A time domain decomposition based time-frequency analysis for radar signal processing

Cai, Chengjie

2006

Cai, C. (2006). A time domain decomposition based time-frequency analysis for radar signal processing. Doctoral thesis, Nanyang Technological University, Singapore.

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<https://doi.org/10.32657/10356/4824>

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A Time Domain Decomposition Based Time-Frequency Analysis for Radar Signal Processing

Cai Chengjie

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2006

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

Date

Signature

ACKNOWLEDGMENTS

The completion of this project would not have been possible without the help and encouragement of many people. I would like to express my profound appreciation and sincere gratitude to my supervisor, Associate Professor Fu Shiang, Jeffrey, for his guidance and inspiration throughout this study.

I also gratefully acknowledge many professors and researchers whom I have honor to know. Among them, special thanks go to Dr. Liu Weixian for his professional advices and technical support through my PhD research. It is also a great pleasure to thank my friends in Communication Laboratory I for their kind assistance and services in whatever ways they can.

Finally but not least, I would especially thank my father, mother, and husband for their love and support during my graduate career.

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SUMMARY

Radar signal processing aims to extract target signal from clutter and noise as well as to extract signal features as accurate as possible. Time-frequency analysis for radar signal processing has been investigated by radar researchers since last decade. Lots of exciting results have been achieved in many aspects of radar applications (signal analysis, feature detection, SAR imaging, motion compensation, and so on), but there are still many problems remaining unsolved. Since specific time-frequency analysis technique has to be selected for given radar problem, a more adaptive and general time-frequency method is expected.

In this thesis, we proposed a new approach for time-frequency analysis of radar signals. The essence of this Hilbert Huang Transform (HHT) approach is the time domain decomposition, called Empirical Mode Decomposition (EMD), according to which any complicated signal can be decomposed into a finite (and often small) number of functions, called Intrinsic Mode Function (IMF). These IMFs, derived from the different intrinsic oscillatory modes of the signal, are always physically meaningful. Thus the HHT can efficiently extract desired signal components from the interference signals (clutter and noise). At the same time since every IMF admits well-behaved Hilbert transforms, instantaneous frequency can be obtained in its associated Hilbert spectrum. It offers a higher time-frequency resolution that the other Time-Frequency Analysis (TFA) techniques can hardly achieve.

In our current work, the HHT is applied to Ground Moving Target Indication (GMTI) in FOLIage PENetration (FOPEN) radar application and micro-Doppler signature analysis

radar application. Results based on simulative signals and experimental signals show that EMD successfully extracts the target signal and Hilbert spectrum gives a clear description of the time-varying Doppler frequency of the motions. The HHT outperforms traditional TFA methods by solving their deficiencies in these radar applications.

Using both simulative and experimental signals, EMD is further compared with other two signal decomposition techniques, i.e. Discrete Wavelet Transform (DWT) and Adaptive Chirplet Decomposition (ACD), in terms of physical meaning, adaptivity, sensitivity to signal type, interpretation of method, complexity of algorithm and computing time. In most cases, EMD is a better choice.

LIST OF ACRONYMS

ACD	Adaptive Chirplet Decomposition
CIT	Coherent Integration Time
CW	Continuous Wave
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
FM	Frequency Modulated
FOPEN	FOliage PENetration
GMTI	Ground Moving Target Indication
GSM	Global System for Mobile Communication
HHT	Hilbert Huang Transform
IMF	Intrinsic Mode Function
NA	Network Analyzer
PMF	Proto-Mode Function
PSD	Probability Spectral Density
SAR	Synthetic Aperture Radar
SDR	Signal to Disturbance Ratio
SNR	Signal to Noise Ratio
SP	Spectrogram
SCALO	Scalogram
SPWVD	Smoothed Pseudo Wigner Ville Distribution
STFT	Short Time Fourier Transform

TFA	Time-Frequency Analysis
TFT	Time-Frequency Transform
UHF	Ultra-High Frequency
VHF	Very High Frequency
WVD	Wigner Ville Distribution

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Radar is an electromagnetic instrument used for the detection and location of targets, such as aircraft, ships, and ground vehicles. It transmits electromagnetic waves to a target. The energy that is scattered from target back to the radar antenna is the received signal. From the received radar signal, target-related information such as location and velocity can be measured. However, the working states of radar are unavoidably affected by combined wave distortion rather than targets. The predominant factors which cause distortion are clutters and noise. Any unwanted radar return which may interfere with the detection of the desired target is referred to as clutter, consisting of ground objects, cloud and rain, and sea wave clutter etc. In addition to the signal reflected from the target and clutter, there is additive noise. The signal-to-noise ratio (SNR) at the radar receiver is determined by the intensity of the received signal, the features of the noise, and the bandwidth of the receiver. Fig. 1-1 gives an example of radar operational scenario: transmitter, receiver, target, clutter and noise [1-4].

Signal processing is the technique (or science) of extracting the maximum amount of information from a signal. In radar metrology, it includes all the signal manipulations and computations required to turn the raw returns into clean feature measurements. The main aim of radar signal processing is to

Figure 1-1 Example of radar operational scenario.

- Extract the desired targets from the formidable background (clutter and noise)
- Estimate target information (range, angle of azimuth, elevation and Doppler frequency etc.) as accurate as possible.

In order to extract the information presented in the radar data and use it to its full potential, we turn to the field of signal analysis and data representations. Traditionally, radar signals have been analyzed in either the time or the frequency domain. The Fourier transform, an effective tool for transforming signal between time and frequency domain, is the foundation of a wide range of techniques that are used in radar data analysis and processing. Mapping the data into the frequency domain is an effective way to record the data such that their global characteristics can be assessed. However, the change of frequency content with time is one of the main features we observe in radar signals. And lots of radar signals belong to nonstationary signals since they are not a sum of elements which have constant instantaneous amplitude and instantaneous frequency. The analysis of nonstationary signals requires techniques that extend the notion of a global frequency spectrum to a local frequency description. The spectral energy density function that is obtained by means of a Fourier transform, the so-called power spectrum, shows the

frequencies that are present in the radar data, but does not reveal when those changes in the frequency content occur. Consequently, in order to interpret radar data in terms of changing frequency content, we need a representation for the data as a function of both time and frequency.

During the last decade, Time-Frequency Analysis (TFA) has been investigated by radar researchers as a special tool for radar signal analysis. The time-frequency distributions characterize signals over a time-frequency plane, where the analyses of time-domain and frequency-domain are combined to yield a potentially more revealing picture of the temporal localization of a signal's spectral components. TFA may also serve as a basis for de-noising, signal detection, imaging, characterization, coding, and processing. It is distinct that high resolution TFA can improve both the detectability and the detailed characterization of radar signals. Here high resolution means more accurate and local representation in time-frequency plane.

The TFA methods are categorized as linear and quadratic transforms:

1) Linear Time-Frequency Transforms:

Linear Time-Frequency Transform (TFT) is a linear signal transform that decomposes a signal into time-frequency or time-scale elements. These elements are well-localized in the time-frequency or in the time-scale plane. All linear TFT satisfy the superposition or linearity principle which states that if $s(t)$ is a linear combination of some signal components, then the TFT of $s(t)$ is the same linear combination of the TFT of the signal components. Two common linear TFTs are Short Time Fourier Transform (STFT) and the Continuous Wavelet Transform (CWT).

2) *Quadratic Time-Frequency Transforms:*

Although linearity is a desirable property, the quadratic structure of a TFT is an intuitively reasonable assumption when we want to interpret a TFT as a time-frequency energy distribution or “instantaneous power spectrum”. This leads to the class of quadratic TFT which are also known as “energy distributions”. The natural transition from a linear TFT to the quadratic TFT is to square the modulus of the linear TFT.

Nowadays, various quadratic TFA techniques are widely used in radar applications, such as target recognition and SAR imaging, radar signature analysis and so on. Among those, spectrogram, scalogram and Wigner-Ville Distribution (WVD) are the most successfully used approaches.

However, none of these TFA techniques is always effective for various applications of the modern radar. In this thesis, we focus our study on the TFA of two particular radar applications, that is, the ground moving target indication in foliage environment and micro-Doppler signature analysis. These are both challenging problems for the traditional TFA techniques.

Ground moving target indication in foliage environment is to identify target concealed in foliage area and reveal the Doppler frequency in the time-frequency domain. The strong echoes from dense foliage environment and big attenuation of the radar microwave often make it difficult to clearly and locally represent the Doppler frequency. Conventional quadratic TFA methods may not effectively find the target and estimate the motion parameters, because it is difficult for them to extract the target signal from the severe background clutter in this situation.

Micro-Doppler signature analysis is another interesting topic which has been raised recently. It is valuable for many practical applications such as vehicle identification, engine malfunction diagnosis, human gait measurement, natural resonance frequency measurement, jet engine modulation analysis and so on. Analysis of the time-varying micro-Doppler signature with the TFA techniques can provide useful information for target detection, classification and recognition. However, the analysis results of traditional quadratic TFA methods are subject to their kernels, which may cause some corresponding problems. Smearing and stationary time-frequency distributions will be obtained instead of a clear micro-Doppler skeleton line if the parameters of smoothing windows are not properly set. Therefore it is difficult to accurately depict the frequency modulated micro-Doppler and estimate the motion parameters consequently.

Besides, quadratic TFA methods have a compromise of time-frequency resolution and cross-terms level. They cannot give out the desired instantaneous Doppler frequency. Many of their disadvantages and limitations will be explained in detail in Chapter 2. These drawbacks in current TFA techniques motivate us to find better methods to alleviate the problems in the above two applications. It is obvious that the expected TFA is the one which can give more local and accurate time-frequency distribution of the desired target signal. TFA technique possesses such properties will increase the probability of target detection and the accuracy of feature estimation.

1.2 Objectives

The main objective of this project is to study and develop an effective and adaptive time-frequency analysis for radar signal processing. We attempt to propose a novel algorithm to alleviate problems caused by conventional TFA techniques and enhance the capacity

of target extraction and feature estimation. Efforts have to be made to conquer the difficulties in GMTI of foliage environment and micro-Doppler signature analysis. The following tasks are going to be completed in my research work:

- 1) Give a comprehensive literature review of traditional TFA methods for radar signal processing. Survey on the limitations of conventional analysis in time or frequency domain and the advantages of TFA methods, in order to radically understand the motivation of TFA implementations. Study and analyze the most popular and successfully used TFA techniques. By comparing the different methodologies and performances of those TFA techniques, the intrinsic problems of them will be clearly addressed.
- 2) Investigate a novel TFA method named Hilbert Huang Transform (HHT) which is effective for analyzing nonlinear and nonstationary signals. Propose and modify it for radar signal processing, based on thorough evaluation and validation of its efficiency for target extraction and feature estimation. By applying it on some representative simulation signals, the intrinsic predominance of it over the conventional TFA methods as well as the potential use of it in radar applications must be found.
- 3) Apply this new TFA method on practical foliage penetration (FOPEN) radar applications in order to solve the challenging problem of extracting and estimating Doppler frequency of moving target from large echo signals caused by foliage environment. As a theoretical basis for analyzing the foliage penetration radar signals, the phenomenological model for the radar clutter echoes from foliage vegetation is to be investigated. Validate the efficiency of the HHT after

successfully generating the simulative FOPEN data. Thereafter, collect field data of FOPEN experiment and apply the HHT on real signals. In responding to the inefficiency of traditional TFA methods, two intractable cases need to be studied, i.e. weak Doppler signal which is severely contaminated by clutter and noise, and Doppler signal with a small offset. Analyze the results and draw out conclusion.

- 4) Attempt to seek the solution of capturing the micro-Doppler signatures generated by micro-motions of a target besides its major translation. First work is to explore the time-frequency characteristics of micro-Doppler signature by modeling the signal returned from a vibrating target. In succession, examine the performance of traditional TFA methods for this particular radar application. Then we need to evaluate the efficiency of the proposed HHT on the simulative signals by carrying out a complete results analysis for both strong modulated micro-Doppler signal and fairly weak modulated micro-Doppler. Real micro-Doppler signals of various targets are to be collected through several experiments, followed by detailed results discussion and methods comparison.
- 5) Extend the study on signal decomposition techniques. The proposed empirical mode decomposition (EMD) is to be compared with discrete wavelet transform (DWT) and adaptive chirplet decomposition (ACD), which have different theories and features. This task begins with a theoretical review and study of these methods to find the advantages and disadvantages of them. Discover afterwards the differences and similarities between them based on results comparison of numerical simulated signals and experimental signals.

- 6) Provide an insight into the theory of the HHT, since it is far from being a mature tool and lacks mathematical foundations. In our study, some modifications of the HHT implementation will be made according to the radar signal processing situation.

1.3 Major Contribution of the Thesis

In this thesis, extensive research works have been done on the time-frequency analysis for radar signal processing, especially on radar applications of GMTI in foliage environment and micro-Doppler signature analysis. A novel HHT approach has been proposed and implemented successfully. The following is the summary of the main contributions of the thesis:

- 1) We have explored full interpretations of a new technique, HHT, and have proposed it for radar signal processing. By investigating the time domain decomposition, EMD, in various typical simulative signals, it has been illustrated that this new method is very useful for target extraction due to its capacity of discriminating the different oscillations embedded in a complicated nonstationary radar signal. Combined with Hilbert transform, EMD produces a Hilbert spectrum of desired signal components. This new TFA has been proven to present accurate instantaneous frequency of the analyzed signal, which is very attractive for target identification and motion parameters estimation. We have provided a thorough theoretical comparison between the HHT and the traditional TFA methods. The different results of them on a simulative pure Doppler signal have further demonstrated the predominance of the proposed HHT.

- 2) For the radar application of GMTI in dense foliage environment, the HHT is used to solve the challenging problem of extracting Doppler frequency of a moving target from those severe interference signals backscattering from foliage environment. To accomplish this goal, we have studied the phenomenological model derived for the Doppler spectrum of radar clutter echoes from windblown foliage vegetation. The HHT has been applied after programming and generating the simulative signals based on the signal model. Results show that the HHT has good performance on the signal extraction and instantaneous Doppler frequency estimation. This has proved the efficiency of the HHT for GMTI in a statistical way. Two cases of GMTI in foliage environment have been examined after collecting real data from FOPEN trial. One case is a weak Doppler signal which is severely imbedded in clutter and noise; the other is a Doppler signal with a small offset to the zero-Doppler. Both cases prohibit proper working of the traditional TFA techniques in different aspects. However, the adaptive HHT works effectively, offering higher signal to disturbance ratio and higher resolution in the time-frequency distribution. This has demonstrated the validity and accuracy of the HHT for practical GMTI applications.
- 3) In the scope of micro-Doppler signature analysis, the analysis results of traditional TFA methods are subject to their kernels, which may cause some corresponding problems. For the weak modulated micro-Doppler, conventional TFA techniques usually fail to present its time-frequency characteristics clearly and accurately, rendering the data useless. We have investigated the signal models of vibration-induced micro-Doppler. Two types of signals, strong modulated micro-Doppler signal and fairly weak modulated signal, have been simulated by our developed program. After applying the HHT, the desired micro-Doppler can be successfully extracted and contribute to further feature estimation. Three different micro-Doppler

trials have been carried out. They are respectively the experiments of detecting an Engine-induced vibrating truck, studying car combustion engine vibration and analyzing a running man with swing arms and legs. With the help of the HHT, clear instantaneous micro-Doppler has been obtained. The results have shown good agreement with the observed ground truth.

- 4) We have studied the resemblance and diversity of EMD, DWT and ACD as signal decomposition techniques, in order to better understand the way they behave and find out the optimal choice. We have generated a mono-frequency target signal and a multi-frequency target signal and compared the analysis results of EMD, DWT and ACD. Renyi entropy of time-frequency information has been used to demonstrate the accuracy of signal extraction. Relative error calculation between the original signal and extracted component also has been used as proofs. Three methods have then been applied on real FOPEN data and micro-Doppler data. Based on their comparison, positive and negative remarks involved with each method have been discussed.
- 5) We have provided an insight into the theory and implementation of the HHT. The criteria settings in EMD, the intermittence phenomenon, the end effect of spline fitting, the sifting basis, the time-frequency precision of Hilbert spectrum and the orthogonality of IMFs have been discussed in detail. We have made our clarifications and modifications in these aspects based on our radar signal processing study.

1.4 Organization of the Thesis

This thesis is organized into eight chapters.

Chapter 1 introduces the main motivations, objectives, contributions and organization of the thesis.

Chapter 2 provides a survey on time-frequency analysis methods for radar signal processing. Comparisons of these techniques are carried out and questions are raised. Based on a well understanding of why the TFA techniques are needed rather than analysis in either time or frequency domain, we study and analyze typical TFA techniques, i.e. spectrogram, scalogram and Wigner Ville Distribution, in terms of their methodologies and performances.

Chapter 3 introduces the new HHT method. Based on the background introduction about Hilbert transform and instantaneous frequency, the definitions of intrinsic mode function, empirical mode decomposition and Hilbert spectrum are explained. To generally validate the efficiency of the proposed HHT for radar signal processing, three signals, an amplitude modulated signal, a multicomponent signal and a noisy data, are simulated and analyzed.

In Chapter 4, the HHT method is applied to FOPEN radar applications. Problem definition of GMTI in foliage environment is first described. A performance comparison of the HHT and traditional TFA methods is given on the basis of simulative signal analysis. Afterwards, the HHT is implemented on two cases of experimental data, i. e.

weak Doppler signal and Doppler signal with small offset to solve the problems corresponding to the prior methods.

Chapter 5 proposes the HHT on micro-Doppler signature analysis. After introducing about this radar application, a signal model of vibration-induced micro-Doppler is developed. Then the limitations of traditional TFA methods for this sinusoidal modulated signal are examined. Comparison results of the HHT and traditional TFA methods are illustrated for both simulative signal with modulation index $B > 1$ and signal with $B < 1$. The HHT is further proved as an effective and flexible approach by respectively analyzing the micro-Doppler of an engine-induced vehicle surface vibration, a car combustion engine caused vibration and a running man with swing arms and legs.

Chapter 6 extends the study of signal decomposition techniques. Besides EMD, alternative DWT and ACD are introduced. A contaminated mono-frequency target signal and a multi-frequency target signal are simulated and analyzed by these methods. Following that, DWT, ACD and EMD are applied on real signal of the above applications, i.e. FOPEN data and micro-Doppler data. The summary of results gives a general conclusion of their advantages and disadvantages.

Chapter 7 further discusses some theoretical and practical aspects of the HHT, i.e. the criteria settings in EMD, the intermittence phenomenon, the end effect of spline fitting, the sifting basis, the time-frequency precision of Hilbert spectrum and the orthogonality of IMFs.

Finally, Chapter 8 concludes the thesis and the future works are recommended.

CHAPTER 2

OVERVIEW OF TIME-FREQUENCY ANALYSIS FOR RADAR SIGNAL PROCESSING

2.1 The Doppler Effect

This research work is about time-frequency analysis for radar signal processing. Its main aim is to extract target signal from formidable background and extract the Doppler frequency information from the time-frequency distributions. A simplified block diagram of TFA for continuous wave (CW) radar is shown in Fig. 2-1.

Figure 2-1 Block diagram of a continuous wave radar.

The output of the CW transmitter at frequency f_c Hz is routed through a circulator to the antenna. The wave transmitted by the antenna propagates to and is scattered from a moving target and the wave is received back at the antenna. The received wave has a frequency of $f_c - f_d$ Hz. The wave passes through the circulator to the receiver. Some of the transmitted signal at f_c Hz leaks through to the receiver. At the front end of the

receiver is a mixer that heterodynes the two signals together to produce a Doppler signal with frequency of f_d Hz. The transient recorder digitizes and records the Doppler signal. The digitized Doppler signal is then sent to a computer whereby the joint time-frequency analysis of the Doppler signal is performed.

The frequency shift f_d occurs because of the well-known Doppler Effect [3, 5], which is the basis of the operating principle for target detection and feature estimation. If the range from radar to the target is R , then the total number of wavelengths λ_c in the two-way path from radar to target and return is $\frac{2R}{\lambda_c}$. Each wavelength corresponds to a phase change of 2π radians. The total phase change in the two-way propagation path is then

$$\phi = 2\pi \times \frac{2R}{\lambda_c} = \frac{4\pi R}{\lambda_c} \quad (2.1)$$

If the target is in motion relative to the radar, R is changing and so will the phase. Differentiating (2.1) with respect to time gives the rate of change of phase, which is the angular frequency

$$\omega_d = \frac{d\phi}{dt} = \frac{4\pi}{\lambda_c} \frac{dR}{dt} = \frac{4\pi v_r}{\lambda_c} = 2\pi f_d \quad (2.2)$$

where $v_r = \frac{dR}{dt}$ is the radial velocity (meters/second), or rate of change of range with time. If the angle between the target's velocity vector and the radar line of sight to the target is θ , then $v_r = v \cos \theta$, where v is the speed, or magnitude of the vector velocity. The rate of change of ϕ with time is the angular frequency $\omega_d = 2\pi f_d$, where f_d is the Doppler frequency shift. Thus from (2.2)

$$f_d = \frac{2v_r}{\lambda_c} = \frac{2f_c v_r}{C} \quad (2.3)$$

where f_c is the radar frequency.

Obviously, the Doppler frequency shift is determined by the radial velocity of the target and wavelength of the radar transmitted waveform. In most cases, target motion is complicated at time-varying speed and therefore the Doppler frequency becomes a time-varying function. This causes the nonstationary nature of radar signal.

2.2 Need of Joint Time-Frequency Analysis

As indicated above, the operation principles of radar is mainly based on the time-varying Doppler frequency, measurements in both time and frequency are fundamental to radar signal processing [6]. We are interested in the spectral content as well as the temporal information. Such information can be obtained directly from a signal or by transforming the signal into other representations, where different aspects of the signal are emphasized in different representations. This mainly can be done in four ways:

- Time Domain Analysis
- Frequency Domain Analysis
- Instantaneous Frequency and Group Delay
- Time-frequency Analysis

2.2.1 Limitation of Time Domain Analysis

The time domain analysis is normally the most natural description of a signal that we consider, because most physical signals are obtained by receivers recording variations with time. However from the time representation, it is not possible to tell what the initial and final frequencies are, and whether the signal is of linear, parabolic, hyperbolic, or frequency modulation.

2.2.2 Limitation of Frequency Domain Analysis

The time series signals of radar targets have been traditionally analyzed in the frequency domain. The transformation of a time series into a frequency domain using the Fourier transform (2.4) provides useful information regarding the target. Fourier analysis can be thought as a mathematical technique for transforming our view of a signal from a time-based one to a frequency-based one.

$$S(f) = \int_{-\infty}^{\infty} s(t)e^{-j2\pi ft} dt \quad (2.4)$$

Fourier transform-based techniques are effective as long as the frequency contents of the signal do not change much over time, that is, the so-called stationary signal. However, radar target signals are nonstationary and have highly complex time-frequency characteristics [7]. The Fourier spectrum does not indicate the evolution in time of the frequency content, because the Fourier transform decomposes the signal into complex exponential. These complex exponentials are of infinite duration and therefore are totally unlocalized in time. Time information is in fact encoded in the phase of the Fourier transform. However, it is difficult to extract the time information from the phase of the Fourier transform. A number of difficulties including phase unwrapping will have to be solved, thus the spectrum essentially shows the frequencies presented in the signal and the corresponding amplitudes and phases, but it does not tell when these frequencies occur. Although the Fourier transform allows passing from one domain to the other, it does not allow a simultaneous combination of the two domains.

It is realized that signal analysis either in time domain or frequency domain is neither sufficient nor valid for representing time-dependent frequency characteristics in radar signals. Other alternative methods should be considered.

2.2.3 Limitation of Instantaneous Frequency and Group Delay

A method combine the information of time and frequency domain is by using the instantaneous frequency (2.5) and group delay (2.6).

$$f(t) = \frac{1}{2\pi} \frac{d}{dt} \arg\{s_a(t)\} \quad (2.5)$$

$$t(f) = \frac{1}{2\pi} \frac{d}{df} \arg\{S_a(f)\} \quad (2.6)$$

where $s_a(t)$ is the *analytic signal* for the real valued signal $s(t)$, $S_a(f)$ is the Fourier transform of $s_a(t)$.

The time localization of the spectral components is described by the instantaneous frequency and the group delay for a group of signals. The instantaneous frequency $f(t)$ represents the frequency as a function of time, and assumes there exists a single frequency component at each time t . This assumption does not apply in the case of the signal $s(t) = e^{2\pi f_1 t} + e^{2\pi f_2 t}$, containing two frequency components (f_1 and f_2) at all times. For the group delay, it is assumed that a given frequency is concentrated around a single instance of time. Real radar signal can hardly satisfy these conditions, therefore these methods are not applicable for radar signal processing.

If the signal can be described by a surface spanning the time-frequency plane instead of a curve on this plane, the restrictions associated with the instantaneous frequency and the group delay can be minimized. This concept of a surface spanning the plane corresponds to a joint function $T_s(t, f)$ of time and frequency and is know as the time-frequency analysis of the signal.

2.2.4 Advantages of Time-Frequency Analysis

The joint Time-Frequency Analysis (TFA) has been a topic of much interest in the signal processing community in the past decade. Over the past ten years, radar researchers have also investigated time-frequency analysis as a unique tool for radar-specific signal analysis and image processing applications [8-14]. Both traditional TFA techniques, and the new tools developed in the signal processing community have been applied to various radar problems. Like the developments in other fields, such as underwater acoustics and speech processing, it is found that time-frequency analysis methods provide additional insight into the analysis, interpretation, and processing of radar signals. This is superior to what is achievable in the traditional time or frequency domain alone. The specific applications where TFA has been used include target signal analysis and feature extraction, motion compensation and image formation, signal de-noising, imaging of moving targets, and detection of moving targets.

TFA transform a one-dimensional time signal into two-dimensional representation in the time-frequency plane. This representation can combine time and frequency information and give a more revealing representation of the temporal localization of the spectral components of a signal. The most important virtue of TFA is that it can clearly bring out the nonstationary behavior of the radar signal. It provides an indication of the specific times during which certain spectral components of the signal are observed. Through the use of time-frequency distribution, the analysis of the signal is greatly simplified. The image of the transform allows for quick, visual analysis of the target signal. Another important advantage of time-frequency distributions is the ease of identifying target signals. A waveform with multiple signals or noise can become too complicated for visual analysis. Even the Fourier spectral analysis can become garbled beyond

recognition. Since time-frequency distributions display time-varying frequencies, the signals are distinguishable from the noise. The nature of each signal can be easily seen.

Many papers concerning the theory and applications of TFA have been published. In the next section we will review some of these works and provide a detailed account of them. Specifically we evaluate and compare the ability of three typical quadratic TFA methods which are most broadly used in radar signal processing [15-23]. They are spectrogram, scalogram and Wigner Ville distribution.

2.3 Comparison of Typical Quadratic Time-Frequency Analysis Methods

To compare the different performances of the spectrogram, scalogram and WVD, we take a Doppler signal for example. A fixed radar working at $f_c = 1.147 \times 10^7$ Hz is used to detect a target moving with a constant velocity $v_r = 1$ m/s. The target moves towards radar first and then away from it. The observation time is 5 seconds and the sampling frequency $f_s = 50$ Hz. In order to represent clearly the time-frequency resolutions, it is assumed that no interference from clutter and noise exists.

Theoretically, the Doppler signal should have two constant frequency values. The moving directions of the target, either towards the receiver or away from it, induce the frequency difference. The normalized frequency values are respectively

$$f1 = (f_w + f_d) / f_s = (13 + 7.6) / 50 \approx 0.4 \text{ Hz}$$

$$f2 = (f_w - f_d) / f_s = (13 - 7.6) / 50 \approx 0.1 \text{ Hz}$$

where, $f_d = 2v_r / \lambda_c \approx 7.6$ Hz

2.3.1 Spectrogram

To overcome the deficiency of losing time information in Fourier transform, Dennis Gabor (1946) adapted the Fourier transform to analyze only a small section of the signal at a time, a technique called windowing the signal. Gabor's adaptation, named the Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency. In order to retain the time information in the signal, STFT uses a sinusoidal window of fixed width and shifts it along the analyzed data, shown as Fig. 2-2. Many functions have been successfully used as STFT windowing functions: Gaussian, Hamming, Hanning, and square/rectangular functions. In contrast to only frequency representation $S(\omega)$ in case of Fourier transform, STFT employs a time-frequency distribution $S(\omega, t)$ of the signal $s(t)$ as in the following (2.7).

$$S_{stft}(\omega, t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-j\omega\tau} s(\tau) h(\tau - t) d\tau \quad (2.7)$$

where $h(t - \tau)$ is a window function [9, 24, 25].

The spectrogram is the square modulus of the STFT and is described by

$$S_{spectrogram}(\omega, t) = |S_{stft}(\omega, t)|^2 \quad (2.8)$$

Figure 2-2 STFT view of a signal.

Among those TFA methods, spectrogram is probably one of the earliest and most widely used methods. The advantages of spectrogram are that it is positive by definition, it

contains no visible cross-terms and therefore is easy to interpret, and, it can be computed efficiently using the Fast Fourier Transform.

However, spectrogram has severe drawbacks, both theoretically, since it provides biased estimators of the signal instantaneous frequency and group delay, and practically, since the Heisenberg uncertainty principle [26] makes a tradeoff between temporal and spectral resolutions unavoidable.

Figure 2-3 Spectrogram of the pure Doppler signal.

Fig 2-3 shows the spectrogram of the pure Doppler signal as described before with a 35 points (data has 256 sampling points) hamming window. It gives the real part of this signal in time domain, the signal's energy spectral density in frequency domain and its spectrogram representation respectively. As we can see in the figure, the frequencies smear in a big range. Although spectrogram presents a distinct Doppler shift, it is hard to tell the exact frequency value. The time representation also blurs in a certain range,

making it impossible to tell the exact time of the frequency change. Obviously, a poor time and frequency resolution is the main drawback of spectrogram.

Another drawback of spectrogram is that it suffers from the Heisenberg uncertainty principle, which makes it impossible to have perfect resolution in both time and frequency simultaneously. Once the window width is chosen, then the obtained time-frequency resolution remains fixed over the entire time-frequency plane. One can get either good time resolution or good frequency resolution in the analysis, but not both. A wide window gives better frequency resolution, but worsens the time resolution. On the contrary, a narrow window improves time resolution but worsens frequency resolution. These conflicting requirements render this method of limited usage.

In addition, since spectrogram relies on the traditional Fourier spectral analysis, the data has to be assumed piecewise stationary. This assumption causes the difficulty of deciding the window size. And impalpable questions are raised, like How to guarantee the size adopted always coincides with the stationary time scales? What can be learned about the variations longer than the local time scales?

2.3.2 Scalogram

In the case of STFT, once a window is chosen for the analysis, the time-frequency resolution is fixed over the entire time-frequency plane. Many signals require a more flexible approach, where we can vary the window size to determine more accurately either time or frequency. To give better time-frequency resolution, wavelet analysis has been developed [27]. It has been widely used in radar signal processing, such as correlator detection [28], time-varying spectrum estimation [29], SAR and ISAR imaging [30], wideband processing [31], and target detection [32, 33].

Instead of a fixed window function in STFT, the wavelet approach is essentially an adjustable window Fourier spectral analysis, as in Fig. 2-4, with the following general definition

$$S_{\text{wavelet}}(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t) \psi\left(\frac{t-b}{a}\right) dt \quad (2.9)$$

where ψ is called ‘mother wavelet’, a is the dilation parameter, and b the translation parameter. Even though time and frequency do not appear explicitly in this equation, the variable $1/a$ gives the frequency scale and b gives the temporal location of an event. An intuitive physical explanation of equation is very simple: $S_{\text{wavelet}}(a, b)$ is the instantaneous energy of time series $s(t)$ of scale a at $t = b$.

The energy density function of a wavelet transform, called a scalogram, is defined as

$$S_{\text{scalogram}}(a, b) = |S_{\text{wavelet}}(a, b)|^2 \quad (2.10)$$

Figure 2-4 Wavelet view of a signal.

The main improvement of scalogram to spectrogram lies in the shape of the window function. In spectrogram, the window $e^{-j\omega\tau}h(\tau-t)$ used to measure the signal's time-frequency property is made up of a time-shifted and frequency-modulated single prototype function $h(t)$. Therefore, all elementary functions have the same envelope, regardless of the frequency value. Once $h(t)$ is chosen, both the time and frequency resolutions of the elementary functions are fixed. On the other hand, the window

functions $\psi(a^{-1}(t-b))$ used in scalogram have different shapes adapted to their frequencies: high frequency window is narrow, while low frequency window are much broader. This indicates that both time and frequency resolutions depend on the frequency: the frequency resolution (time resolution) becomes poorer (better) as the analysis frequency grows. Result is clearly shown in Fig 2-5.

Figure 2-5 Scalogram of the pure Doppler signal.

The scalogram of the Doppler signal has an asymmetric and frequency-dependent shape, unlike its spectrogram. With a more localized frequency resolution, especially in lower frequencies. The instantaneous Doppler law can be estimated more accurately, in spite of the poor time resolution.

Similar to STFT, in wavelet transform, the mother wavelet has to be chosen beforehand and cannot be changed during the analysis. The important step of choosing the mother wavelet for a particular signal requires a great amount of judgments. Both spectrogram

and scalogram compute correlations between the signal and a family of window functions. The time-frequency resolution of these methods is thus determined by a corresponding set of elementary functions. Since the relationship between the time and frequency resolutions of any given function is governed by the Heisenberg uncertainty principle, neither spectrogram nor scalogram can achieve arbitrary fine resolutions in both time and frequency simultaneously. In other words, the better the time resolution, the poorer the frequency resolution, and vice versa.

To analyze the nonstationary signals, these window methods are based on the assumption of short-time stationarity of the signal. This has serious drawback that the length of the assumed short-time stationarity determines the frequency resolution which can be obtained. To increase the frequency resolution, a longer measurement interval has to be considered, which in turn means that non-stationarities occurring during this interval will be smeared out in time and frequency.

Since spectrogram and scalogram are quadratic TFA, they may be affected by the so-called cross-term. For a multicomponent signal, for example $s(t) = s_1(t) + s_2(t)$, the corresponding time-frequency distribution $S_s(\omega, t)$ is

$$S_s(\omega, t) = S_{s_1}(\omega, t) + S_{s_2}(\omega, t) + 2 \operatorname{Re}\{S_{s_1, s_2}(\omega, t)\} \quad (2.11)$$

Obviously, $S_s(\omega, t)$ of this two-component signal is the sum of each component's time-frequency distribution, i.e. two auto-terms, added to one cross-term $S_{s_1, s_2}(\omega, t)$. The cross-terms in the spectrogram and the scalogram are oscillatory structures, which are restricted to those regions of the time-frequency plane where the corresponding auto representations (signal terms) overlap. Hence, if two signal components are sufficiently

far apart in the time-frequency plane, their cross-terms will be essentially zero [34]. This property is generally deemed desirable.

2.3.3 Wigner-Ville Distribution

Besides the above TFA techniques, Wigner-Ville Distribution (WVD) is a good choice due to its potential for high resolution. WVD possesses a perfect localization in the time-frequency plane, and satisfies a number of desirable theoretical properties [10]. It accomplishes those constraints in spectrogram and scalogram and is quite efficient in many radar applications [35-37].

WVD is no more a correlation-based approach as the previous two. It is a different type of time-frequency distribution that is motivated by the time-frequency energy density, defined as

$$S_{WVD}(\omega, t) = \int_{-\infty}^{\infty} s\left(t + \frac{\tau}{2}\right) s^*\left(t - \frac{\tau}{2}\right) e^{-j\omega\tau} d\tau \quad (2.12)$$

where $s^*(t)$ is the complex conjugate of $s(t)$.

Compared with spectrogram and scalogram, WVD gives a better time-frequency resolution, without any smearing of the frequencies due to the window effect. There are no predetermined window functions, so there is no loss of resolution in WVD. Moreover, WVD possesses many remarkable properties desirable for time-frequency analysis.

Since WVD is the Fourier transform with respect to τ of the central covariance function $s(t + \tau/2)s^*(t - \tau/2)$, it is a measure of the signal's local time-frequency energy. It can exactly localize sines or Dirac impulses; this is not the case for spectrogram and scalogram.

WVD can give out the instantaneous frequency of the analyzed signal. This is a very attractive property for radar signal extraction. We assume signal $s(t) = A(t)\exp\{j\phi(t)\}$, where $A(t)$ and $\phi(t)$ denote its instantaneous amplitude and phase, respectively. Then $\phi'(t)$, considered as the instantaneous frequency, is equal to the mean frequency of WVD at any time instant t .

$$\phi'(t) = \frac{\int \omega WVD(t, \omega) d\omega}{\int WVD(t, \omega) d\omega} \quad (2.13)$$

Unfortunately, WVD does not satisfy the positive distribution property for all signals, except for the Gaussian function. This non-positive property prevents an energy interpretation of WVD.

Figure 2-6 Wigner-Ville distribution of the pure Doppler signal.

One major disadvantage of WVD is that the existence cross-term interference limits its applications a lot. As shown in Fig. 2-6, we can see that although the signal terms are well-localized in the time-frequency plane, cross-terms due to the quadratic nature of

WVD are present at positions in the time-frequency plane where the energy should be zero. The cross-terms have a rather big energy and make the interpretation difficult. It is hard to distinguish the cross-terms without prior knowledge of the distribution.

In order to remove the cross-term, smoothing windows are applied, resulting in other Wigner-type quadratic TFA of Cohen's class. For example, in 1994, Stankovic proposed in [38] a method for the computation of the smoothed pseudo Wigner-Ville distribution (SPWVD) defined in the frequency domain. He showed that this method provides some substantial advantages over the WVD, since the effects of the cross-terms associated with the WVD were reduced significantly. SPWVD is defined as

$$S_{SPWVD}(\omega, t) = \int_{-\infty}^{\infty} h(\tau) \int_{-\infty}^{\infty} g(u - t) s(u + \frac{\tau}{2}) s^*(u - \frac{\tau}{2}) du \cdot e^{-j\omega\tau} d\tau \quad (2.14)$$

Although smoothing of WVD can greatly suppress the cross-terms, it will reduce the time-frequency resolution. Under some conditions, the resulting smoothed WVD becomes a spectrogram and no longer possess WVD's advantages of signal localization. A trade-off exists between the degree of smoothing and the resolution.

Table 2-1 Comparison of spectrogram, scalogram and WVD.

Methods \ Aspects	spectrogram	Scalogram	WVD
Time-frequency resolution	Poor	Average	High
Trade-off in time and frequency resolution	Better time resolution → worse frequency resolution, vice versa		Independent
Cross terms	Not obvious		Severe

As it turns out, none of these TFA techniques are effective for every signal class. Each method offers advantages and disadvantages. Their characteristics are briefly listed in Table 2-1.

2.4 Problems of All Quadratic Time-Frequency Analysis Methods

The above section has reviewed three typical quadratic TFA methods, and there are many other quadratic TFA methods being used for radar signal processing. With respect to all these quadratic TFA methods, their common limitations are:

- 1) Linearity is violated in quadratic TFA methods. That means, there are cross-terms between two signal components in the time-frequency distributions of the sum. This quadratic superposition principle can be generalized to an N -component signal. That is, for an N -component signal $s(t)$, the TFA will comprise N signal terms and $\frac{N(N-1)}{2}$ cross-terms. Note that the number of terms grows quadratically with the number of signal components, which is a fact that often makes the visual analysis of the TFT of the signal difficult.
- 2) Most of quadratic TFA methods are based on Fourier spectral analysis, therefore they suffer from the limitations of the Fourier analysis. “The most widely used signal processing tool is the FFT (Fast Fourier Transform); the most widely misused signal processing tool is also the FFT” [8]. One prominent shortcoming of Fourier spectral analysis is that it assumes linearity and stationarity of the time series. Assuming stationarity, in particular, is generally not warranted for radar signals that are under consideration in our study. Additionally, Fourier transform expands the analyzed signal into the orthogonal basis functions (i.e. sine and cosine waves)

globally to the entire data set. It is rather a successful mathematic method of signal analysis. For nonstationary signals like radar signals, it often loses their physical meaning.

- 3) When the energy of interference and target signal are distributed separately, we can visually separate them in the time-frequency domain by applying quadratic TFA methods. However in the case of the overlap of the spectrum of the moving target and those of interferences, they fail to extract the desired target. Consequently, the motion parameters may not be measured successfully.
- 4) Quadratic TFA methods cannot directly reveal the instantaneous Doppler frequency. Their time-frequency resolution is restrictive because of the trade-off between it and interference level. Higher time-frequency resolution will bring out more cross-terms, but suppressing the cross-terms results in a decrease in the time-frequency resolution with a loss of some theoretical properties.

2.5 Summary

In this chapter, a concise review of time-frequency analysis is provided as background. We then describe and illustrate the advantages of using time-frequency analysis techniques to analyze radar signals. It is clearly demonstrated that time-frequency analysis techniques can significantly improve the detection performance of radar and add considerable physical insight over what can be achieved by conventional time or frequency processing methods. We compare the ability of three typical TFA methods, i.e. the spectrogram, scalogram and Wigner-Ville distribution, for radar signal processing. An example of detecting a target in ideal environment (no noise and clutter) is used for

simulation. As it turns out, each of these approaches fails in one way or another. Spectrogram and scalogram cannot give a high resolution both in time and frequency, due to the Heisenberg uncertainty principle. WVD gives a much higher resolution by extracting local characteristics of the signal, while it suffers from the severe cross terms induced by their quadratic form. All the quadratic TFA methods have some common limitations which prohibit their efficiency for radar signal processing.

To solve these problems, we attempt to offer a new TFA method. This new method is expected to be very efficient of extracting signal from clutter and noise in spite of the complexity of radar application environment. At the same time, the new TFA method is anticipated to give a higher resolution than traditional TFA techniques. To give a local and accurate presentation of both time and frequency information of a target signal, this TFA method should capture the nonstationary nature of the signal well. There will be significant improvements in signal feature extraction if the exact instantaneous Doppler frequency can be obtained.

Fortunately, a new method for nonlinear and nonstationary signal analysis, named Hilbert Huang Transform (HHT) seems to have such properties. The key feature of the HHT is a time domain decomposition named Empirical Mode Decomposition (EMD), which provides a unique basis for expansion of the signal, derived from and based on the signal. After this preprocess, the analyzed signal will be decomposed into intrinsic oscillatory modes which have different physical meanings. Thus the target signal may be extracted from clutter and noise before time-frequency analysis. The decomposed components, called Intrinsic Mode Function (IMF), allow the calculation of a meaningful instantaneous frequency with Hilbert transform and can probe thoroughly the local properties of the signal.

The HHT is first invented by N. E. Huang and his colleagues [39, 40]. It has been successfully used already in earthquakes, brain wave disturbances in epileptic seizures, turbulence in blood flow, astronomical effects on tides, El Nino effects on large scale changes in the Pacific, sound and vibration analysis, to name just a few[41-49]. It is a very efficient technique for analyzing nonlinear and nonstationary signals, different from other techniques based on Fourier transform. Because of the nonstationary characteristic of radar signal, this novel approach may bring lots of benefits in radar signal processing. In the following chapter, concept of this new method will be given out.

CHAPTER 3

A NOVEL TIME DOMAIN DECOMPOSITION BASED TIME-FREQUENCY ANALYSIS

3.1 Hilbert Transform and Instantaneous Frequency

The frequency of a sinusoidal signal is a well-defined quantity. However, the radar signals are nonstationary signals, which are not truly sinusoidal, or even aggregates of sinusoidal components. At this time, the notion of frequency loses its effectiveness, and one needs to use instantaneous frequency [50] to account for the time-varying nature of radar signals.

The notion of the “instantaneous frequency” has been highly controversial. Existing opinions range from editing it out of existence [51] to accepting it but only for special ‘monocomponent’ signals [9, 50]. One difficulty of accepting the idea of instantaneous frequency arises from the non-unique way in defining it. Nevertheless, this difficulty is no longer serious since the introduction of the means to make the data analytical through the Hilbert transform.

For an arbitrary time series, $X(t)$, we can always have its Hilbert Transform, $Y(t)$, as

$$Y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{X(\tau)}{t - \tau} d\tau \quad (3.1)$$

where P indicates the Cauchy principal value.

With this definition, $X(t)$ and $Y(t)$ form the complex conjugate pair, so we can have an analytic signal, $Z(t)$, as

$$Z(t) = X(t) + jY(t) = a(t)e^{j\theta(t)} \quad (3.2)$$

in which

$$a(t) = \sqrt{X^2(t) + Y^2(t)} \quad (3.3)$$

$$\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right) \quad (3.4)$$

Theoretically, there are infinitely many ways of defining the imaginary part, but the Hilbert transform provides a unique way of defining the imaginary part so that the result is an analytic function. In the frequency domain, this method for doing so is first to find the Fourier Transform of the real signal and then suppress the amplitudes belonging to negative frequencies and multiply the amplitudes of positive frequencies by two.

Essentially (3.1) defines the Hilbert transform as the convolution of $X(t)$ with $1/t$; therefore, it emphasizes the local properties of $X(t)$. In (3.2), the polar coordinate expression further clarifies the local nature of this representation: it is the best local fit of an amplitude and phase varying trigonometric function to $X(t)$. Thus we generate a unique complex signal from a real signal and obtain its instantaneous amplitude $a(t)$ and instantaneous phase $\theta(t)$.

Even with the Hilbert transform, there is still considerable controversy in defining the instantaneous frequency as

$$f = \frac{1}{2\pi} \frac{d\theta(t)}{dt} \quad (3.5)$$

This leads Cohen [9] to introduce the term, ‘monocomponent function’. In principle, some limitations on the data are necessary, for the instantaneous frequency given in (3.5) is a single value function of time. At any given time, there is only one frequency value; therefore, it can only represent one component, hence ‘monocomponent’. Unfortunately, no clear definition of the ‘monocomponent’ signal was given to judge whether a function is or is not ‘monocomponent’.

In order to obtain meaningful instantaneous frequency, restrictive conditions have to be imposed on the data as discussed by [26, 52] and, more recently, [50]: for any function to have a meaningful instantaneous frequency, the real part of its Fourier transform has to have only positive frequency.

Detailed discussions are given by [39, 40]. It is illustrated that the necessary conditions to define a meaningful instantaneous frequency are that the functions are symmetric with respect to the local zero mean, and have the same numbers of zero crossings and extrema. This suggests a method to decompose the complicated data into components such that they all satisfy the conditions imposed on them. Reference [39] proposed a definition for such components, designated as intrinsic mode functions.

3.2 Intrinsic Mode Functions

An Intrinsic Mode Function (IMF) is a function that satisfies two conditions:

- 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.

The first condition is similar to the traditional narrow band requirements for a stationary Gaussian process. The second condition is a new idea; it modifies the classical global requirement to a local one; it is necessary so that the instantaneous frequency will not have the unwanted fluctuations induced by asymmetric waveforms.

Ideally, the requirement should be ‘the local mean of the data being zero’. For nonstationary data, the ‘local mean’ involves a ‘local time scale’ to compute the mean, which is impossible to define. As a surrogate, the local mean of the envelopes defined by the local maxima and the local minima is used to force the local symmetry instead. This is a necessary approximation to avoid the definition of a local averaging time scale.

The name ‘intrinsic mode function’ is adopted because it represents the oscillation mode imbedded in the data. With this definition, the IMF in each cycle, defined by the zero crossings, involves only one mode of oscillation, no complex riding waves are allowed. With this definition, an IMF is not restricted to a narrow band signal, and it can be both amplitude and frequency modulated. In fact, it can be nonstationary. As discussed above, purely frequency or amplitude modulated functions can be IMFs even though they have finite bandwidth according to the traditional definition.

In order to use this unique definition of instantaneous frequency, we have to reduce an arbitrary data set into IMF components from which an instantaneous frequency value can be assigned to each IMF component. Consequently, for complicated data, we can have more than one instantaneous frequency at a time locally. We will introduce the empirical mode decomposition method to reduce the data into the needed IMFs.

3.3 Empirical Mode Decomposition

Empirical mode decomposition is a new method to deal with both nonstationary and nonlinear data by decomposing the signal. Contrary to almost all the previous methods, this new method is intuitive, direct, posteriori and adaptive, with the basis of the decomposition based on, and derived from, the data.

The decomposition is based on the assumptions:

- 1) The signal has at least two extrema----one maximum and one minimum;
- 2) The characteristic time scale is defined by the time lapse between the extrema;
- 3) If the data were totally devoid of extrema but contained only inflection points, then it can be differentiated once or more times to reveal the extrema. Final results can be obtained by integration(s) of the components.

The essence of the method is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically, and then decompose the data accordingly. According to [53], the first step of data analysis is to examine the data by eye. From this examination, one can immediately identify the different scales directly in two ways: by the time lapse between the successive alternations of local maxima and minima; and by the time lapse between the successive zero crossings. The interlaced local extrema and zero crossings give us the complicated data: one undulation is riding on top of another, and they, in turn, are riding on still other undulations, and so on. Each of these undulations defines a characteristic scale of the data; it is intrinsic to the process. We have decided to adopt the time lapse between successive extrema as the definition of the time scale for the intrinsic oscillatory mode, because it not only gives a much finer resolution of the oscillatory modes, but also can be applied to data with non-zero mean,

either all positive or all negative values, without zero crossings. A systematic way to extract them, designated as the sifting process, is described as follows.

By virtue of the IMF definition, the decomposition method can simply use the envelopes defined by the local maxima and minima separately. Once the extrema are identified, all the local maxima are connected by a cubic spline line as the upper envelope. Repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. Their mean is designated as m_1 , and the difference between the data and m_1 is the first component, h_1 , i.e.

$$X(t) - m_1 = h_1 \quad (3.6)$$

The procedure is illustrated in Fig. 3-1.

The sifting process serves two purposes: to eliminate riding waves; and to make the wave-profiles more symmetric. Toward this end, the sifting process has to be repeated more times. In the second sifting process, h_1 is treated as the data, then

$$h_1 - m_{11} = h_{11} \quad (3.7)$$

We can obtain a much improved result after the second sifting, but in most time it is not an IMF yet. We can repeat this sifting procedure k times, until h_{1k} is an IMF, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \quad (3.8)$$

Then, it is designated as

$$c_1 = h_{1k} \quad (3.9)$$

the first IMF component from the data.

Figure 3-1 Illustration of the sifting process. (a) The original data. (b) The original data (thin solid line), the upper and the lower envelopes (dot-dashed lines), and their mean (thick solid line) which bisects the data very well. (c) The difference between the data and the local mean as in (3.6).

As described above, the process is indeed like sifting: to separate the finest local mode from the data first based only on the characteristic time scale. Overall, c_1 should contain the finest scale or the shortest period component of the signal. We can separate c_1 from the rest of the data by

$$X(t) - c_1 = r_1 \quad (3.10)$$

Since the residue, r_1 , still contains information of longer period components, it is treated as the new data and subjected to the same sifting process as described above. This procedure can be repeated on all the subsequent r_j s, and the result is

$$r_1 - c_2 = r_2, \dots, r_{n-1} - c_n = r_n \quad (3.11)$$

The sifting process can be stopped by any of the following predetermined criteria: either when the component, c_n , or the residue, r_n , becomes so small that it is less than the predetermined value of substantial consequence, or when the residue, r_n , becomes a monotonic function from which no more IMF can be extracted. Even for data with zero mean, the final residue can still be different from zero; for data with a trend, then the final residue should be that trend. By summing up (3.10) and (3.11), we finally obtain

$$X(t) = \sum_{i=1}^n c_i + r_n \quad (3.12)$$

Thus, we achieved a decomposition of the data into n-empirical modes, and a residue, r_n , which can be either the mean trend or a constant. The complete EMD procedure is briefly shown Fig. 3-2.

3.4 Hilbert Spectrum Analysis

Having obtained the intrinsic mode function components, we will have no difficulties in applying the Hilbert transform to each component, and computing the instantaneous frequency according to (3.5). After performing the Hilbert transform on each IMF component, we can express the data in the following form:

$$X(t) = \sum_{i=1}^n a_i(t) \exp\left(j \int \omega_i(t) dt\right) \quad (3.13)$$

Here we have left out the residue, r_n , on purpose, for it is either a monotonic function, or a constant. Although the Hilbert transform can treat the monotonic trend as part of a longer oscillation, the energy involved in the residual trend could be overpowering. In consideration of the uncertainty of the longer trend, and in the interest of information contained in the other low-energy and higher-frequency components, the final non-IMF

component should be left out. It, however, could be included, if physical considerations justify its inclusion.

Figure 3-2 Flowchart of the empirical mode decomposition.

Eq. (3.13) gives both the amplitude and the frequency of each component as functions of time. The same data if expanded in Fourier representation would be

$$X(t) = \sum_{i=1}^{\infty} a_i e^{j\omega_i t} \quad (3.14)$$

with both a_i and ω_i constants. The contrast between (3.13) and (3.14) is clear: the IMF represents a generalized Fourier expansion. The variable amplitude and the instantaneous frequency have not only greatly improved the efficiency of the expansion, but also enabled the expansion to accommodate nonstationary data. With IMF expansion, the amplitude and the frequency modulations are also clearly separated. Thus, we have broken through the restriction of the constant amplitude and fixed-frequency Fourier expansion, and arrived at a variable amplitude and frequency representation. This expression is numerical. If a function is more desired, an empirical polynomial expression can be easily derived from the IMFs.

Eq. (3.13) also enables us to represent the amplitude and the instantaneous frequency as functions of time in a three-dimensional plot, in which the amplitude can be contoured on the frequency-time plane. This frequency-time distribution of the amplitude is designated as the Hilbert amplitude spectrum, $H(\omega, t)$, or simply Hilbert spectrum. If amplitude squared is more desirable commonly to represent energy density, then the squared values of amplitude can be substituted to produce the Hilbert energy spectrum just as well.

3.5 Validation of Empirical Mode Decomposition and Hilbert Spectrum

Through the empirical mode decomposition and the associated Hilbert spectral analysis we obtained the probabilistic Hilbert spectrum representation of the nonstationary data. The HHT method is wholly different from other TFA because the result produced by the HHT is the only one that is adaptive (with no *a priori* basis assigned), and time varying

(the frequency is a function of time define by differentiation rather than convolutionary analysis as in the Fourier type analysis). Now, we will validate the approach and the results, to see whether it is efficient for radar signal processing.

Radar signals are multicomponent signals composed of target signal, clutter and noise. The basis of good radar signal processing result is effective target signal extraction from background interference. Now by applying EMD, the signal of the moving target is expected to be extracted from strong clutter echoes and noise on the time domain. To show the advantage of EMD for extracting the desired signal, we will examine three cases. The first case is an amplitude modulated signal. The second case is a multicomponent signal. The third case is a signal present in noise.

3.5.1 Amplitude Modulated Signal

In radar application, the amplitude of the signal sequence always expands in a big range. The irregular trend of the signal can bring a DC component with big energy. This is a zero Doppler frequency mainly returned by stationary objects distributed everywhere. The trend also lies in the coupling effect of the reflected signal from different directions. Now we will use a simple sinusoidal signal S_1 with a sharp drift to emulate such kind of problem and to see whether EMD can isolate the desired signal and the irregular trend.

As discussed here, to apply the EMD method, a mean or zero reference is not required; EMD only needs the locations of the local extrema. The zero references for each component will be generated by the sifting process. Without the need of the zero reference, EMD eliminates the troublesome step of removing the mean values for the large DC term in data with non-zero mean, an unexpected benefit.

Figure 3-3 EMD result of signal S_1 with sharp drift in its amplitude.

Fig. 3-3 shows the EMD result of S_1 . It has been decomposed into one IMF and the residue. The IMF is mainly the pure sinusoidal component of the signal. And the drift in amplitude has been successfully extracted from original signal. The small fluctuations are caused by spline numerical interpolations in sifting process.

Figure 3-4 Frequency analysis of the original signal S_1 .

We use traditional Fourier transform to present the signal on the frequency domain. As it is clearly shown in Fig. 3-4, there are mainly two frequency components. One is the frequency of the sinusoidal component. The other is a DC component caused by the amplitude drift. It induced a lot of harmonics besides the DC too. If the DC component and its associated harmonics are large enough, desired frequency component will be hard to be distinguished.

Figure 3-5 Scalogram for raw S_1 .

Figure 3-6 Scalogram for the extracted IMF from S_1 .

To show the ability of EMD for extracting desired signal from S_1 , we compare the scalogram of the original S_1 (Fig. 3-5) and the extracted IMF (Fig. 3-6). It should be noted that the whole frequency distribution is shifted a bit towards the positive direction in order to show the DC component clearly.

In Fig. 3-5, we can see severe smearing of the frequency due to lots of harmonics. The energy of DC components is as big as the desired signal. If the signal frequency has a small offset to the DC frequency, it will become very difficult to extract the desired frequency information.

However, with the help of the time domain decomposition, the frequencies produced by the signal trend are greatly eliminated. In Fig. 3-6, we can see a clean and accurate frequency component, which is just the wanted information.

3.5.2 Multicomponent Signal

Radar signal is a compound signal which is composed of a great many of signals at any time. More than one moving target in the background may produce a complicated Doppler frequency spectrum. In the second validation we choose a simple signal S_2 of two sinusoidal components with different frequency values. We aim to simply test the efficiency of EMD to separate components with different frequencies so as to get the desired target signal and greatly suppress the interference from other moving targets. Additionally, if EMD works, a multicomponent signal may be decomposed into several monocomponent signals according to their different frequencies. Then, the cross terms in WVD will be removed without sacrificing WVD's high time-frequency resolution.

Figure 3-7 EMD result of signal S_2 consisting of two sinusoidal signals.

As shown in Fig. 3-7, after EMD the multicomponent signal has been accurately decomposed into two sinusoidal monocomponents with respective frequencies. In this example the residue appeared to be x axis. We have not presented it here since it gives no information.

Fig. 3-8 shows the WVD of the original S_2 . Although the two components of S_2 are well localized in the time-frequency plane, very clear cross-terms exist between the two auto-terms, which is a big trouble for signal interpretation and feature extraction.

After sifting, we apply WVD methods on S_2 and the two IMFs. Refer to Fig. 3-9, components with different frequencies are exactly separated by EMD, and WVD performance is greatly improved with no more visible cross terms. Thus the example

simply illustrates that the frequency sifting property offered by EMD may greatly improve the detectability of signal from clutter. A practical example is the target identification on the ground.

Figure 3-8 WVD for the original S_2 .

Figure 3-9 (a) WVD of IMF1 from S_2 . (b) WVD of IMF2 from S_2 .

3.5.3 Noisy Signal

Now we come to another validation of the EMD for de-noising. The signal-to-noise ratio (SNR) at the radar receiver is determined by the received power reflected from the target, the noise feature, and the bandwidth of the receiver. Improvement in the SNR will increase the probability of target detection and the accuracy of feature estimation.

The third signal S_3 to be tested is a sinusoidal signal emerged into a white Gaussian noise. It is assumed that $\text{SNR}=0$ dB. EMD has been shown very useful to perform the noise cancellation. Results are shown in Figs. 3-10, 3-11 and 3-12.

Figure 3-10 EMD result of signal S_3 emerged into a 0 dB white Gaussian noise.

We can see from Fig. 3-10, the deified signal is decomposed into two IMFs and one residue. IMF1 is mainly the white Gaussian noise and IMF2 is mainly the sinusoidal signal. The residue with a small value can be ignored. We choose IMF2 as the desired signal for analysis and compare the WVDs of original signal and extracted signal. Distinctly, most of noise has been eliminated. So EMD is validated to be useful for noise cancellation.

With all these preliminary results, we can tell that EMD is quite an efficient approach to extract target signal from unwanted clutter and noise interferences. Sometimes matched filter approach is used to extract the desired signal in radar signal processing. However, in order to design an ideal match filter we need *a priori* knowledge of all signal features. In practice we can hardly get or know all the *a priori* knowledge about the signals,

therefore we need to investigate the method which can filter the received signal according to its characteristics for different applications, in order to improve the detection performance. EMD offers an approach of suppressing background clutters and noises based on their different intrinsic oscillatory mode with the moving target signals. Thus EMD is a *posteriori* and adaptive filter based on the intrinsic characteristic of each received signal.

Figure 3-11 WVD of the original signal S_3 .

Figure 3-12 WVD of the IMF2 extracted from S_3 .

EMD's advantages are more than that. After the decomposition, each IMF admits well-behaved Hilbert transforms thus instantaneous frequency can be obtained. With the help of EMD, we can represent the signal with very high time-frequency resolution in the associated Hilbert spectrum.

Figure 3-13 Hilbert spectrum of the pure Doppler signal.

We use the pure Doppler signal described in Section 2.3 again here to compare its Hilbert spectrum with the TFA methods discussed before. As we can see from the following Fig. 3-13, Hilbert spectrum provides a much higher time and frequency resolution than any other time-frequency distributions. In the Hilbert spectrum, two frequency components are accurately localized in the time-frequency plane. The exact frequency value at each time instant is revealed since it is the instantaneous frequency.

3.6 Summary

In this Chapter, we have introduced the HHT approach based on time domain decomposition for radar signal processing. Knowledge and techniques corresponding to the empirical mode decomposition and Hilbert spectral analysis are explained.

We have shown the results of analysis for an amplitude modulated signal, a multicomponent signal, a noisy signal and the pure Doppler signal. It is illustrated that the HHT is very efficient for target detection and feature extraction. EMD decomposes radar signal in the time domain. This enables us to pick up the desired signal and abandon the interference signals before implementing time-frequency transforms. With the successful extraction of signal, we can efficiently apply Hilbert spectrum analysis even if the interference spectrum submerges the signal's spectrum, when the other TFA techniques failed. On the other hand, the decomposed components allow the calculation of a meaningful instantaneous frequency. Thus the Hilbert spectrum can give a local and accurate presentation of both time and frequency information, with a much higher resolution other TFA techniques can hardly achieve. In the following Chapters, we will try to modify and implement the HHT in practical radar signal processing applications.

CHAPTER 4

GROUND MOVING TARGET INDICATION IN FOLIAGE ENVIRONMENT WITH THE HILBERT HUANG TRANSFORM

4.1 Ground Moving Target Indication in Foliage Environment

The ability of traditional microwave radars in operating in an environment with dense foliage is severely limited by foliage backscatters and attenuation of microwave frequencies through foliage. As attenuation and foliage backscatter fall with increasing wavelength, lower frequencies such as those in the VHF and UHF bands (30 MHz – 1000 MHz) may be suitable for Foliage PENetration (FOPEN) radar applications [54].

Some propagation studies on FOPEN have been conducted and empirical results have been derived by various agencies such as FOA and MIT Lincoln Laboratory in places such as Panama, Maine, California, Michigan and Pennsylvania [55-59]. Most of the studies were concentrated on temperate vegetation. In equatorial vegetation, there might be some differences due to the high biomass, high humidity (e.g. relative humidity is typically above 80%) and numerous rain seasons (as much as 1,000 centimeters of rain annually), which for instance, tend to increase the backscatter and the attenuation. On the other hand, dense undergrowth in equatorial vegetation may limit the double bounce effects created by the trunks and wet soil by attenuating the signal before it reaches the soil. Hence, these uncertainties drive the researchers of Radar Laboratory of Nanyang

Technological University into investigating and modeling of the foliage parameters in Singapore [60].

The scope of their work includes field measurements in Singapore using different methodologies, such as one-way propagation measurement, backscattering measurements, GMTI (Ground Moving Target Indication) and boomSAR (Synthetic Aperture Radar) measurements.

In this Chapter we focus on the GMTI in foliage environment. The concept about airborne surveillance of enemy ground forces with a ground moving target indicator radar, was proposed in 1968 [61]. Ground surveillance radar systems are tasked with detecting moving vehicles on the surface of the earth. This function of radar system is known as ground moving target indication. Ideally, GMTI radar maintains coverage of a large area, necessitating a high area coverage rate with frequent revisits to specific regions of interest. Traditionally, GMTI radars have been implemented using airborne (aircraft) platform.

In this Chapter the HHT is proposed to improve the performance of GMTI in foliage environment. In the next section, we address the problems of the TFA methods for FOPEN GMTI. Section 4.3 presents the radar signal model of forest vegetation. Then the HHT is implemented to extract Doppler frequency information using the simulative signal and the results are reported. To further prove its efficiency, in Section 4.4, the HHT is applied on the experimental data from the GMTI trial. Finally the conclusion is drawn in Section 4.5.

4.2 Traditional Time-Frequency Analysis Methods for Ground Moving Target Indication in Foliage Environment

By revealing time-varying frequency information embedded in radar signals, TFA methods have been successfully applied to improve radar performance for moving target indication and Doppler frequency representation [12]. However, to clearly and locally represent the Doppler frequency of moving targets in dense foliage environment is still a great challenge for traditional TFA methods. Their abilities are severely limited because of the strong backscatters and attenuation of microwave frequencies through foliage.

Backscatters from relatively motionless parts of the tree trunks near ground level as well as those from the ground surface itself compose the strong zero-Doppler in the spectral power. Meanwhile, the backscatters from higher parts of tree trunks and major limbs flexing slightly at very slow rates compose of the quasi-dc, which spread at a certain frequency band. However the energy reflected from moving targets is sharply weakened by foliage backscatter, prohibitive foliage-induced attenuation and the multipath effects. All these make the Doppler frequency very difficult to be clearly shown in the time-frequency domain.

To solve the problem, we should suppress the energy of disturbance (clutter and noise) while preserving the Doppler information. However the spectral signature of the target is unknown *a priori* because of its dependence upon unmeasured environmental variables, uncertainties in factors affecting the emissivity and reflectivity of the target's surface, as well as the unknown operating history. Obviously, it is a challenge to find a robust method for the disturbance rejection and target signal extraction.

Another major drawback of traditional TFA methods is that they cannot locally and accurately represent the Doppler frequency. The requirement for locality is much crucial for radar signals, since there is no time scale in such nonstationary data. Therefore, all events have to be identified by the time of their occurrences. Consequently, we require both the amplitude and the frequency to be functions of time. Unfortunately the time-frequency resolution of traditional TFA methods cannot be high enough to offer the instantaneous amplitude and frequency because of their intrinsic characteristics. Moreover, for most time-frequency transforms, the rectangular tiling of the time-frequency plane does not match the shape of many FOPEN radar signals. For those basis decomposition techniques such as the wavelet, the basis function, “mother” wavelet, is fixed during the signal processing and does not necessarily match varying nature of signals. In this regards, the nonstationary radar signals are just successfully represented in a mathematical way. A local representation of Doppler frequency with more physical meaning is expected for accurate motion parameters estimation. Thus, the HHT technology is investigated to alleviate these problems with traditional TFA methods.

4.3 Simulation Results and Analysis

In order to validate the proposed HHT in a statistical way, we will apply it to the signals generated from a general signal model of forest vegetation in this section.

The simulative received signal is composed of signal $s = \alpha p$ and disturbance d . Here p is a perfectly known complex vector with components $[p]_i = \exp(j2\pi i f_d T)$, $0 \leq i \leq N-1$, where f_d is the target Doppler frequency. f_d is assumed to be known. We assume α to be a circular complex Gaussian random variable with zero mean and variance σ_α^2 , which corresponds to the Swerling I target model.

The disturbance d is a mixture of clutter and noise as follows: $d = c + n$. The results obtained from the windblown trees data reported in [62] show the clutter to be approximately Gaussian distributed. So clutter c is characterized by a complex Gaussian probability distribution function with zero mean, variance $\text{var}\{c_i\} = \sigma_c^2$, and normalized covariance matrix M_c (i.e., $[M_c]_{ii} = 1$ for $i = 1, 2, \dots, N$). In shorthand notation we write $c \sim CN(0, \sigma_c^2 M_c)$. The thermal noise n is a complex circular random vector of uncorrelated Gaussian random variables, with zero mean and variance σ_n^2 , i.e., $n \sim CN(0, \sigma_n^2 I)$, where I is $N \times N$ identity matrix. Under these hypotheses the vector d is Gaussian distributed, i.e. $d \sim CN(0, \sigma_d^2 M_n)$. M_n is the normalized covariance matrix, such that $E\{dd^H\} = \sigma_c^2 M_c + \sigma_n^2 I = \sigma_d^2 M_n$, where $\sigma_d^2 = \sigma_c^2 + \sigma_n^2$ is the total disturbance power. The elements of M_c are derived from the normalized correlation coefficient $\rho[\cdot]$ as $[M_c]_{ik} = \rho[k-i]$, for $i, k = 1, 2, \dots, N$, which is obtained by inverse Fourier transforming the Power Spectral Density (PSD) function.

The PSD modeling information of the windblown foliage clutter is measured by MIT Lincoln Laboratory [63] on the statistical analysis of 29,558 measured clutter histograms from the 1,733 pure patches. In contract to the widely-used spectral models, i.e. Gaussian and power-law, they introduced an exponential model to approximate the windblown foliage clutter spectral measurements. We generalize here the exponential model as following:

$$S(f) = \frac{\sigma_c^2 r}{1+r} \cdot \frac{\beta_1 \lambda}{4} \exp\left(-\frac{\beta_1 \lambda}{2} |f|\right) + \frac{\sigma_c^2}{1+r} \cdot \frac{\beta_2 \lambda}{4} \exp\left(-\frac{\beta_2 \lambda}{2} |f|\right) \quad -\infty < f < \infty \quad (4.1)$$

where λ is the radar transmission wavelength, β_1 and β_2 are the shape parameters of the two exponentials modeling the low-frequency power and the medium-high-frequency

power in the spectrum, respectively. Parameter r represents the ratio between the two components in the spectrum. The autocorrelation coefficient $\rho[\cdot]$ is given by

$$\rho[k] = \frac{r}{1+r} \cdot \frac{\sigma_c^2}{\left(\frac{4\pi T}{\beta_1 \lambda}\right)^2 k^2} + \frac{1}{1+r} \cdot \frac{\sigma_c^2}{\left(\frac{4\pi T}{\beta_2 \lambda}\right)^2 k^2} \quad (4.2)$$

Using this simple but complete model, we get simulative signals characterizing the complex physical phenomenon of windblown forest vegetation. Here is a typical result of the simulative signal. f_d is set to be 5 Hz and the signal to disturbance (clutter and noise) ratio is -30 dB. (Other parameters are also set to some reasonable values.)

Figure 4-1 Empirical mode decomposition result of simulative FOPEN data.

After applying the EMD, signal is decomposed into 6 IMFs and the residue. Both the original signal and the disintegrated components are shown in Fig. 4-1. The results prove EMD to be a sifting process which picks out the highest frequencies of the signal. Obviously, IMF1 and IMF2 have much higher frequencies than other components. They

mostly compose the random noise. Components from IMF4 to the residue oscillate so slowly that they may only contain very small frequencies. They especially contribute to the DC component.

Figure 4-2 Fourier Spectra of the original simulative FOPEN signal and its decomposed IMF3.

Figure 4-3 Hilbert spectrum of IMF3 of the simulative FOPEN signal.

IMF3 is found to contain the Doppler frequency by comparing the spectra of original signal and all decomposed components. As shown in Fig. 4-2 the spectrum of IMF3 just covers the Doppler value in the original spectrum. We use the Hilbert transform and get the Hilbert spectrum of IMF3 in Fig. 4-3. It gives a clear and proper instantaneous Doppler frequency oscillating around 5 Hz.

We changed the parameters and test the efficiency of the HHT many times. It is validated to be efficient in a large range for the GMTI in foliage environment. After this successful validation in a mathematical and statistical way, the HHT is to be applied in practical experimental data.

4.4 Experimental Results and Discussion

A set of foliage penetration radar data was collected by the Radar Laboratory in Nanyang Technological University, Singapore [60]. Fig. 4-4 is the configurations of measurement setup for GMTI trial. Two linearly polarized ultra-wideband antennas for transmission and reception are used respectively. During the GMTI foliage penetration experiment, both transmitter antenna and receiver antenna were kept stationary. They were installed on the top end of arm of the boom-lift. The boom-lift can extend its arm up to 32 meters high, thus different trials are carried out by adjusting the receiver and transmitter height, either above the canopy of the foliage or below the canopy.

Figure 4-4 Configurations of measurement setup for GMTI trial.

Figure 4-5 Photos of the GMTI trial in foliage environment.

A Network Analyzer (NA) was programmed to generate the transmitted signal and acquire the received signal. The NA is in a Continuous Wave mode, and time samples are acquired at a repetition rate compatible with the Doppler frequencies of interest. Because of the frequency restriction, only four frequencies at different height were tried. A laptop was used to drive the whole experiment, store the results and provide limited real time processing.

In the GMTI experiments, data sampling time is 16 seconds for each measurement. The moving truck with the corner reflector ran at velocity of 10-20 km/hour inside the forest. The truck ran along the same itinerary each time and entered the radar antenna detectable range at the time slot of around 2 second. Photos of the GMTI trial are given in Fig. 4-5.

When the signal is badly corrupted by the disturbance, the weak Doppler frequency information can hardly be revealed in the time-frequency domain. Even if target signal can be identified in the time-frequency domain, the signal is difficult to be isolated from disturbance when it is too close to the strong clutter. The quasi-dc component covers a certain frequency band. This Doppler spreading makes the slow moving target more difficult to be separated from zero-Doppler bin. We choose two data, i.e. GBHH1333 and GBHH1031, from this GMTI trial. They stand for the situations of weak Doppler signal and Doppler frequency with a small offset respectively.

4.4.1 Case 1: Weak Doppler Signal

Data GBHH1333 is received by transmitting a UHF signal above the forest canopy. The target signal is nearly buried in the noise level and its energy is much smaller than the strong clutter. Empirical mode decomposition has divided the signal into 5 IMFs and the residue. The final stop criterion is that residue has no more than 15 extrema.

From Fig. 4-6 we can clearly see that each IMF contains lower frequency oscillations than the one extracted just before. This just proved EMD is a sifting process, which picks out the highest frequency oscillation that remains in the signal each time.

Figure 4-6 EMD result of data GBHH1333.

For GBHH1333, the transmit frequency is 563 MHz and the velocity of the moving truck is at constant velocity between 10 to 20 km/hour. Doppler frequency should be in the

$$\text{range of } \left[\frac{2v_{\min} f_r}{c} = \frac{2 \times (10^4 / 3600) \times 563 \times 10^6}{3 \times 10^8}, \frac{2v_{\max} f_r}{c} = \frac{2 \times (20 \times 10^4 / 3600) \times 563 \times 10^6}{3 \times 10^8} \right] \approx [10, 20]$$

Hz. Fig. 4-7(a) gives the traditional time-frequency distribution of data GBHH1333. We used spectrogram here and the results of other methods are similar as in [64]. We can hardly find any information about the Doppler shift. But we can find a very weak peak in the received signal's frequency representation (Fig. 4-7(b)). It is in the range of [10, 20] Hz, and may designate the Doppler frequency. It is shown that even in a logarithmic scale, the Doppler frequency is hard to be separated from interferences. The ratio of the peak amplitude of clutter and Doppler signal is about 32 dB. To estimate which

component is mainly the target signal, we used FFT to obtain the frequency representations of all the IMFs and compared them with the frequency representation of original signal. Fig. 4-7(b) also shows that the second intrinsic mode function IMF2 has the peak value at the Doppler frequency range. Hence the Doppler information is mainly contained in the IMF2 component.

Figure 4-7 (a) Traditional time-frequency distribution of data GBHH1333. (b) The Fourier spectral comparison of original data and the extracted component.

We plot spectrogram, scalogram, SPWVD and Hilbert spectrum of the IMF2 respectively in Fig. 4-8. They show that the energy of IMF2 mainly distributes at the frequencies between 10 Hz and 20 Hz. After EMD, the extracted Doppler frequency became visible and feature estimation can be further carried on. By comparing the results, the traditional time-frequency distributions only give general information of Doppler frequency. The representations of the spectrum all smear in a large range. For these cases we cannot get clear Doppler frequency information.

Figure 4-8 Time-frequency distributions of IMF2 from GBHH1333. (a) spectrogram, (b) scalogram, (c) SPWVD, and (d) Hilbert spectrum.

Most traditional time-frequency distributions are based on Fourier transform which is on the basis of the properties of the function over the whole time span through integration. They represent the global rather than any local properties of the signal. However, Hilbert spectrum does not rely on the convolution any more. It probes thoroughly the local properties of the signal, for both amplitude and frequency obtained by Hilbert transform are functions of time. As in Fig. 4-8 the instantaneous Doppler frequencies perfectly localize in the time-frequency domain. The Hilbert spectrum gives a higher resolution in time and frequency than prior distributions, almost with no smearing in frequencies.

A 3-D view of time-frequency distributions of IMF2, respectively as spectrogram, scalogram, SPWVD and Hilbert spectrum are depicted in Fig. 4-9. The comparisons of amplitude are more obvious than the 2-D view in Fig. 4-8.

(a)

(b)

(c)

Figure 4-9 3-D view of time-frequency distributions of IMF2 from GBHH1333. (a) spectrogram, (b) scalogram, (c) SPWVD and (d) Hilbert spectrum.

As observed, the instantaneous amplitude of Hilbert spectrum is more uniform than the global amplitudes in spectrogram, scalogram and SPWVD. Considering a matter of fact that the instantaneous amplitude is determined by the backscattering energy from the moving truck, Hilbert spectrum represents a much more reasonable amplitude result without big mutations. This proves the physical meaning of the extracted IMF again.

4.4.2 Case 2: Doppler Signal with a small offset

It is well known that Doppler shift becomes smaller when the frequency of transmitted radio wave decreases. Because of the lowest frequency used in this GMTI trial, i.e. 178 MHz, the Doppler frequency will be the smallest. It is about [3, 6] Hz, which is so small that it will be very close to the zero Doppler frequency and the quasi-dc. Data GBHH1031 is gotten at 178 MHz when the transmitter and receiver are below the canopy. Although the interference is milder and Doppler shift can be seen in the time-frequency distributions, the Doppler frequency is still difficult to be extracted.

The primary technical challenge to the successful extraction of Doppler frequency with such a small offset from the Doppler signal generated by clutter is how to remove the large zero-Doppler signal without removing the desired Doppler shift. The Doppler frequency in the sidebands is below the main zero-Doppler by a factor of 14 dB, making the extraction of the Doppler frequency difficult.

Now we attempt to use EMD to extract the Doppler frequency of moving target first. The EMD results are shown in Fig. 4-10.

Figure 4-10 Empirical mode decomposition result of data GBHH1031.

The time-frequency distribution of original signal given in Fig. 4-11(a) illustrates that the Doppler frequency and the clutter have a small separation in the spectrum. Even though a clutter-rejection filter may be effective on rejecting the clutter, it may also attenuate much of the target signal. By using the EMD which acts like an adaptive filter banks, the Doppler frequency is successfully extracted in IMF2. Compared with the frequency representation of original signal, IMF2's peak frequencies exactly cover the Doppler shift, as shown in Fig. 4-11(b).

Figure 4-11 (a) Traditional time-frequency distribution of data GBHH1031. (b) The Fourier spectral comparison of original data and the extracted component.

To further prove the conclusion, we plot spectrogram, scalogram, SPWVD and Hilbert spectrum of the IMF2, giving the results in Fig. 4-12. As we can see, the Doppler frequency allocates in the time-frequency domain just beneath the zero-Doppler frequency line. Thus the target signal is successfully extracted again. The Doppler frequency is observed to occur at 2 second, which agrees with the fact that the truck entered the radar beam at around 2 second. This proves the physical meaning of EMD.

For data GBHH1031, the energy of Doppler frequency is more concentrated than the one in data GBHH1333, because radar's detection ability has been improved by reducing the radar frequency. Although the Doppler frequency is shown clearly in traditional time-frequency distributions, it is not in detail and smearing. In the Hilbert spectrum, the target signal is separated and the skeleton curve gives many details in frequencies. Thus the motion parameters can be successfully estimated.

(a)

(b)

(c)

(d)

Figure 4-12 Time-frequency distributions of IMF2 from GBHH1031. (a) spectrogram, (b) scalogram, (c) SPWVD and (d) Hilbert spectrum.

(a)

(b)

(c)

(d)

Figure 4-13 3-D view of time-frequency distributions of IMF2 from GBHH1031. (a) spectrogram, (b) scalogram, (c) SPWVD and (d) Hilbert spectrum.

Fig. 4-13 offers the corresponding 3-D view of IMF2's spectrogram, scalogram, SPWVD and Hilbert spectrum. The differences of these distributions are obvious.

4.5 Summary

In this Chapter we apply the HHT technology to improve the performance of GMTI in foliage environment. EMD is implemented to extract target signal from disturbances and the associated Hilbert spectrum is applied to reveal time-varying Doppler frequency information embedded in radar signals. Comparing with the traditional TFA methods, Doppler frequency can be more clearly, locally and accurately represented on the time-frequency domain.

Both simulative and real FOPEN data showed that the EMD method does yield more efficient disturbance reduction in the received signal and keep the target signal less affected. The target signal has been successfully extracted in the weak signal and small offset cases. Thus it can be clearly shown in the time-frequency plane, while it is invisible or blurry in traditional time-frequency distributions. By removing most clutter and noise, the signal to disturbance ratio had been improved by almost 30 dB.

Results show that the novel Hilbert spectrum offers very high resolution of time and frequency by giving the instantaneous Doppler law. And EMD decomposition is based on the intrinsic oscillations of the signal. All the IMFs are Am-Fm components, so EMD is much applicable to nonstationary radar signals and extracted components possess more physical meaning. Moreover, the HHT is more adaptive since the decomposition basis is not predetermined and fixed but derived from every analyzed signal itself.

CHAPTER 5

MICRO-DOPPLER ANALYSIS WITH THE HILBERT HUANG TRANSFORM

5.1 Radar Micro-Doppler Signature Analysis

As indicated in Chapter 2, radar transmits a signal to a target, interacts with the target, and returns back to the radar. The change in the properties of the returned signal contains characteristics of target of interest. When the transmitted signal of a CW radar system hits moving targets, the carrier frequency of the signal will be shifted, known as the Doppler Effect. The Doppler frequency shift reflects the velocity of the moving target. Mechanical vibration or rotation of an object, or structures on the target may induce additional frequency modulations on the backscattered radar signal which generate sidebands about the target's Doppler frequency. This phenomenon is called the micro-Doppler effect.

It is originally introduced in coherent laser radar or ladar system [65, 66]. Since the radar uses the same principle as ladar, this concept is adopted for radar applications [12]. Recently, there has been increasing interest in studying the so-called micro-Doppler phenomenon for radar target identification applications [12, 67-71]. Analysis of the micro-Doppler signature can provide useful information for target detection, classification and recognition.

In radar signal processing, rigid-body motion is usually assumed. However, non-rigid-body motion is common in reality. Structure or target on the target may have some

micro-motions dynamics in addition to the target translations, such as helicopter's rotor blade and the swinging arms of a walking man. In CW radar system, the phase of a signal returned from a target is sensitive to the vibration in range. From the electromagnetic point of view, the micro-motions dynamics will produce frequency modulation on the backscattered signals and induce additional Doppler variations to the translation Doppler shift [72-74]. Then the micro-Doppler phenomenon can be observed. It can be regarded as a characteristic of the interaction between the vibrating or rotating structures and the target body.

In some situations, micro-motions dynamics are of the highest importance. We then wish to detect them, estimate object parameters and possibly identify them. A particular class of moving targets is vibrating targets, i.e. targets that have oscillatory motion. Vibrations and oscillations can be important to characterize the target. In many cases, a target with vibrations may be assumed to contain an engine or other moving parts.

In this Chapter we analysis the micro-Doppler signature induced by vibration. A unique micro-Doppler signature may be produced by the oscillating parts of a target. Even fairly small oscillations can have significant impact on radar signatures. We are able to determine some parameters of the target from this micro-Doppler signature. Such parameters may be useful for describing the target, or serve as inputs to automatic target recognition algorithms. Therefore, how to correctly detect the micro-Doppler signature and estimate oscillation parameters becomes an important issue.

It turns out that micro-Doppler signature is a periodic and time-varying function. Cohen's class time-frequency methods with high resolution are suitable tools for it. However, the analysis result of traditional Cohen's class is subject to its kernel, which

may cause some corresponding problems. Hilbert-Huang transform is proposed to solve these problems.

In the following Section 5.2, we present the model and formulation of the micro-Doppler signal returned from a vibrating target. Section 5.2 examines the problems of traditional TFA methods, particularly the Cohen's class, for micro-Doppler analysis. After comparing the performance of Cohen's class and the HHT based on simulative signal in Section 5.4, we show results from three sets of experimental data in Section 5.5. Results are summarized in Section 5.6.

5.2 Vibration-Induced Micro-Doppler

In this section, the point scatterer model is used for modeling micro-Doppler induced by vibrating targets. Fig. 5-1 illustrates a radar located at the origin of the radar coordinate system (U, V, W) and a point-scatterer P vibrating about a center point Q which located at $(r_0 \cos \beta \cos \alpha, r_0 \cos \beta \sin \alpha, r_0 \sin \beta)$. Here, r_0 is the distance between radar and point Q , α and β are respectively the azimuth angle and elevation angle of point Q relative to the radar.

As shown in the Fig. 5-1, P located at the coordinate (X, Y, Z) with the azimuth angle α_p and elevation angle β_p with respect to the origin Q . Thus $P = (d_t \cos \beta_p \cos \alpha_p, d_t \cos \beta_p \sin \alpha_p, d_t \sin \beta_p)$. d_t is the range from P to origin Q , which is decided by the vibrating rate ω_v and the maximum vibrating amplitude d_v . $d_t = d_v \sin(\omega_v t)$. Then the range from P to radar is

$$r_t = |\vec{r}_t| = [(r_0 \cos \beta \cos \alpha + d_t \cos \beta_p \cos \alpha_p)^2 + (r_0 \cos \beta \sin \alpha + d_t \cos \beta_p \sin \alpha_p)^2 + (r_0 \sin \beta + d_t \sin \beta_p)^2]^{1/2} \quad (5.1)$$

The received signal becomes

$$s(t) = \rho \exp[j2\pi f_c t + j4\pi r_t / \lambda_c] \quad (5.2)$$

where f_c and λ_c are respectively the carrier frequency and wavelength. ρ is the reflectivity of P , which is in the range of 0 to 1. Since ρ does not affect the frequency of the signal, it is always set to be 1 during our simulation. In this Chapter we use this signal model to generate simulative signal.

Figure 5-1 Geometry of a radar and a vibrating point-scatterer.

The characteristic of the received signal $s(t)$ has already been indicated in [12, 67, 68, 70, 75], it can be expressed as a sinusoidal modulated signal

$$s(t) = \rho \exp[j2\pi f_c t + jB \sin(\omega_v t)] \quad (5.3)$$

So the instantaneous frequency is

$$f_{\text{Doppler}} = f_c + f_{\text{micro-Doppler}} = f_c + Bf_v \cos(\omega_v t) \quad (5.4)$$

with

$$B = 4\pi D / \lambda_c \quad (5.5)$$

$D = d_v [\cos(\alpha - \alpha_p) \cos \beta \cos \beta_p + \sin \beta \sin \beta_p]$ which is the line-of-sight oscillation displacement. If the azimuth angle α of the point Q and elevation angle β_p of the reflector P are all zero, $D = d_v \cos \beta \cos \alpha_p$.

From (5.4), it is clearly shown that a vibrating target or structure simply induces a sinusoidal frequency modulation to the phase. Quite small oscillations can cause large modulation as the peak-to-peak Doppler deviation is given by $2Bf_v$. The modulation index B is proportional to D / λ_c .

5.3 Cohen's Class for Micro-Doppler Analysis

Eq. (5.4) makes it clear that vibrating targets induce periodic and time-varying micro-Doppler frequency. Our basic problem is to estimate the instantaneous frequency of the signal as accurately as possible. To analyze the time-varying frequency characteristics of the micro-Doppler, spectrogram and scalogram with poor time-frequency localization may not possess the necessary resolution for extracting these features. The received radar signal $s(t)$ should be analyzed in the joint time-frequency domain by applying high resolution time-frequency transforms. In this way, the vibration parameters can be found by using (5.4) and (5.5) from the micro-Doppler signature in time-frequency domain.

Wigner Ville distribution (WVD) is a useful tool to analyze radar signal due to its high resolution. However, it suffers the problem of cross-term interference. To avoid this interference, the WVD is often replaced by the smoothed WVD which filters the original

WVD with kernel ψ . The WVD with a linear lowpass filter are characterized as the Cohen's class as expressed in (5.6) and (5.7).

$$C(t, f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W(u, v) \psi(u - t, v - f) du dv \quad (5.6)$$

$W(t, f)$ is the baseline Wigner-Ville distribution

$$W(t, f) = \int_{-\infty}^{\infty} s\left(t + \frac{\tau}{2}\right) s^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (5.7)$$

Cohen's class time-frequency methods, such as SPWVD, are suitable tools for micro-Doppler analysis [67]. However, all Cohen's class methods will show the dependence on the effective window length of kernel since they can be seen as filtered versions of the WVD. Kernel ψ serves as a smoothing function which will attenuate in a particular way the cross-terms of the WVD. The cost of the filter smoothing is the reduction of WVD's time-frequency resolution. Besides, Cohen's class method must be chosen carefully if we want to produce the instantaneous Doppler frequency, as the time integration window of kernel cannot be longer than about one cycle of the modulation frequency [70]. The reason is that if the window is not short enough to make the signal over the window be approximated as a linear chirp, the Cohen's class loses its time-frequency localization.

In a word, the analysis result of traditional Cohen's class is subject to its kernel, which may cause some corresponding problems. The HHT is proposed to solve these problems. In our study, we compare its performance with traditional Cohen's class methods using both simulative data and real experimental signal. SPWVD is used as representative of Cohen's class, comparing with the Hilbert spectrum in terms of the accuracy and resolution of micro-Doppler signature.

The SPWVD compares favorably with many other traditional time-frequency methods. It uses a separable smoothing function $\psi = g(t)H(-f)$ as time and frequency window respectively. $H(f)$ is the Fourier transform of a smoothing window $h(t)$. The obtained distribution is

$$SPWVD(t, f) = \int_{-\infty}^{+\infty} h(\tau) \int_{-\infty}^{+\infty} g(u-t) s(u+\tau/2) s^*(u-\tau/2) du e^{-j2\pi f \tau} d\tau \quad (5.8)$$

5.4 Simulation Results and Analysis

As discussed in Section 5.2, $s(t) = \exp[j\omega_c t + jB \sin(\omega_v t)]$ is representative of the received signal backscattering from a vibrating target. This sinusoidal frequency modulated signal has symmetric amplitude, and it already satisfies the condition of an IMF. Therefore there is no need to invoke EMD in our simulations and the Hilbert spectrum is drawn directly. For the multicomponent signal which has more than one frequency at one time, we should divide it into IMFs and then draw the Hilbert spectrum.

It is clear that the instantaneous micro-Doppler frequency of the simulative signal is determined by B and ω_v . The modulated frequency ω_v decides the modulation frequency which is illustrated in the time-frequency domain as the velocity of micro-Doppler frequency changes. The modulation index B decides the modulation amplitude. When $B < 1$, $s(t)$ becomes a fairly weak modulated signal which has some particular characteristics. Consequently, in this Section, we will study two cases distinguished by different B .

5.4.1 Case 1: A Simulative Signal with $B > 1$

To make a fair comparison, we use the same signal studied in [70] as first example to compare the performance of SPWVD and Hilbert spectrum. The results are shown in Fig.

5-2. The modulation index is given by $B=30$ and the vibration frequency is $f_v = \omega_v / (2\pi) = 0.5$ Hz which serves as the modulation frequency. The constant frequency is $f_c = \omega_c / (2\pi) = 7.9$ Hz and sampling frequency $f_s = 100$ Hz. As a result of the parameter settings, the peak-to-peak frequency deviation will be $2 \times (0.5 \times 30) = 30$ Hz.

(a)

(b)

Figure 5-2 SPWVD of a returned signal from a vibrating target with different kernel settings.

(a) Time-frequency distribution by setting $g = 0.17$ s, $h = 0.9$ s.

(b) Close-up of the time-frequency signature.

(c) Time-frequency distribution by setting $g = 4$ s, $h = 2$ s.

(d) Time-frequency distribution by setting $g = 0.03$ s, $h = 4$ s.

To analyze the effect of kernel to the time-frequency distribution, we draw SPWVD with different window length of g and h , which are time and frequency smoothing function respectively. Three representative results are shown in Fig. 5-2.

Fig. 5-2(a) is the SPWVD of the micro-Doppler signature when $g = 0.17$ s, $h = 0.9$ s. For reference, the theoretical instantaneous frequency is given as a white line, and we see that the SPWVD gives a meaningful picture of the time-dependent frequency content of the signal. However it is not concentrated enough.

Fig. 5-2(b) shows the close-up of the time-frequency signature. Cross-terms and frequency smearing make it difficult to get the exact instantaneous frequency line. In order to estimate the vibrating parameters, a signal model is often used to fit the form [71]. The fit will be done with an exhaustive search over the parameter space. However, estimating the amplitude and frequency in this simple method produces an inevitable error. Meanwhile it is time-consuming.

Fig. 5-3 illustrates Hilbert spectrum of the same signal, giving a precise instantaneous frequency line as the function of time. From the sinusoidal form shown in Hilbert spectrum and (5.4), we can directly get the parameters $f_v = 0.5$ Hz, $B = 30$ and $f_c = 7.9$ Hz which agree with the prior settings.

Another limitation of Cohen's class for micro-Doppler analysis is indicated in [70]. To resolve the instantaneous frequencies, the kernel time smoothing window of Cohen's class method has to be sufficiently short. Effective time smoothing window of the kernel should not be longer than one cycle of the modulation signal. Fig. 5-2(c) shows the

SPWVD when $g = 4$ s, $h = 2$ s. The time-frequency distribution becomes stationary. Because the length of time window g is about two cycles of the modulation and the signal cannot be approximated by a linear chirp over the window. When the analysis window is long enough that there are significant deviations from a linear phase modulation within it, we get a sliding spectrum. In the case of sinusoidal phase modulation the sliding spectrum becomes stationary.

Not only time window g has a certain relation with the time-frequency distribution of the analyzed signal. The frequency window H may also affect the time-frequency signature. In order to observe the relationship between window size and time-frequency resolution of micro-Doppler, we analyze the results using many selections of time and frequency window size. Order 3 Renyi entropy is used as a measure of the time-frequency concentration of the Doppler information in the time-frequency plane, i.e. the time-frequency resolution. A small entropy value implies a small instantaneous bandwidth as compared to a large entropy value. A small instantaneous bandwidth in turn means higher accuracy in the instantaneous frequency result.

Fig. 5-4 shows that smaller g and bigger h result in higher time-frequency resolution. Nevertheless, highest time-frequency resolution will not lead to best time-frequency distribution for sure. For example, when we set a sufficiently short time smoothing window, e.g. $g = 0.03$ s, but make frequency smoothing window longer, e.g. $h = 4$ s, we get a confusing SPWVD as shown in Fig. 5-2(d). The reason is the trade-off between the joint time-frequency resolution and the level of the cross-terms: the more you smooth in time and/or frequency, the poorer the resolution in time and/or frequency. In this

case, h is too broad, which leads to many cross-terms and the failure of finding the instantaneous frequency.

Figure 5-3 Hilbert spectrum of the same signal in Fig. 5-2.

Figure 5-4 Relationship between time-frequency resolution and window size.

Above examples all show that the window length of kernel must be carefully selected while using Cohen's class time-frequency methods. Fortunately, Hilbert spectrum has not such restriction since no kernel is used.

5.4.2 Case 2: A Simulative Signal with $B < 1$

For fairly weak modulated ($B < 1$) micro-Doppler signal, SPWVD usually fails to show the instantaneous frequency effectively. For example, we calculate SPWVD on a simulative signal with modulation frequency $f_v = 20$ Hz, the modulation index $B = 0.1$ and constant frequency $f_c = 0$ Hz, with the sampling frequency $f_s = 1000$ Hz. According to (5.4), the peak-to-peak frequency modulation is $2 \times (0.1 \times 20) = 4$ Hz. This small value makes it difficult for SPWVD to give perfect time and frequency localization.

We set $g = 0.003$ s, which is short enough since one cycle of the modulation is 0.05 s. In order to attenuate the cross-terms while keeping sufficient frequency resolution, we set an appropriate frequency window length $h = 0.12$ s. As we can see from the result in Fig. 5-5(a), little information can be learned about the instantaneous frequency (shown as the white line).

Then we try to improve the frequency resolution by increase length of h . Fig. 5-5(b) is the SPWVD of signal when $g = 0.003$ s, $h = 0.4$ s. A stationary time-frequency distribution is obtained. Weak energy locates at ± 20 Hz corresponding to the Fourier spectrum shown in Fig. 5-5(d). The peak-to-peak frequency deviation of the spectrum changes from $2Bf_m$ to $2f_m$. The reason is well known from communication theory [76].

We consider initially a sinusoidal modulated signal of the form

$$\begin{aligned} s(t) &= \rho \exp[j\omega_c t + jB \sin(\omega_v t)] \\ &= \rho e^{j\omega_c t} e^{jB \sin(\omega_v t)} \end{aligned} \quad (5.9)$$

(a)

(b)

(c)

(d)

Figure 5-5 SPWVD and power spectrum of a fairly weak phase modulated micro-Doppler signal.

- (a) Time-frequency distribution by setting $g = 0.003$ s, $h = 0.12$ s.
- (b) Time-frequency distribution by setting $g = 0.003$ s, $h = 0.4$ s.
- (c) Time-frequency distribution by setting $g = 0.0003$ s, $h = 0.05$ s.
- (d) Power spectrum of the signal.

The function $e^{jB \sin \omega_v t}$ is clearly a periodic function with period $T = 2\pi / \omega_v$. It therefore has a Fourier-series representation:

$$e^{jB \sin \omega_v t} = \sum_{n=-\infty}^{\infty} c_n e^{jn \omega_v t} \quad (5.10)$$

where

$$\begin{aligned} c_n &= \frac{1}{T} \int_{-T/2}^{T/2} e^{jB \sin \omega_v t} e^{-jn \omega_v t} dt \\ &= \frac{1}{T} \int_{-T/2}^{T/2} e^{j(B \sin \omega_v t - jn \omega_v t)} dt \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j(B \sin \omega_v t - jn \omega_v t)} d(\omega_v t) \equiv J_n(B) \end{aligned} \quad (5.11)$$

$J_n(B)$ is the n th-order Bessel function of the first kind.

Substituting (5.11) back into (5.9), the desired Fourier expansion result is

$$s(t) = \rho \sum_{n=-\infty}^{\infty} J_n(B) e^{j(\omega_c + n \omega_v)t} \quad (5.12)$$

Since $J_n(B) = J_{-n}(B)$ for n odd and $J_n(B) = -J_{-n}(B)$ for n even, we can rewrite (5.12) as

$$\begin{aligned} s(t) &= \rho \{ J_0(B) e^{j2\pi f_c t} \\ &\quad + J_1(B) [e^{j2\pi(f_c + f_v)t} - e^{j2\pi(f_c - f_v)t}] \\ &\quad + J_2(B) [e^{j2\pi(f_c + 2f_v)t} + e^{j2\pi(f_c - 2f_v)t}] \\ &\quad + J_3(B) [e^{j2\pi(f_c + 3f_v)t} - e^{j2\pi(f_c - 3f_v)t}] + \dots \} \end{aligned} \quad (5.13)$$

We see that angle modulation with a sinusoid results in a line spectrum with lines at $\omega_c \pm n \omega_v$, and with the height of the lines given by $J_n(B)$.

The general shape of $J_n(B)$ as a function of B is shown in Fig. 5-6.

Figure 5-6 Shape of $J_n(B)$ as function of B .

Because the modulation index B is set to be 0.1 in this example, we can see from Fig. 5-6, only $J_0(B)$ and $J_1(B)$ have significant values. Thus we may approximate (5.13) by

$$s(t) = \rho \{ J_0(B) e^{j2\pi f_c t} + J_1(B) [e^{j(2\pi f_c + 2\pi f_v)t} - e^{j(2\pi f_c - 2\pi f_v)t}] \} \quad (5.14)$$

Obviously, frequencies only appear at three locations: f_c , $f_c + f_v$ and $f_c - f_v$. Therefore, we can estimate the vibrating frequency to be 20 Hz from Fig. 5-5(b) and Fig. 5-5(d). However, SPWVD does not represent the correct time-varying micro-Doppler and we cannot get any further information from it. And as we can see, much stronger cross-terms are induced at ± 10 Hz. This brings additional difficulties in finding useful vibrating parameters.

Another way to improve the time-frequency resolution is to increase the sampling frequency. When we set $f_s = 10000$ Hz, SPWVD of $g = 0.0003$ s, $h = 0.05$ s is shown in Fig. 5-5(c). We can approximately find two modulation periods in 0.1 s. But the time-

frequency distribution is still much broader than the instantaneous frequency which is given as the white line.

Figure 5-7 Hilbert spectrum and theoretical instantaneous frequency of the same signal in Fig. 5-5.

In contrast, Fig. 5-7(a) shows the Hilbert spectrum of the same signal. Comparing with the theoretical result drawn in Fig. 5-7(b), Hilbert spectrum gives the instantaneous frequency accurately and clearly in the time-frequency domain. Vibration parameters can

be easily obtained. Hilbert spectrum is proved again efficient for the micro-Doppler signature analysis.

5.5 Experimental Results and Analysis

Micro-Doppler signature analysis is valuable for many practical applications such as vehicle identification, engine malfunction diagnosis, human gait measurement, natural resonance frequency measurement, jet engine modulation analysis and so on. In this Section, we investigate the validity of the HHT for three applications.

5.5.1 Micro-Doppler of an Engine-induced Vehicle Surface Vibration

Micro-Doppler phenomenon enables us to determine some properties of the object. For example, vibrations generated by a vehicle's engine may be detected from the surface of the vehicle. From the micro-Doppler signature of the surface vibration, one could distinguish a gas turbine engine of a tank from a diesel engine of a bus. The micro-Doppler effect can be used to identify specific types of vehicles and to determine their movement and engine speed.

In this first experiment, we try to capture the micro-Doppler signature from engine-induced vibrating truck surface. The real signals are reflected from a stationary truck with its engine on. The radar antenna is located 10 meters away, pointing towards the truck compartment (Fig. 5-8).

Sampling frequency is $f_s = 100$ Hz. Radar is working at VHF and UHF band (from 100 MHz to 900 MHz). Four particular Fourier spectra of received signals with different carrier frequencies are shown in Fig. 5-9.

Figure 5-8 Real signals returned from a truck with engine on.

As we deduced in Section 5.4.2, vibration induced micro-Doppler signal is a sinusoid modulated signal which results in a line spectrum with lines at $f_c \pm nf_v$, and with the height of the lines given by $J_n(B)$. In these Fourier spectra, f_c has been down converted to zero, so the peak lines will appear at $\pm nf_v$. In some spectra there are several peak lines can be found, and we have to decide which one is f_v .

According to (5.5), i.e. $B = 4\pi D / \lambda_c$, we can roughly estimate the range of B . Since the vibration caused by engine is in the scale of millimeter and f_c is from 100 MHz to 900 MHz, we get $B < 1$. That means the micro-Doppler signal is fairly weak modulated, and the peak line only appears at $\pm f_v$. As we can find with naked eyes in all these Fourier spectra, the strongest peak frequencies besides the zero-Doppler frequency all locate at nearly ± 30 Hz. Hence the vibration frequency is about 30 Hz, and the other interferential peaks are reflected from the open environment.

To further confirm our conclusion, an autocorrelation analysis of the received signal is shown in Fig. 5-10. This is the analyzing result of 563 MHz signal which has a confusing spectrum and is selected as the representative. Autocorrelation is a means to estimate fundamental frequency from the waveform directly. The autocorrelation function for a section of signal shows how well the waveform shape correlates with itself at a range of

different delays. We can see that the autocorrelation function peaks at zero delay and at delays corresponding to ± 1 period, ± 2 periods, etc. We can estimate the fundamental frequency by looking for a peak in the delay interval.

Fig. 5-10(a) is the autocorrelation result in 1 s. There are multiple peaks. Fig. 5-10(b) is a zoom-in picture of the result in 0.1 s. The period of the signal is determined to be 0.033 s from this figure. This agrees with the estimated vibrating frequency of 30 Hz.

Figure 5-9 Fourier spectra of signals with different carrier frequencies, respectively as: (a) 178 MHz (b) 474 MHz (c) 563 MHz (d) 802 MHz.

Figure 5-10 Fundamental frequency estimation using autocorrelation (a) result in 1 s.
(b) result in 0.1 s.

When carrier frequency becomes higher, the micro-Doppler signature becomes much weaker, as shown in Fig. 5-9(c) and Fig. 5-9(d). It is hard to identify them from the plot as the vibration induced signal is heavily contaminated by the environment return.

In the following sections, we study the experimental signals with carrier frequency 563 MHz and 802 MHz respectively, to see whether the HHT can alleviate these problems.

5.5.1.1. Case 1: Carrier Frequency is 563 MHz

We first choose the signal with the carrier frequency being 563 MHz. The Fourier spectrum of the returned signal is shown in Fig. 5-11. In addition to the micro-Doppler frequency, there are many harmonics and some interferential peaks which make it too confusing to distinguish the micro-Doppler frequency. The reason is that the returned signal is a complicated signal, combined with the signal reflected from the vibrating truck surface, the return from other objects in the environment and noise. Our first attempt focuses on the extraction of the weak micro-Doppler signal.

Figure 5-11 EMD result of the 563 MHz signal.

We apply EMD first, giving the result in Fig. 5-11. After that, the original signal is divided into one IMF and the residue. We noticed that the lowest frequency is kept out by the second IMF, so we can easily reduce the zero-Doppler components by eliminating this mode from the signal. The Fourier spectrum of the left IMF1 is given in Fig. 5-12 and compared with the one of original signal. We can see that after removing the IMF2, micro-Doppler gains the peak energy.

Then we compare the Cohen's class analysis results of original 563 MHz signal and the decomposed IMF1. Fig. 5-13, representing a particular spectrogram of original signal (± 30 Hz is out of the processing scale of SPWVD in *MATLAB* program when $f_s = 100$ Hz, so we use spectrogram as the respective of Cohen's class methods instead), shows big energy of zero-Doppler. As a result, the lowest frequencies coming from relatively motionless environment are the majority of returned signal. Except for the zero-Doppler frequency there are several paired lines. We can hardly tell which one is the micro-

Doppler frequency information we need. And the results cannot be significantly improved when we change the window size settings.

Figure 5-12 Fourier spectra of 563 MHz signal and the extracted IMF1.

Figure 5-13 Spectrogram of the 563 MHz signal.

Figure 5-14 Spectrogram of IMF1 of 563 MHz signal.

As expected, after EMD, the spectrogram of IMF1 in Fig. 5-14 clearly shows the micro-Doppler signature in the time-frequency domain. Zero-Doppler frequency and clutter interference have been greatly removed. A micro-Doppler spreading symmetrically at around ± 30 Hz is apparent in the figure. It is caused by the disciplinary vibration of the truck engine. Therefore we can estimate engine vibration frequency to be 30 Hz.

Figure 5-15 Hilbert spectrum of IMF1 of 563 MHz signal.

On the other hand, after EMD, we can easily get Hilbert spectrum of IMF1 of this signal as in Fig. 5-15. The instantaneous micro-Doppler appears as a sinusoidal modulated frequency with the oscillations clearly seen. This proves the physical meaning of the Hilbert spectrum. Although the sinusoidal modulation is not very regular, there is some certain periodicity in the time-frequency distribution. We may make a coarse eyeball estimation of the oscillation period of 0.034 s, with an average peak-to-peak deviation of around 40 Hz. This corresponds to the vibration frequency $f_v = 29$ Hz with amplitude $D_v = 2.8$ cm. The vibration frequency almost agrees with the prior observation. But the estimated vibration amplitude has some deviation with the ground truth. This is due to the fact that micro-Doppler is sensitive to the frequency band of operation, it is better to be observed in microwave radar, that is, the radar frequency should be above 1 GHz. Considering the limited ability of UHF radar for detecting such tiny micro-motions and look angle of radar antenna, the estimated vibration amplitude is still in a reasonable range. This validates that Hilbert spectrum is much powerful than traditional TFA methods for revealing the micro-Doppler.

5.5.1.2. Case 2: Carrier Frequency is 802 MHz

We use another case to further test the efficiency of EMD for extracting micro-Doppler frequency. The signal is reflected from the same situation but the transmitted frequency changes to 802 MHz. Thus the disturbances from environment become severer and make the target signal nearly submerges in the spectrum.

After EMD, as in Fig. 5-16, the signal is decomposed into one IMF and the residue. We discard the residue as it contains lowest frequencies of the original signal.

Figure 5-16 EMD result of the 802 MHz signal.

Fig. 5-17 represents the Fourier spectra of original 802 MHz signal and the IMF1. It is clear that the micro-Doppler frequency energy is successfully extracted after EMD.

Figure 5-17 Fourier spectra of 802 MHz signal and the extracted IMF1.

Figure 5-18 Spectrogram of the 802 MHz signal.

Figure 5-19 Spectrogram of IMF1 of 802 MHz signal.

The spectrogram comparison of original signal and the correlative IMF1 are given in Fig. 5-18 and 5-19. For the original signal, we try to suppress the zero-Doppler energy simply by subtracting its mean value. Although it is helpful, the micro-Doppler spreading is still very weak in the time-frequency domain.

With the help of EMD, micro-Doppler can be seen in the spectrogram of IMF1. The micro-Doppler is basically separated from other interferences, clearly showing the sign of moving target. It is very valuable for detecting the vehicles no matter it is moving or not.

Figure 5-20 Hilbert spectrum of IMF1 of 802 MHz signal.

The Hilbert spectrum of IMF1 of this signal is depicted in Fig. 5-20. As we can see the oscillation frequency of the instantaneous micro-Doppler is close to 30 Hz and average peak-to-peak deviation is around 60 Hz. This example indicates the vibration frequency $f_v = 30$ Hz with amplitude $D_v = 2.98$ cm. This example validates that even though the vehicle signal is very weak and can hardly be distinguished by traditional TFA methods, Hilbert spectrum can obtain the characteristic micro-Doppler signature. It is helpful to detect a vehicle with only engine on and identify the vehicle type.

5.5.2 Micro-Doppler of Car Combustion Engine Caused Vibration

The purpose of this trial is to investigate time-frequency analysis of engine vibration. In order to understand engine vibration caused by malfunctions such as improper spark-

plug gap, deposit, spark-plug wear, injector failure, unfit belt tension, loosening of spark-plug cable, misfire, TFA methods are employed to indicate the time-frequency characteristics of the engine vibration in different cases [77-80].

For malfunction diagnosis, pressure or structural vibration signals that contain information on pressure resonance can be used. These engine signals may be detected by radar returns from the surface of the car [81] or the engine itself. Fig. 5-21 is the photo showing the system configuration of this trial. A CW C-band radar ($f_c = 6$ GHz) was used to detect signatures of a four-cylinder engine running at idle speed. The distance between the radar and engine is 0.5 m. Network analyzer was used to record the received data at a sampling rate $f_s = 2000$ Hz.

The Fourier spectrum of a one second signal is represented in Fig. 5-22 where the characteristic of frequency modulated multiple peaks can be seen. After EMD, we obtain eight IMFs, as shown in Fig. 5-23. Among those IMFs, the fourth IMF extract the desired micro-Doppler frequencies. Its Fourier spectrum is compared with the one of original signal in Fig. 5-22. From the result, we can see the first and second order frequency modulation clearly. The vibration frequency is about 50 Hz.

Figure 5-21 Photos of experiment set-up.

Figure 5-22 Fourier spectral comparison of original signal and IMF4.

Figure 5-23 EMD result of a one second engine vibration signal.

Fig 5-24 is the SPWVD of original engine vibration signal. Although the time and frequency window is set to appropriate values as $g = 0.001$ s, $h = 0.5$ s, the micro-Doppler signature distribution is not satisfactory. As comparison, the SPWVD of the extracted IMF4 (Fig. 5-25) gives a much stronger energy distribution at the multiples of modulation frequencies. However it does not show the sinusoidal frequency modulation of the micro-Doppler signature yet.

With the implementation of Hilbert transform, Hilbert spectrum of IMF4 is successfully drawn in Fig. 5-26. The instantaneous frequency is clearly a sinusoidal line with many oscillations in one second. The average peak-to-peak frequency deviation is about 100

Hz. Thus the estimated vibration amplitude is 4 mm, which has a good agreement with the ground truth.

Figure 5-24 SPWVD of engine vibration signal.

Figure 5-25 SPWVD of the extracted IMF4.

Figure 5-26 Hilbert spectrum of the extracted IMF4.

5.5.3 Micro-Doppler of a Running Man with Swinging Arms and Legs

The human walking gait is a complex motion mechanism that comprises different movements of individual body parts. Human experience shows that it is possible to recognize a friend by gait. However, gait recognition by machine is a challenge. Various computer vision and ultrasound techniques have been developed to measure gait parameters. Recently, radar based gait analysis is also under development [12, 14, 67, 68, 75, 81-83]. Radar has the advantage of detecting and identifying humans at distances in all weather conditions.

This trial is to study micro-Doppler effect of a running man. The radar measurement data was collected by passive GSM (Global System for Mobile Communication) radar (data provided by Radar Laboratory, NTU). A human was running away from passive radar and then returned to the starting point. The U-turn point is approximately 20-30 meters away from receive antenna. For this data measurement, the sampling frequency $f_s = 200$

KHz, Coherent Integration Time (CIT) is 0.2 s. More details about the experiment settings can be found in [84].

Fig. 5-27 depicts the time-frequency distribution of the signal's Doppler frequency using STFT (received data is too big to be processed by quadratic time-frequency analysis). The Doppler frequency induced by the running human corresponding to the event sequences as stated has been prominently tracked. However, human's arms and legs motion while running induce severe micro-Doppler spreading on the main Doppler frequency trace.

Figure 5-27 Time-frequency distribution of running human.

Figure 5-28 Time-frequency distribution of IMF1 and IMF2.

Figure 5-29 Time-frequency distribution of the residue.

We decompose the signal in each CIT segment by EMD. This 40 second data contains 200 segments, so in order to save time, we restrict the number of IMFs to be no more than 4. After all the IMFs successfully obtained, we combine all the IMF1s and IMF2s. The time-frequency distribution of the resulting signal is shown in Fig. 5-28. It is clear that the main Doppler induced by the human body has been effectively extracted. The

time-frequency distribution of the remaining residue is shown in Fig. 5-29. It contains mostly the micro-Doppler signature of swinging arms and legs. Thus the proposed HHT effectively discriminate the micro-Doppler from the main Doppler frequency.

5.6 Summary

By exploiting the unique micro-Doppler signature of the target, we can get additional information that is complementary to existing methods. However micro-Doppler is usually too weak to be easily detected by traditional TFA methods. In this Chapter, we use EMD to decompose signal into different oscillatory modes and to extract the micro-Doppler signature. Since the EMD is based on the local characteristic time scale of the data, it has more physically meaningful interpretation. Hilbert spectrum outperforms the traditional TFA methods by giving the sinusoidal modulated micro-Doppler signature clearly. Based on this signature, vibrating parameters can be estimated.

After studying the simulative results we find Cohen's class methods encounter such difficulties:

- The time-frequency distribution is smearing due to the kernel's smoothing effect, so time-frequency resolution is not necessarily high. To obtain the vibration parameters we have to find the fittest signal model from the time-frequency distribution. This indirect way is time consuming and may bring inevitable error.
- The kernel used in these methods also causes a compromise between the joint time-frequency resolution and the level of the cross-terms. The window size selection

should consider both time-frequency resolution and the cross-terms interference level.

- An effective time integration window of the kernel should not be longer than about a cycle of the modulation signal. Otherwise, the time-frequency distribution becomes stationary and loses all the useful information.
- Cohen's class can hardly present the micro-Doppler signature correctly when signal is fairly weak modulated.

Simulations based on signal model backscattered from the vibrating target validate the efficiency of the HHT. It outperforms Cohen's class methods in aspects as:

- Compared with Cohen's class, Hilbert spectrum can represent the instantaneous micro-Doppler line clearly. Thus we can directly obtain the vibration parameters for further process. It is more accurate and simpler.
- Hilbert spectrum can be applied to the received signal directly without considering the window selection. Therefore, it gets rid of the restrictions of time frequency window size.
- For fairly weak phase modulated signal, Hilbert spectrum still gives good representation.

The effectiveness of the HHT for practical application is evaluated by applying the methodology to experimental signals.

- For the first trial about the micro-Doppler of an engine-induced vehicle surface vibration, the EMD allows us to display the micro-Doppler signature clearly while micro-Doppler signal is contaminated with interference and the main echoes from target body. EMD is validated to be efficient for the vehicle detection even when the vehicle is not moving. Instantaneous micro-Doppler frequency can be depicted in the correct sinusoidal frequency modulated form by Hilbert spectrum, and the vibration parameters estimation results approach the field observations. This enables us to identify the vehicle type according to the micro-Doppler signature.
- In the second trial of analyzing a car combustion engine caused vibration, the HHT captures the micro-Doppler signature very well. Separated from clutter and noise, the extracted IMF presents a clear and accurate micro-Doppler line. This produces the potential use of the HHT for engine malfunction diagnosis.
- For the third trial about the micro-Doppler of a running man with swing arms and legs, the HHT successfully discriminate the micro-Doppler caused by arms and legs, from the main Doppler frequency caused by human body movement.

CHAPTER 6

EXTENDED RESEARCH ON SIGNAL DECOMPOSITION METHOD FOR TARGET EXTRACTION

6.1 Signal Decomposition Method

The HHT has been validated to be efficient for the radar signal processing in the previous Chapters. EMD, which is the basis of the HHT plays an important role. The essence of this time domain decomposition method is to decompose the data into its intrinsic oscillation modes. After the decomposition the signal of interest can be selected from all the decomposed components. And Doppler frequency will be clearly revealed in time-frequency domain by greatly removing a wide variety of clutter and noise.

As we indicated before, one major task of radar signal processing is to suppress the interference (clutter and noise) energy and extract Doppler frequency of the moving target. However, the Doppler frequency characteristics are unknown, which render the decision of frequency band of traditional filtering very difficult. And filters cannot be used adaptively for different signals because of its fix frequency band. Moreover, the target signal is not simply a combination of sinusoids, so conventional frequency-domain filtering may distort waveforms of the target signal by filtering out harmonics of the Doppler frequency. Therefore, interference signal contaminated in target signal cannot be eliminated by using conventional frequency filtering without affecting the target signal.

Adaptive filtering technique can improve the quality of the target signal. However, it requires a reference signal that is the comprehensive signal of the interference to be removed. Obviously, it is difficult and sometimes unrealistic to obtain such a reference signal in practical applications, because interference is variable, and their nature of distribution is unknown.

Signal decomposition method such as EMD is recently used as an adaptive filter bank for the interference reduction and target extraction. It is particularly important for representing the signal components whose localization in time and frequency vary widely. The complexity of structures encountered in some signals requires adaptive low level decomposition.

Besides EMD, discrete wavelet transform is also a powerful method for nonstationary signal processing because of its multiresolution decomposition characteristics. It is widely used in many applications including detection and de-noising [85-87].

Another signal decomposition based target extraction algorithm is the adaptive chirplet decomposition. It shows good efficiency to reject interference and enhance the target detection ability [88-91].

This Chapter presents a comparative study of the effectiveness of the proposed EMD based target extraction methodology with these early two successful target extraction techniques namely discrete wavelet transform, and adaptive chirplet decomposition method. These techniques are compared with numerical simulated signal and raw received radar signal. Their different principles and performances are discussed.

First, we present a brief background of the methodology behind the techniques of interest in the study. Their signal decomposition characteristics are also discussed.

6.1.1 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is obtained by dilation and translation of a prototype wavelet. The dilation parameter ‘ a ’ and the translation parameter ‘ b ’ are discretized by using the dyadic scale i.e.

$$a = 2^j \quad b = k.2^j \quad j, k \in \mathbb{Z} \quad (6.1)$$

where $\mathbb{Z}$ is the set of positive integers.

Contracted and dilated versions of the wavelet forms high- and low-pass filters. Like a dyadic tree, the wavelet transform permits decomposition into the sum of a approximation (low frequency) elements plus detail (high frequency) elements. Early works prove the connections between those wavelet families and the pyramid-dyadic tree expansion of a signal [85, 92]. The orthonormal wavelets of compact support imply FIR perfect reconstruction quadrature mirror filter (PR-QMF) banks.

Figure 6-1 multiresolution (pyramid) decomposition structure for a three-level discrete wavelet transform.

Given a signal s of length N , DWT consists of $\log_2 N$ stages at most. The decomposition procedure is shown in Fig. 6-1. In the figure, the halfband low-pass and high-pass filters are L_o_D and H_i_D , respectively, and $\downarrow 2$ means subsampling by 2 (dropping samples with odd indexes). Starting from s , the first step produces two sets of coefficients: approximation coefficients $cA1$, and detail coefficients $cD1$. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail, followed by dyadic decimation. Consequently the wavelet decomposition of the signal s analyzed at level j has the following structure: $[cA_j, cD_j, \dots, cD1]$. The structure in Fig. 6-1 shows for $j = 3$ the terminal nodes of the following tree. The DWT of the signal with each level of decomposition results in halving the time resolution and doubling the frequency resolution. The signal can be easily reconstructed, as the dyadic wavelet filter family forms an orthonormal basis. After reconstructing the coefficients, signal is the sum of the coarsest approximation $cA3$ and the details at levels 1 to 3, i. e., $s = cA3 + cD3 + cD2 + cD1$.

The wavelet analysis of the signal can be seen as a filter bank with adjustable time and frequency resolution. For lower frequencies, the wavelet window is large, which in turn limits the time localization. Changing the mother wavelet parameters, e.g. the center frequency and the bandwidth parameter, should be done carefully as long as a good frequency localization implies a poor time localization and vice versa.

Obviously, the frequency band of the filter depends on the level of decomposition and wavelet window. Once they are selected, the decomposition is unique. For time-varying signals, the selection of the bandwidth should be made carefully in order to prevent a leakage of modal components and possibility of false target extraction.

DWT results in symmetrical orthogonal components when a symmetrical orthogonal wavelet is used as a decomposition wavelet. As a signal can be decomposed into symmetrical orthogonal components with DWT, they also guarantee well behaved Hilbert transform. These facts motivate to combine a sifting process based on DWT and Hilbert spectral analysis to analyze nonstationary signal, and it may be used as a TFA technique for radar signal processing as the HHT.

The prominent advantage of DWT is its fast processing speed because it can be implemented based on FFT. An inherent weakness of this band-pass filter structure is that it is static as the same structure is always used regardless of the particular signal being analyzed. The DWT is not able to provide an optimal time-frequency distribution of the signal.

6.1.2 Adaptive Chirplet Decomposition

The chirplet basis function [93, 94] is well suited for parameterising the AM–FM radar signal. A chirplet is a four-parameter basis of the form

$$h_k(t) = \left(\frac{\pi}{\alpha_k} \right)^{\frac{1}{4}} \exp \left\{ -\alpha_k (t - t_k)^2 \right\} \exp \left\{ -j2\pi f_k (t - t_k) - j\pi \beta_k (t - t_k)^2 \right\} \quad (6.2)$$

where t_k is the time centre of the signal, f_k is the centre frequency, β_k is the frequency modulation rate and α_k defines the time extent of the signal. The joint time–frequency plot of a chirplet function is illustrated in Fig. 6-2. Actually, the chirplet basis is one of the many options that can be used to model the radar signal accurately. However, there are some attractive attributes of this basis. First, the basis function is an AM–FM signal and only a sparse set of these bases is needed to approximate the time–frequency structure of the radar signal. Secondly, the chirplet basis is a well understood basis with only four parameters. Thirdly and most importantly, the parameters of the chirplet can be

used to separate the two components of the signal. This is because signals from different targets and the background may be captured by chirplet bases with different parameters.

Figure 6-2 Time-frequency distribution of a chirplet basis.

To decompose the radar signal into a set of chirplet bases, we apply the adaptive signal parameterisation algorithm [95, 96]. First, we parameterize the received radar signal $S_r(t)$ by projecting it onto chirplet bases of different parameters and find the one with the maximum projection value. Next, a residual signal is generated by subtracting the contribution of the just-found basis from the signal. This process is then iterated to generate a series of chirplet basis functions that, when summed, can approximate the original signal. The steps are summarised below:

Step 1. Set iteration index number k to 1 and the residual signal $R_k(t)$ to $S_r(t)$

Step 2. Find the k th chirplet $h_k(t)$ by maximising the projection from the residual signal

$R_k(t)$ onto the basis, i.e.

$$\{t_k, f_k, \alpha_k, \beta_k\} = \arg \max \left| \langle R_k(t), h_k(t) \rangle \right| \quad (6.3)$$

where the inner product is defined as

$$\langle R_k(t), h_k(t) \rangle = \int_{t_0}^{t_1} R_k(t) h_k^*(t) dt \quad (6.4)$$

The radar data are assumed to exist over the time interval t_0 to t_1 . The coefficient of the chirplet is the corresponding projection

$$c_k = \langle R_k(t), h_k(t) \rangle \quad (6.5)$$

Step 3. Subtract the extracted signal from the residual

$$R_{k+1}(t) \leftarrow R_k(t) - c_k h_k(t) \quad (6.6)$$

Step 4. Increase k by one and repeat steps 2 and 3 until k reaches a preset number or until the energy of the residual signal is below some threshold set based on the signal-to-noise ratio. Suppose N chirplets are found from this procedure, the radar signal is parameterized as

$$S_r(t) \approx \sum_{k=1}^N c_k \left(\frac{\pi}{\alpha_k} \right)^{\frac{1}{4}} \exp \left\{ -\alpha_k (t - t_k)^2 e^{-j2\pi f_k (t - t_k)} e^{-j\pi \beta_k (t - t_k)^2} \right\} \quad (6.7)$$

After the parameterization of the radar signal, the desired target signal can be isolated from the interference signal using different parameters. A better target image may be reconstructed after removing the interference part components.

This sifting process of this Adaptive Chirplet Decomposition (ACD) is a similar iteration procedure as in EMD. To precisely approximate the original signal, more chirplets basis usually leads to better results. This requirement results in a big number for the iteration index k , therefore much computation time is needed to search for the basis parameters. After ACD, we must construct signal with chirplets of appropriate parameters, which also increases the complexity of the algorithm. For the cases when we are not clear about the desired target signal's time-frequency characteristics, it is impossible to classify the chirplets with correct parameters, and ACD partly loses its capability for target extraction.

6.1.3 Empirical Mode Decomposition

The methodology of EMD has been amply explained in Section 3.3. We give a brief review here. In the case a time series is $x(t)$, EMD has the following major steps:

Initialize $r_0(t) = x(t)$ and $i = 1$

Step 1. Set $h_0(t) = r_{i-1}(t)$ and $j = 1$

Step 2. Extract the local minima and maxima of time series $h_{j-1}(t)$. Interpolate the local maxima by a cubic spline to form upper envelope H_{up} of $h_{j-1}(t)$. And construct the lower envelope H_{low} of $h_{j-1}(t)$ by fitting all the local minima with cubic spline. The upper and lower envelopes should cover all the data between them.

Step 3. We calculate the mean value of the envelopes by $m_{j-1}(t) = (H_{up} + H_{low}) / 2$. The difference between $h_{j-1}(t)$ and its mean is $h_j(t) = h_{j-1}(t) - m_{j-1}(t)$.

Step 4. If $h_j(t)$ meets the criteria of an IMF, designate this $h_j(t)$ as $imf_i(t)$. If $h_j(t)$ is not an IMF, then increase j , return to step 2 and repeat the procedure.

Step 5. Define the residue as $r_i(t) = r_{i-1}(t) - imf_i(t)$. If $r_i(t)$ becomes monotonic or its extrema is less than a predetermined small number, the whole procedure stops here. If not, increase i and return to step 1.

The sifting process separates the IMFs with decreasing order of frequency, i.e. it separates high frequency component first and decomposes the residue obtained after separating each IMF, until no more IMF can be obtained. Till date, there is no mathematical formulation derived for EMD method and the studies done in order to analyze the behavior of this method in stochastic situations involving broadband noise shows that the method behaves a dyadic filter bank when applied to analyze a fractional

Gaussian noise [97]. In this sense, the sifting process in the EMD method may be viewed as an implicit wavelet analysis and the concept of the intrinsic mode function in the EMD method is parallel to the wavelet details in wavelet analysis.

Compared with DWT, the most significant innovation of EMD is the generation of adaptive decomposition basis functions. With the EMD approach, the basis functions themselves are nonlinear functions which can be derived directly from the data, or in other words, an adaptive basis called IMF can be found. In EMD, the frequency is defined locally as the oscillation between successive local extrema (minima or maxima). The EMD is a sifting process which picks out the highest local frequencies of signal in each IMF. Since the decomposition is based on the local characteristic time scale of the data, the decomposition components usually have more physically meaningful interpretation.

Although the IMFs are well behaved in their Hilbert Transform, they may not necessarily have any physical significance. In the case a digitized time series has a much different envelop with the original continuous time series, EMD may result in mode mixture [39] and partly lose its physical meaning. Therefore the empirical sifting process does not guarantee exact modal decomposition all the time.

6.2 Comparison Results of Numerical Simulated Signals

To further investigate the different performances of DWT, ACD and EMD, the methods are applied in this section for different simulated signal and results are compared. The similarities and differences between these signal decomposition techniques are studied

by applying these methods for two test signal: (1) a narrow-band mono-frequency target signal in presence of foliage clutter (2) a broad-band multi-frequency target signal

6.2.1 A Contaminated Narrow-band Mono-frequency Target Signal

For one simple constant moving target, target signal is a mono-frequency component, whose Doppler frequency is well localized in some certain frequency band. In these cases, the major task of signal decomposition is to separate target from clutter and noise. As example in this direction, a model signal in the forest environment which is built in Section 4.3 has been used. In the model signal, f_d is set to be 5 Hz and the signal to disturbance (clutter and noise) ratio is -30 dB. The decomposition results of DWT, ACD and EMD are respectively given in Fig. 6-3. For DWT, we decompose the signal into 6 components using symlet as mother wavelet; For ACD, we parameterize the signal using 50 chirplets. The chirplet bases with Doppler frequency $f_k = 5$ Hz are picked out to reconstruct part 1 of the original signal, which contributes to the target signal. The left chirplet bases construct the part 2 of original signal; For EMD, we obtain 6 IMFs.

After the decomposition, target signal is successfully extracted out separately in D4, part 1 and IMF3. As shown in Fig. 6-4, the spectra of these components have most energy locating at 5 Hz. That means they all capture the target signal very well. In this case, the DWT, ACD and EMD give comparable results. For all the cases, the SDR is greatly increased. DWT and EMD work as the band pass filter, abandoning lots of interference signal, meanwhile preserving the energy of target signal. As we can observe from the decomposition results, ACD gives a most clear target signal spectrum due to its ability to extract the target according to the exact Doppler frequency value.

(a) DWT

(b) ACD

(c) EMD

Figure 6-3 Decomposition result of DWT, ACD and EMD.

Figure 6-4 Fourier spectra of original signal and the extracted components.

To quantify the performance of these methods, the following relative error is defined:

$$\delta = \frac{\sum_f [P(f) - P'(f)]^2}{\sum_f P^2(f)} \quad (6.8)$$

where $P(f)$ is the spectral density of the numerical simulating target signal and $P'(f)$ is the spectral density of the extracted signal. Indeed, the ACD yields smallest relative error (0.0125) than that of DWT (0.1144) and EMD (0.0963). In conclusion, all three techniques behave efficiently for extracting this constant frequency target signal. The Doppler frequency extracted by ACD is most accurate among all the results. EMD has a slight superiority than DWT.

6.2.2 A Broad-band Multi-frequency Target Signal

The above data is a narrow-band signal returned from target moving at constant speed. In contrast, targets moving at an accelerating velocity may result in a broad-band Doppler frequency. Extracting this Doppler frequency is obviously much more difficult than the narrow-band signal. For the case when received signal contains multi-frequency

components which are scattered from multiple targets in the background environment, the target extraction becomes more challenging. To explore the efficiency of these three signal decomposition methods in such situation, we use a signal composed of three components which significantly overlap in time and frequency. The signal is the sum of two sinusoidal FM components and one Gaussian wavepacket [98].

Fig. 6-5 is the DWT result of the three component signal. Signal is decomposed by symlet into 5 levels. There is no more significant detail information in the final approximation component A5, so there is no need to further decompose the signal. And the wavelet selection is not crucial. Different wavelets give the similar results in the case.

The first three detail components $D1, D2, D3$ pick out most of the signal. The time-frequency distribution of them evidences that DWT just decomposes the signal by the frequencies as QMF banks. Every detail component gets part of each mono-frequency signal, with the continuous sinusoidal frequency modulation of the first two signals broking down into segments.

ACD of this signal is a much complex process. Following the steps in Section 6.1.2, we first parameterize the signal using 50 chirplets. Next, we separate the contributions from two FM signals and one AM signal based on the frequency f_k and the frequency rate β_k of the chirplet bases. AM signal can be easily extracted because chirplet bases contributing to the AM signal have smallest β_k which is close to 0. Two sinusoidal FM signals can also be separated mainly according to their different β_k . However, the chirplet bases approaching the turning point of the sinusoidal modulation also have a small β_k as the AM signal does. At this time, center frequency f_k of the chirplet must be

used as criteria to separate them. Fig. 6-6 is the ACD results of the separated three components.

(a)

(b)

Figure 6-5 DWT of a three component signal. (a) Decomposition result. (b) Time-frequency distribution of original signal and extracted components.

(a)

(b)

Figure 6-6 ACD of a three component signal. (a) Decomposition result. (b) Time-frequency distribution of original signal and extracted components.

As we can tell from both the time series and time-frequency distribution of the reconstructed part 1, part 2 and part 3, ACD has successfully extracted three different signals although they overlap in both time and frequency. The deficiency of ACD is that it failed to discriminate two FM signal at the bottom turning points, because the

parameters of the chirplets here are very similar, we cannot find an enough precise threshold for separating them.

(a)

(b)

Figure 6-7 EMD of a three component signal. (a) Decomposition result. (b) Time-frequency distribution of original signal and extracted components.

Fig. 6-7 is the EMD of this three component signal. The signal is decomposed into 9 IMFs and the final residue. The time-frequency signatures of the first 3 IMFs extracted

by EMD evidence that EMD separated three monocomponent signals from the mixed one by their intrinsic differences.

As indicated here, EMD gives best performance in this complicated case. The high vs. low frequency discrimination in EMD applies only locally and corresponds by no way to a pre-determined subband filtering as in DWT. Selection of modes is an automatic and adaptive (signal-dependent) time-variant filtering, no more threshold setting need to be done artificially as in ACD.

6.3 Comparison Results of Experimental Signal

In this Section, we implement these methods to our radar applications, i.e. the GMTI in foliage environment and micro-Doppler signature analysis.

6.3.1 Foliage Penetration Data

We select GBHH1031 as the test FOPEN data. It is a similar narrow-band signal as first simulative signal. We have in Fig. 6-8 the result of time-frequency distribution obtained from the received signal. One can observe a weak Doppler frequency right beside the zero Doppler line. This requires high efficiency of target extraction of these signal decomposition techniques. DWT, ACD and EMD are respectively implemented to this data and give out the decomposition results in Fig. 6-9 to Fig. 6-12.

We plot the Fourier spectra of every extracted component in frequency domain and compare it with the Fourier spectrum of original signal. It is shown that D5 obtained by DWT, part 1 reconstructed from parameterized chirplets by ACD and IMF2 extracted by

EMD are the desired components. They mainly covered the Doppler frequency as presented in Fig. 6-9.

Figure 6-8 Time-frequency distribution of original FOPEN signal.

Figure 6-9 Fourier spectra of original signal, D5, IMF2 and part1.

Time-frequency distributions of selected components after decomposition are given respectively in Fig. 6-10, 6-11 and 6-12. They both show clearly the Doppler frequency with the clutter and noise greatly suppressed. But the differences are also visible.

(a) Decomposition result

(b) Time-frequency distribution

Figure 6-10 DWT of the FOPEN data.

(a) Decomposition result

(b) Time-frequency distribution

Figure 6-11 ACD of the FOPEN data.

(a) Decomposition result

(b) Time-frequency distribution

Figure 6-12 EMD of the FOPEN data.

The Doppler frequency captured by DWT is not so clean. Some other frequency components can also be seen in the time-frequency domain with the energy as big as the

desired one. The Doppler frequencies extracted by ACD and EMD are much purer. And we can observe in Fig. 6-12 that Doppler frequency captured by EMD begins at around 2 second, which agrees with the fact. Therefore this Doppler frequency is more accurate than the ones extracted by DWT and ACD.

Renyi entropy of order 3 is used to measure the time-frequency plane information of these representations [99]. A small entropy value implies a small instantaneous bandwidth as compared to a large entropy value. A small instantaneous bandwidth in turn means higher accuracy in the instantaneous frequency result. The entropy of the time-frequency analysis of D5, part 1 and IMF2 are respectively 19.3560, 19.1743 and 18.9826 bits. EMD performs best with regard to the smallest entropy.

6.3.2 Micro-Doppler Data

Engine vibration signal discussed in Section 5.5.2 is used here to compare different performances of DWT, ACD and EMD. It is a sinusoidal FM signal which cannot be represented by conventional TFA methods accurately. However, the Fourier spectrum of the micro-Doppler data illustrated in Fig. 6-13 shows evident multiple peaks due to the frequency modulation. The decomposition results of three methods are given in Fig. 6-14 to Fig. 6-16.

After DWT in 6 levels with symlet, no single decomposed component captures the micro-Doppler frequency. We combine detail components D4 and D5 to approach it together. The time-frequency distribution of the extracted signal is not satisfactory, since the Doppler frequency smears in a big range.

Figure 6-13 Fourier spectra of original signal, D4~D5, IMF4 and part1.

Figure 6-14 DWT of the micro-Doppler data.

For ACD, we choose a 100 level decomposition. We have known in advance about the radar frequency and the range of vibration amplitude. This priori knowledge about the time-frequency characteristics of the target signal enables us to set a reasonable parameterization threshold. After reconstruct target signal with chirplets satisfying the micro-Doppler frequency, we get the extracted signal part 1. Although it locates in the micro-Doppler frequency range, it loses many parts of the micro-Doppler, referring to its Fourier spectrum in Fig. 6-13 and its time-frequency distributions in Fig. 6-15.

Figure 6-15 ACD of the micro-Doppler data.

Figure 6-16 EMD of the micro-Doppler data.

EMD results in 8 IMFs, among which IMF4 successfully extract the desired micro-Doppler signal. With the help of Hilbert transform, IMF4 can track the instantaneous micro-Doppler correctly as validated in Section 5.5.2.

6.4 Summary

A comparison study among DWT, ACD and EMD for the target extraction is carried out. Now we conclude their advantages and disadvantages in terms of physical meaning, adaptivity, sensitivity to signal type, interpretation of method, complexity of algorithm and computing time.

Physical meaning

DWT acts as a dyadic filter bank. The successive detail component always draws out the high frequencies of last approximated component. The EMD draws out the successive high frequencies component according to local frequencies. Since all the components are obtained according to the intrinsic oscillations imbedded in the signal, they are more reasonable in physical meaning. Both methods can extract symmetrical mono-frequency component which admit well-behaved Hilbert transform. This enables them to display the instantaneous Doppler frequency in the time-frequency domain, thus instantaneous physical motions of the moving target may be estimated. For ACD technique, desired signal can be extracted according to its exact time-frequency characteristics if they are known before the decomposition. Based on this precondition, signal extracted by ACD is physically meaningful. However, instantaneous frequency cannot be obtained after ACD, because the signal is a combination of eligible chirplet bases, which cannot be proved to guarantee well-behaved Hilbert transform. Consequently, no more physical meaningful time-frequency distribution can be obtained.

Adaptivity

The band-pass filter structure of the DWT is always used no matter which signal is being analyzed. For ACD, the parameter thresholds for discriminating different components

have to be decided according to the analyzed signal every time. EMD is a more adaptive decomposition because its filter structure and decomposition threshold will be determined by the signal itself. Besides, the mother wavelet and the decomposition level of wavelet analysis should be carefully selected for the decomposition, and the iteration index of ACD must be preset artificially based on experience. This is not a problem in EMD. It can generate proper and reasonable decomposition basis automatically.

Sensitivity to signal type

In the case of narrow-band frequency signal, such as returned signal from target with constant velocity, all three methods showed similar results. They can decompose the signal into monocomponents and give meaningful results. Nevertheless, for a broad-band frequency signal, DWT worked ineffectively by dividing a monocomponent into different frequency bands. ACD and EMD worked better as validated by the results in Section 6.2.2 and 6.3.2. However ACD failed to separate multicomponent signal if the components have similar time-frequency characteristics. And ACD's efficiency is based on the pre-assumption that we know the time-frequency characteristics of the analyzed signal, so that the parameterization can be validly carried out and the desired signal may be extracted. For those radar signals that the target's characteristics are unknown beforehand and unable to be estimated from traditional TFA, ACD fails to set the parameter thresholds and extract target. Thus, in this point of view, EMD may serve as a better signal analysis method than the other two.

Interpretation of method

Factually, DWT and ACD are backed up by well-established mathematical theory of wavelet analysis and chirplet analysis, which facilitates their implementation and physical interpretation of the results obtained. In contrast, a direct EMD provides an

efficient and robust procedure to decompose a signal into its IMFs. The sifting process is based on subjective criteria such as envelope definition and stopping criteria. Because of the absence of the mathematical formulation of this method, one cannot guarantee that the IMFs obtained are the same as the modal components of the signal.

Complexity of algorithm and Computing time

The algorithm of DWT is the simplest. Based on FFT, this method can be implemented very fast which produces the potential use for real-time application. EMD has a moderate complexity and its computing time varies erratically according to the analyzed signal itself. For some certain signals which may require lots of iteration times, in order to save time, we can adjust the stopping criteria under the premise that the desired signal remains unaffected. ACD is the most complicated one because finding a large number of chirplets costs much time. And the threshold setting afterward nearly forbids its real-time application.

All these methods have many potential applications in radar signal processing. For a practical application, selection among these methods should be based on the signal type and processing requirement. A robust framework for target extraction may be developed either by making a parallel use of these methods or by implementing a methodology incorporating all these methods in an efficient way.

CHAPTER 7

DISCUSSIONS ABOUT THE HILBERT HUANG TRANSFORM

Although Hilbert Huang Transform is promising for time-frequency analysis of nonstationary signals, it lacks solid theoretical foundations and is not a mature tool yet. As versatile as it has proved to be, the method still needs further clarifications and improvements. The HHT has some numerical problems such as end swing caused by spline fitting, convergence problem in sifting procedure, ambiguity of local symmetry requirement of IMFs, difficulty with intermittence and so on. In this Chapter, we are going to discuss some aspects of the HHT which should be taken into consideration during its implementation.

7.1 Criteria Settings in Empirical Mode Decomposition

As it has been defined in Section 3.3, the EMD algorithm depends on a number of options which have to be controlled by the user and which require some expertise. There are two main criteria in the EMD algorithm, and each of the criteria can be set independently of the others. The first is the stopping criterion for extracting each IMF. The second is the stopping criterion for the whole EMD process.

These criteria settings are of critical significance and could affect the resulting IMFs and consequently, the Hilbert spectrum. To have physically meaningful IMFs, one should

select the criteria in EMD carefully such that the resulting IMFs and the ensuing simulation accurately represent the underlying physical process.

7.1.1 Stopping Criterion for Producing an Intrinsic Mode Function

This inner loop stopping criterion actually determines the number of sifting steps to produce an IMF. It is of critical importance in the successful implementation of the EMD processing. As described in Section 3.3, after one single sifting process, we get a much improved component h_k which is usually not an IMF yet. Therefore, the function h_k can only be designated as a proto-mode function (PMF). The PMF needs to be further refined to be an IMF. Therefore, the sifting process has to be repeated as many times as necessary.

There are two purposes of sifting process: to eliminate riding waves and to make the wave profiles more symmetric with respect to zero. In order to satisfy these purposes, sifting should be done as many times as needed. Unfortunately, sifting process brings a side effect: to make the neighboring wave have more even amplitudes. Too many sifting steps will reduce the IMF to be a constant-amplitude frequency-modulated function, which would obliterate the intrinsic amplitude variations and render the results physically less meaningful. Although eliminating riding waves and forcing the mean to be zero are essential for computing instantaneous frequency through the Hilbert transform, the side effect actually decreases the range of variations in the IMF by smoothing the amplitudes. Therefore, the effects of sifting must be balanced with its side effects.

To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulations, sifting must be limited to as few steps as are mathematically

permissible; the choice must be selected judiciously. What exactly the stopping criterion should be is a difficult decision. Two possibilities have been proposed.

The first one, used in [39], is the Cauchy-type convergence criterion. Standard Deviation

$$SD_j = \sum_{t=0}^T \frac{|h_{j-1}(t) - h_j(t)|^2}{|h_{j-1}(t)|}$$

computed from two consecutive loops results replaces the two

conditions of IMFs as stopping criterion. A standard deviation value of 0.2-0.3 for the sifting procedure is a very rigorous limitation for the difference between siftings. Hence the threshold value for SD can be usually set between 0.2 and 0.3. The major flaw of this approach is that it is unrelated to the definition of the IMF; it only requires the successive PMFs to be approximately equal. Thus, something better was needed.

The second criterion was proposed by [40], where the sifting is stopped when the number of zero crossings and extrema is the same number for S successive sifting steps. In general, the higher the S number selected, the higher the total number of sifting steps required. As over-sifting can have a detrimental effect on the results, do not select too high a number for the stopping criterion. Typically, a value of $3 \leq S \leq 5$ has proved successful as the default stopping criterion. Nevertheless, this criterion only satisfies half of the IMF definition: the number of extrema and the number of zero crossing must differ at most by one. Therefore the resulting component is only a weak-IMF.

In our study, we adopt the criterion proposed in [98], which corresponds with IMF definition and at the same time prevents the over-sifting. The extraction of a mode is considered as satisfactory when two conditions are fulfilled: the first one is that the number of extrema and the number of zero-crossings must differ at most by 1; the second one is that the mean between the upper and lower envelopes must close to zero according

to some criterion. This criterion is based on two thresholds θ_1 and θ_2 , aimed at guaranteeing globally small fluctuations in the mean while taking into account locally large excursions. This amounts to introduce the *mode amplitude* $a(t) := (e_{\max}(t) - e_{\min}(t))/2$ and the *evaluation function* $\sigma(t) := |m(t)/a(t)|$ so that sifting is iterated until $\sigma(t) < \theta_1$ for some prescribed fraction $1 - \alpha$ of the total duration, while $\sigma(t) < \theta_2$ for the remaining fraction. One can typically set $\alpha \approx 0.05$, $\theta_1 \approx 0.05$ and $\theta_2 \approx 10\theta_1$.

7.1.2 Stopping Criterion for Terminating Empirical Mode Decomposition

As indicated in [39], the EMD process can be stopped by any of the following predetermined criteria: either when the component, c_n , or the residue, r_n , becomes so small that it is less than the predetermined value of substantial consequence, or when the residue, r_n , becomes a monotonic function from which no more IMF can be extracted. This is an intuitive definition of EMD stopping criterion.

In our simulations and experiments, it is found that target signal is contained in the first several IMFs in most times. Based on this observation, we modify the final stop criterion to be that $r_i(t)$ has a predetermined number of extrema, typically 15. This criterion is less strict than the original one and will result in a quicker stop. Such adaptation will not affect the signal extraction in our situation since the residue with limited extrema will only contribute to the zero-Doppler frequency. Additional IMFs sifted from it will increase the computational and algorithmic complexity. Therefore, the new criterion saves time.

Above two settings show that EMD is an empirical algorithm whose stopping criteria are not necessarily unique. Theoretically speaking, there are many ways to decompose a given dataset. The EMD is one method that can generate infinite different IMF sets through different criteria settings. However, Huang has proven in a statistical way that EMD is robust to various adjustable parameters in the sifting process [100].

7.2 Intermittence Phenomenon

Huang pointed out in [40] that EMD may run into difficulties when the data contain intermittence, where a component at a particular time scale either coming into existence or disappearing from a signal entirely. Intermittence can produce mode mixing, a phenomenon caused by having different time-scales (or spatial scales) mixed in a single IMF component, which will introduce additional, but fictitious, variations in the resulting IMFs and, hence, in the instantaneous frequency values.

For example, Fig. 7-1(a) is a given data in which there is a train of large amplitude sine waves with another train of small-amplitude sine waves occurring intermittently. With application of the EMD, we will obtain the components as shown in Fig. 7-1(e)–(h), in which the first two IMFs contain seriously mixed modes, that is, modes of very different periods. Take the component in Fig. 7-1(e) as an example. The small wave train is clearly identified. Wherever the small waves are identified, the underlying large waves will not be included in this IMF component. On the other hand, wherever there is no small-wave component, the large waves are retained as part of the component. As a result, there is a great disparity in the periods of the first IMF component. This is mode mixing; it is caused by intermittence occurring in part of the signal.

A solution to mode mixing is proposed in [100]. The intermittence criterion requires the selection of a number such as n_1 . This number represents the number of data points that correspond with a chosen data limit: only the waves shorter than this limit are to be included in a given IMF. If the distance between the successive extrema is larger than n_1 , the mean is used to replace that data point. This criterion requires that only when the distance between the extrema is less than n_1 will the upper and lower envelopes and the mean be available to extract the IMFs. With this criterion introduced, the result is shown in Fig. 7-1(b)–(d). Clearly, the intermittent small wave was separated from the large waves.

Figure 7-1 Effect of intermittence criterion in the EMD sifting process invoked to eliminate mode mixing. Sequence (b)–(d) with intermittence check; sequence (e)–(h) without intermittence check.

However, this criterion is difficult to set *a priori*, unless there is a strong theoretical basis to establish a distinct scale length. Even in such cases, *a priori* judgment could still

eliminate interesting physical variations in the data. To avoid these problems, the intermittence criterion should be introduced only when serious mode mixing is detected.

As noted in [40] and [100], intermittence is a major obstacle to the use of EMD on some signals. Intermittence for example occurs in turbulent flow or in any signal that is constantly changing such as speech. But for the radar signals we analyzed, there is no mode mixing shown in the EMD results, for the received radar waves do not have great disparity in its periods. Therefore in our EMD implementation, we process the signal without invoking the intermittence criterion.

7.3 End Effect

The implementation of EMD requires some attention to deal with the management of the end points for cubic splines interpolation in the EMD process. Serious problems of the spline fitting can occur near the end points, where the cubic spline fitting can have large swings. Left by themselves, the end swings can eventually propagate inward and corrupt the whole data span especially in the low frequency components. Hence, improving the spline fitting is absolutely necessary.

To eliminate the end effects, some techniques of boundary processing are proposed in literature. They mainly include three classes: 1) the method adopted by Huang [39] which adds two characteristic waves at ends defined by the two consecutive extrema for both their frequency and amplitude of the added waves; 2) the setting of new extrema out of data by symmetry quality [98], neural network training [101] or AR model; and 3) mirror extending [102], which moderately revises the computation matrix of spline fitting for symmetrically extended data.

Considering the time cost and the maintenance of shape and continuity of edges, we choose mirror extending technique for our EMD implementation.

7.4 Sifting Basis

Implementing EMD, we find the intrinsic scale of the oscillation by measuring the local time scales, where we have three choices: the time between successive zero-crossings, the time between successive extrema, and the time between successive curvature extrema. Thus zero-crossings, extrema and curvature extrema can serve as the sifting basis. Zero-crossing is a very crude measure of the data. Unless the data are truly narrow band, there might be many extrema between two consecutive zero-crossings. Therefore, extrema and curvature spans are better choices since the local time scale counts all the waves, whether they cross the zero line or not.

Figure 7-2 Hidden scales and curvature point.

According to different choices, we have two sifting types: an extrema-based sifting and a curvature-based sifting. As discussed in [40], the extrema points can measure wide-band data with multiple riding waves and agrees with the intuition of the time variations of the data. It is usually used as a basis to establish the upper and lower envelopes for sifting. However the extrema basis can miss the gentle humps characterized as hidden scales. As shown in Fig. 7-2, there are weak oscillations that can cause a local change in curvature but not create a local extremum. By computing the curvature, it is possible to get one step further in extracting the fine-scale signal from a given data. Mathematically, finding curvature extrema is equivalent to finding extrema in second derivatives of the signal.

It must be noted that, by choosing a curvature-based sifting, the meaning of the data is totally different from that for the extrema-based sifting. For example, consider the function

$$x(t) = \cos(\omega t + \xi \sin 2\omega t) \quad (7.1)$$

for small ξ ; this is an IMF already based on extrema. According to the classical wave analogy, this signal should be just a frequency-modulated oscillation with the time-varying frequency given by

$$\Omega = \omega(1 + 2\xi \cos 2\omega t) \quad (7.2)$$

If curvature-based sifting is selected, the form will be very different, as the second derivative of the data will become

$$x''(t) = -(\omega + 2\xi\omega \cos 2\omega t)^2 \cos(\omega t + 2\xi \sin 2\omega t) + 4\xi\omega^2 \sin 2\omega t \sin(\omega t + 2\xi \sin 2\omega t) \quad (7.3)$$

In this form, the curvature-based sifting will produce more than one time-scale in different IMF components. For this case, this result is not necessarily better. In fact, it actually masks the clear representation of the frequency modulation given in the

expression of (7.2). And a more practical limitation needs to be heeded: all data contain noise, and differentiation is a noise amplifier, if not a noise-generating mechanism. Therefore, the result from high-order differentiation would be unavoidably contaminated by noise.

Consequently, the selection of the sifting should be made with great care. Experience recommends using the extrema-based sifting as a first trial. The curvature or higher-order-derivative-based siftings should only be invoked for special cases when the result suggests too many hidden scales [100]. In our study, we choose the extrema-based sifting since no distinct hidden scales are detected in the radar signals.

7.5 Time-Frequency Precision in Hilbert Spectrum

To improve the time-frequency precision in Hilbert spectrum, Hilbert transform needs over-sampled data to define the instantaneous frequency precisely. In Fourier analysis, the Nyquist frequency is defined by two points per wave, however the frequency is defined for a wave covering the whole data span. In the HHT, the instantaneous frequency is defined through a differentiation process, and thus more data points will help to define the frequency more accurately. Huang pointed out in [39] that a minimum number of data points to define a frequency is five (or $4\Delta t$). Therefore, when the sampling rate of received signal is not high enough to offer sufficient data points to define the frequency, the resulting Hilbert spectrum will give a less precise time-frequency distribution. The satisfactory sampling rate should be selected individually according to particular case.

Besides increasing the sampling frequency, the lack of fine time steps can be alleviated by interpolating more points between the available data. As a spline interpretation would neither create nor annihilate scales, it also can be used for the interpolation when the data are very jagged from being under-sampled. The smoothed data, though, have a longer length and are sometimes easier to process. The interpretation serves to give better frequency definition. For the micro-Doppler signal of an engine-induced truck surface vibration, when the sampling frequency $f_s = 100$ Hz, which is too slow to define the micro-Doppler oscillations, we implement the interpolation before drawing the Hilbert spectrum.

7.6 Orthogonality of Intrinsic Mode Functions

Huang [39] proposed two posteriori indices of orthogonality. One is the global measure of the orthogonality of the decomposition, which is defined as the ratio of the summation of the inner products of any two IMFs and half of the square of the signal. The other is the measure of orthogonality between two IMFs, which is defined as the inner product of the two IMFs divided by summation of the square of the IMFs. The lower values of the indices indicate higher orthogonality. It was found that in most cases, the indices are typically less than 4%. For extremely short data, the indices could be as high as 5%, which is comparable to those from a set of pure sinusoidal waves with different frequencies of the same data length.

It was further stated, EMD is built on the idea of identifying the various scales in the data, the quantities of great physical significance. Therefore, in the sifting procedure, scales but not orthogonality are considerations. Since orthogonal decomposition is a characteristic for linear systems, violating this restriction is not a shortcoming but a

breakthrough. Therefore, the decomposed IMFs may or may not be orthogonal. As such, this method can be applied to nonlinear data. Though the IMFs in most cases are practically orthogonal, it is a coincidence rather than a requirement of the EMD.

7.7 Summary

In this Chapter, we discussed some theoretical aspects of the HHT. During its implementation, we concern about the criteria settings in EMD, the intermittence phenomenon, the end effect of spline fitting, the sifting basis, the time-frequency precision of Hilbert spectrum and the orthogonality of IMFs. Clarification and modifications of these aspects in our study are explained in detail.

CHAPTER 8

CONCLUSION AND RECOMMENDATION

8.1 Conclusion

In this thesis we have proposed and modified a new time-frequency analysis method for radar signal processing: the Hilbert Huang Transform which consists of the Empirical Mode Decomposition and the Hilbert spectral analysis. We have generally validated its efficiency for radar signal processing in Chapter 3. A successful application of the HHT on GMTI in foliage environment has been introduced in Chapter 4. Next, application in micro-Doppler signature analysis by using the new method has been proposed in Chapter 5. Corresponding experiment results have shown the HHT to be a feasible approach. For extension study of the signal decomposition techniques, EMD has been compared with DWT and ACD in Chapter 6. The results include negative and positive aspects. Finally, discussions about the HHT have been presented in Chapter 7. In this Chapter we will summarize the conclusions.

Radar is a natural time-frequency application because measurements in time and frequency are inherent for radar signal processing. Radar signal processing aims to extract target signal from clutter and noise as well as to extract signal features as accurate as possible. Thus the TFA technique should have good capacity of capturing the target signal and offer time-frequency resolution as high as possible. The traditional TFA methods, especially spectrogram, scalogram and WVD as we investigated in this thesis, are not satisfactory since they fail in one way or another.

To alleviate these problems, we have proposed a novel time-frequency analysis, named Hilbert Huang Transform, which is based on a time domain decomposition, EMD. The essence of this EMD is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically, and then decompose the data accordingly. The decomposition bases, IMFs, are produced directly from the signal itself, therefore they are adaptive according to the signal intrinsic characteristics. And the decomposition components are more meaningful as they are identified by their physical nature.

After EMD, original radar signal has usually been decomposed into a small number of IMFs. Then we extract the IMFs which contains mostly the information of target and discard those are mainly clutter and noise. Thus the signal to disturbance ratio (SDR) can be greatly improved. And the signal of interest from the moving target can be clearly displayed in the time-frequency domain. Incorporating with Hilbert transform, instantaneous amplitude and Doppler frequency of the target signal can be obtained, offering a much higher time-frequency resolution than the traditional methods. In general, the HHT satisfies the requirements of locality and adaptivity for nonstationary radar signal analysis.

For GMTI in foliage environment, the HHT successfully solves the challenging problem of extracting and estimating Doppler frequency of moving target from large echo signals caused by foliage environment. Hilbert spectrum represents the instantaneous Doppler frequency no matter it is weak or with small offset. Both simulation and experiments results demonstrate the predominance of the HHT over traditional TFA methods.

For micro-Doppler signature analysis, the HHT also outperforms the traditional one TFA methods, which is illustrated by simulative signal and real data. Without the constraints

of kernel function, the HHT is able to display the sinusoidal frequency modulated micro-Doppler induced by vibrating targets, for both cases of strong modulated signal and fairly weak modulated signal. Applied to three practical radar applications based on micro-Doppler analysis, the HHT shows feasibility for micro-motion detection and vibrating parameters estimation.

As a signal decomposition technique, EMD is compared with DWT and ACD based on analysis of both simulative data and real radar measurements. It turns out that they act similarly as DWT and ACD in the case of narrow-band monocomponent. For the target signal which we have known its time-frequency characteristics very well, ACD might precisely discrimination it from interference, better than the other two methods. However, in most cases EMD outperforms the DWT and ACD, because it acts as an adaptive data-driven filter bank which makes it possible to dynamically extract the target signal from disturbance according to their different physical characteristics. Detailed comparison results are given in terms of physical meaning, adaptivity, sensitivity to signal type, interpretation of method, complexity of algorithm and computing time. They all have advantages and limitations.

The HHT based on adaptive time domain decomposition has been proven to be highly effective and physically sound, there are however, areas needing further attention. Such as criteria settings in EMD, the intermittence phenomenon, the end effect of spline fitting, the sifting basis, the time-frequency precision of Hilbert spectrum and so on.

8.2 Recommendations for Further Research

Further Theoretical Study about the HHT

Because this thesis focuses on the application aspects of the EMD and the Hilbert transform, future work will continue on finding sophisticated mathematics to describe the EMD procedure and to work out a more efficient algorithm.

Improve the Performance and Accuracy of the HHT

Although the HHT are proved to be very efficient for radar signal processing in this thesis, there is much room for improvement in the HHT algorithm. For example, although the present envelope-mean method works well in most cases, problems still exist. The cubic spline fitting adopted here has both overshoot and undershoot problems. These problems can be alleviated by using more sophisticated spline methods, such as the higher-order spline program.

The HHT is a highly non-linear method that is very time consuming. Therefore, improving the efficiency of EMD is the most important step. Some job has been done, for example in [103], a quicker method called Local Mean Mode Decomposition (LMMD) has been introduced to calculate the mean value of the upper and lower envelopes by a two-tap adaptive time-varying filter. It would be interesting to study this in future work. This might gain a further understanding of the EMD method and may assist to prove it.

Propose a novel method based on the HHT

As the HHT method is developed for a nonstationary signal analysis, the effectiveness of the proposed method may be further improved by combining it with other adaptive signal analysis techniques, such as the discussed DWT and ACD. A hybrid method is expected to give adaptive implementation and better performance.

Moreover, we can study on the characteristics of frequency domain and space domain. Try whether we can implement EMD, the time domain decomposition method into other domains. Or maybe it can be used on a combined way, as a two dimensional decomposition. Some new methods are anticipated to be generated.

Investigate and exploit more radar applications

Quite recently, micro-Doppler phenomenon raises many interests of radar researchers, because it is quite common in reality and may contribute a lot for many real radar applications. Unfortunately, so far there are not many publications on the subject of time-frequency analysis of micro-Doppler phenomena. New methods for extracting weak micro-Doppler features in the time-frequency domain are still needed. Therefore I want to extend my PhD research on micro-Doppler signature analysis, based on my current study on the micro-Doppler caused by vibrating targets. In my future work, the micro-Doppler of oscillating targets and targets have more complicated micro-motions will be analyzed.

TFA has much more applications to radar signal, imaging and target feature extraction than the two we have studied here. We are able to apply the HHT into other specific applications to testify and calibrate its performance. One future work may be the detection of low observable targets within sea clutter. The Bragg lines will severely reduce radar's ability of ship detection. This makes the commonly used Doppler method – MTI invalid. At mean time, because the space difference between targets and the background is almost invisible, the space-region processing cannot work well either. The target extraction from sea-clutter remains a hard work [104, 105]. The HHT is expected to help solve these problems.

AUTHOR'S PUBLICATIONS

Journal Papers

1. C. Cai, W. Liu, J. S. Fu, Y. Lu, "A New Approach for Ground Moving Target Indication in Foliage Environment", *Signal Processing*, vol. 86, no. 1, January 2006, pp. 84-97.

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1. J. S. Fu, Y. K. Neui, C. Cai, Y. Lu and Z. Shen, "Resonator Characterization of 77 GHz Antenna", in *Proceedings of the 5th Topical Symposium on Millimeter Waves (TSMMW2003)*, Japan, Mar. 2003
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