frequency domain, one of the important basic concepts is the instantaneous frequency which is a function of time. According to Eq. (1), the instantaneous frequency of the returned signal is

$$f = f_c + f_{\text{micro-Doppler}} = f_c + \beta f_v \cos(2\pi f_v t) \tag{2}$$

From Eq. (2), it is clear that the micro-Doppler of a regular vibrating target produces a sinusoidal frequency modulation to the phase. Quite small oscillations can cause large modulation as the peak-to-peak Doppler deviation is given by $2\beta f_v$. The modulation index β is proportional to Df_c.

3. Methodology

3.1. EMD

Empirical Mode Decomposition (EMD) is firstly introduced by N.E. Huang for nonlinear and nonstationary signal analysis in 1998. The EMD method is a necessary step to reduce any given data into a collection of intrinsic mode functions (IMFs). An IMF is defined as a function that satisfied the following requirements: 1) in the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one. 2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero [16]. Given a signal $x(t)$, the effective algorithm of EMD can be summarized as follows:

Step 1 Initialize: $r_0 = x(t)$, and $i = 1$.
Step 2 Extract the ith IMF

Initialize: $h_{i(k-1)} = r_i$, $k = 1$.
Extract the local maxima and minima of $h_{i(k-1)}$.
Interpolate between minima and maxima of $h_{i(k-1)}$, ending up with some envelope $e_{\min}(t)$ and $e_{\max}(t)$.
Compute the mean $m_{i(k-1)} = (e_{\min}(t) + e_{\max}(t))/2$.
Let $h_{ik} = h_{i(k-1)} - m_{i(k-1)}$.
If h_{ik} is a IMF then set $\text{IMF}_i = h_{ik}$, else go to step b with $k = k+1$.

Step 3 Define $r_{i+1} = r_i - \text{IMF}_i$.
Step 4 If r_{i+1} still has least two extrema then go to step 2, else the decomposition process is finished and r_{i+1} is the residue of the signal.

After EMD, signal $x(t)$ can be expressed as a summation of n IMFs and a residue $r_n(t)$, i.e.,

$$x(t) = \sum_{j=1}^{n} C_j(t) + r_n(t) \tag{3}$$

Thus, a decomposition of the signal into n-empirical modes is achieved. The components of the EMD are usually physically meaningful, for the characteristic scales are defined by the physical data.

3.2. EEMD based method

One disadvantage of the EMD method is the appearance of mode mixing which is defined as a single IMF including oscillations of dramatically disparate scales or a component of a similar scale residing in different IMFs [16]. It is a result of signal intermittency, and it usually occurs in the EMD procedure for the signal which contains multiple frequency components. To overcome the problem of mode mixing in EMD, the Ensemble Empirical Mode Decomposition (EEMD) method is presented and has been applied in many fields [20–24]. This new approach