Application of Hilbert-Huang Transform to MMW Doppler Radar

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***Abstract*-A millimeter wave (MMW) Doppler radar is introduced. As the Doppler shift is directly proportional to the target speed, the echo is a linear frequency modulated (LFM) signal if the target speed changes linearly. Especially, multicomponent LFM signal exists if the radar is used to analyze the distributed target. The conventional time-frequency analysis methods including short-time Fourier transform (STFT), Wigner-Ville distribution (WVD), and wavelet analysis are not generally adaptive to nonstationary signals. A new approach is proposed to analyze multicomponent LFM signals based on Radon transform and Hilbert-Huang transform (HHT) which is a recently developed method adaptive to nonstationary signals. The echo is decomposed into several Intrinsic Mode Functions (IMF) by the empirical mode decomposition (EMD). After the instantaneous frequency and Hilbert spectrum corresponding to IMFs are computed, target velocity parameter estimation is obtained using Radon transform on the Hilbert spectrum plane. The simulation result shows its feasibility and effectiveness.**

I. INTRODUCTION

Doppler radar measures the motion of the target toward or away from the radar based on Doppler shift. It has enjoyed widespread use for many years including human cardiopulmonary activity detection [1], geophysical research [2], weather detection [3] and muzzle velocity measurement [4]. Doppler radars at millimeter waveband, compared with those at other microwave bands, have larger Doppler frequency at the same target speed (i.e., have better Doppler frequency resolution) because of its shorter wavelength. Thus MMW Doppler radars are widely applied to short-range target velocity measurement systems.

In the scenario that the target moves at a constant radial velocity, conventional FFT-based algorithm can be used to analyze the echo and implement target velocity measurement as the corresponding echo is a single tone signal which is stationary. However, in the scenario that the target moves at a radial velocity changing linearly, the corresponding echo is linear frequency modulated (LFM) signal which is not stationary any longer. Especially, multicomponent LFM signal may exist corresponding to a distributed target with linearly changing velocity. It is obviously that the FFT-based algorithm is not suitable here. For processing of LFM signals, time-frequency-based methods have attracted considerable attention and proven themselves to be effective among other techniques. Initial work based on the time-frequency analysis involved the spectrogram. However, this technique suffers from the fixed time and frequency resolution due to the fixed window length used in the analysis and therefore, limits its applications in practice. The Wigner-Ville distribution (WVD) [5] has been found to be very useful for analyzing time-varying, nonstationary, phase-modulated signals. But in the case of multicomponent LFM signal, WVD suffers from the interference of cross terms and its performance degrades greatly. Pseudo Wigner-Ville distribution (PWVD) and Choi-Williams distribution (CWD), which are based on kernel function, can suppress cross terms. However, performance of signal parameter estimation degrades accordingly.

The recently developed Hilbert-Huang transform (HHT) [6] is a new method adaptive to nonstationary signals. It is composed of empirical mode decomposition (EMD) and Hilbert transform. The complicated signal can be decomposed into several Intrinsic Mode Functions (IMF) by EMD, which can make the consequent instantaneous frequencies meaningful obtained by Hilbert transform. In this paper HHT is applied to analyze the multicomponent LFM signal which is decomposed into individual LFM components utilizing EMD. Then the LFM signal parameter estimation can be obtained from the following Hilbert spectrum and Radon transform. Compared with Wigner-Hough transform (WHT) [7] and discrete Chirp-Fourier transform [8] algorithm which are proved to be effective methods to analyze multicomponent LFM signals, the method proposed in this paper can achieve good signal parameter estimation with additional signal denoising which is implemented by eliminating the IMFs denoting noise.

This paper is organized as follows: Block diagram and basic principle for MMW Doppler radar is given in Section II. The method based on Hilbert-Huang transform for the radar to implement multicomponent LFM signal parameter estimation is given in Section III. Simulation result is presented in Section IV. Finally, some conclusions are drawn in Section V.

II. BLOCK DIAGRAM AND BASIC PRINCIPLE FOR MMW DOPPLER RADAR

Block diagram for MMW Doppler radar is given in Fig. 1. The system maintains phase coherence by using a unique stable master oscillator (STAMO) for mixing and frequency conversion in the transmitter and the receiver. The transmitted signal is denoted as

$$s(t) = k\exp(j2\pi f_0 t) \tag{1}$$

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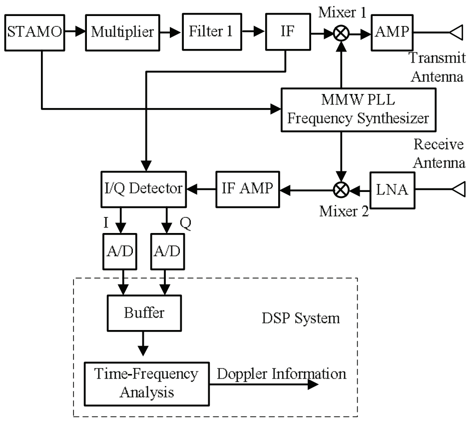

Figure 1. Block diagram for MMW Doppler radar

where f_0 is the carrier frequency and k is the amplitude of the transmitted waveform.

The echo from the target is expressed as

$$s_r(t) = \rho \exp\left[j2\pi \left(f_0 + f_d \right) t + j\varphi_0 \right] \quad (2)$$

where f_d is the Doppler frequency, φ_0 is the initial phase of the echo and ρ is the amplitude of the signal. Given a target moving toward the radar at the radial velocity of v, corresponding Doppler frequency is denoted as

$$f_d = \frac{2v}{\lambda} \quad (3)$$

where $\lambda = c/f_0$ is the wavelength, c is the velocity of light. From (3), the resolution of Doppler frequency is.

$$\Delta v = \frac{\Delta f_d \cdot \lambda}{2} \quad (4)$$

It is shown that the MMW Doppler radar has high frequency resolution at the same target radial velocity because of its short wavelength. Consequently, target radial velocity is obtained after the corresponding Doppler frequency is measured.

III. The Algorithm Based on Hilbert-Huang Transform

A. Hilbert-Huang Transform

The Hilbert-Huang transform is a novel signal processing technique for nonlinear and nonstationary signals which was first proposed by Norden E. Huang of the NASA Goddard Space Flight Center and his collaborators in 1998. Its basis is the combination of the empirical mode decomposition (EMD) and the Hilbert spectral analysis approaches.

The essence of 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 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; and (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.

It separates the intrinsic mode functions (IMFs) form the original signal one by one, until the residue is monotonic. After performing EMD, the original signal is decomposed into a finite and a small number of IMFs, where an IMF is any function with the same number of extrema and zero crossings, with its envelopes being symmetric. A systematic way to extract them, designated as the sifting process, is described as follows.

1) Let $x(t)$ denote the original signal. Once the extrema of $x(t)$ are identified, all the local maxima are connected by a cubic spline line as the upper envelope denoted as $x_{\max}(t)$. Repeat the procedure for the local minima to produce the lower envelope denoted as $x_{\min}(t)$.

2) The mean of the upper and lower envelopes is designated as $m(t)$ with

$$m(t) = \left[x_{\max}(t) + x_{\min}(t) \right] / 2 \quad (5)$$

3) The difference between the data and $m(t)$ is the first component, $h(t)$, i.e.

$$h(t) = x(t) - m(t) \quad (6)$$

For different signals, $h(t)$ may be an IMF or not. In general $h(t)$ does not satisfy all the requirements of IMF. In this case we can repeat the procedure *1)* to *3)* above with $h(t)$ taken as the original signal until $h(t)$ is an IMF. Assume the first IMF is $h_{1k}(t)$, denoted as $c_1(t)$, i.e.

$$c_1(t) = h_{1k}(t) \quad (7)$$

$r_1(t)$ denotes the difference between $x(t)$ and $c_1(t)$, i.e.

$$r_1(t) = x(t) - c_1(t) \quad (8)$$

And $r_1(t)$ is treated as a new original signal and subjected to the same sifting process as described above. The sifting process can be stopped by any of the following predetermined criteria: either when the component, $c_n(t)$, or the residue, $r_n(t)$, becomes so small that it is less than the predetermined value of substantial consequence, or when the residue, $r_n(t)$, becomes a monotonic function from which no more IMF can be extracted. Thus the original signal $x(t)$ can be composed of n-empirical modes and a residue, $r_n(t)$, which can be either the mean trend or a constant, i.e.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (9)$$

On the practical side, before the signal is decomposed by EMD, signal pre-processing or extension should be taken because serious problems of the spline fitting can occur near the ends, 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. It is so-called end effect. In this paper, support vector regression algorithm [9] is taken as the pre-processing to eliminate the end effects, which proves to be effective.

B. *Algorithm of Multicomponent LFM Parameter Estimation*

In this paper the approach presented to implement multicomponent LFM parameter estimation based on HHT is described as follows.

1) After EMD processing, the original multicomponent LFM signal is decomposed into several IMFs which include the IMFs representing those certain LFM components in the original signal.

2) The following Hilbert spectrum is obtained after Hilbert transform on the IMFs corresponding to the certain LFM components.

3) The line integral of the Radon transform is performed over all lines in the Hilbert spectrum plane. The Hilbert spectrum of LFM signal is in shape of oblique line. Thus each LFM signal energy can be converged together in different angel and/or position. After the Radon transform in Hilbert spectrum plane at different angel α is computed, a certain number of maxima according to the number of LFM components in original signal can be found in the resulting $\alpha - u$ plane through 2-dimensional search. Assume one of the maxima locates at (α_0, u_0), then the corresponding initial frequency f_0 and chirp rate k_0 can be denoted as

$$f_0 = u_0 \csc(\alpha_0), \; k_0 = -\cot(\alpha_0) \tag{10}$$

IV. RESULT OF COMPUTER SIMULATION

Given a multi-LFM signal with additive noise, it can be modeled by a linear sum of several LFM signals, i.e.

$$s(t) = \sum_{i=1}^{N} C_i \exp\left[j2\pi \left(f_{0i} t + K_i t^2 / 2 \right) \right] + n(t) \tag{11}$$

where N is the number of LFM components. C_i, f_{0i} and K_i represent the amplitude, initial frequency and chirp rate respectively. $n(t)$ is the additive complex Gaussian white noise. In the simulation the original signal contains three LFM components (i.e., N=3) which are designated as component 1, 2 and 3. Respectively, the amplitudes are 1，0. 5，0.5, and the initial frequencies are 224Hz, 86Hz, 35Hz, and the chirp rates are 70Hz/s, 56Hz/s, 18Hz/s. The sampling frequency is 8KHz and sampling point number is 2000. The signal-to-noise ratios of $n(t)$ to the each LFM component are 18dB，12dB and 12dB respectively. Fig. 2 gives the result after the EMD processing, in which IMF3, IMF4 and IMF5 obviously represent the three LFM components. As EMD is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically, the primary part of noise mainly locates at the initial several IMFs such as IMF1 and IMF2 in Fig. 2. It is dependent on the practical signal to find the actual number of IMFs corresponding to the noise, from which the definition of EMD method derives.

The Wigner-Ville Distribution (WVD) of the original signal is shown in Fig. 3 and the Hilbert-Huang transform of the signal without noise denoted by IMF1 and IMF2 is shown in Fig. 4. Although ideal time-frequency convergence is obtained in figure 2, cross terms appear so severely that it is very difficult to implement signal detection and parameter estimation. Especially for the component 2 and component 3, it is difficult for identification. Through the contrast between Fig. 3 and Fig. 4, it is obviously shown that the three components appear clearly in the HHT of the signal without cross terms and the instantaneous frequencies of the three IMF components are all linearly time-varying. After Radon transform is performed in Hilbert spectrum plane, the result in the $\alpha - u$ plane is given in Fig. 5, which indicates that three peak values appear corresponding to those IMF components respectively. The parameters estimated are: the amplitudes of each component are respectively 1.035, 0.536, 0.518; initial frequencies are respectively 223.1Hz, 83.7Hz, 35.2Hz; chirp rates are respectively 70.6Hz/s, 56.8Hz/s and 17.5Hz/s. The result obviously proves the effectiveness of the method.

V. CONCLUSION

In this paper, a MMW Doppler radar is introduced. And a new approach based on Hilbert-Huang transform and Radon transform is presented for the radar. It is adaptive to

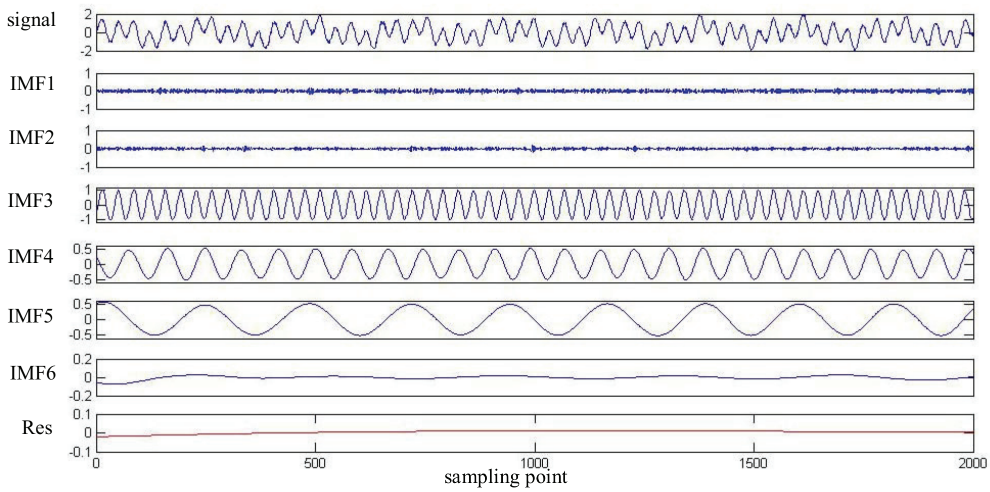

Figure 2. Signal decomposition result after EMD

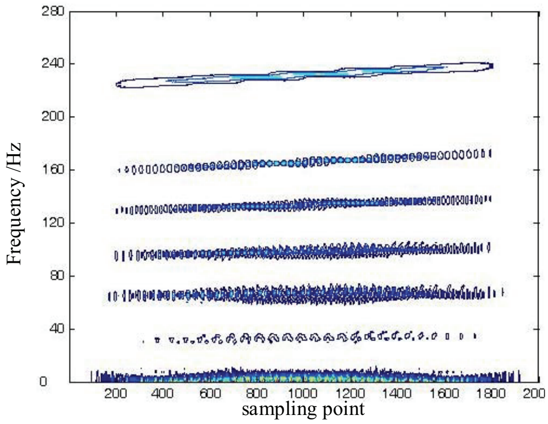

Figure 3. Wigner-Ville distribution of signal

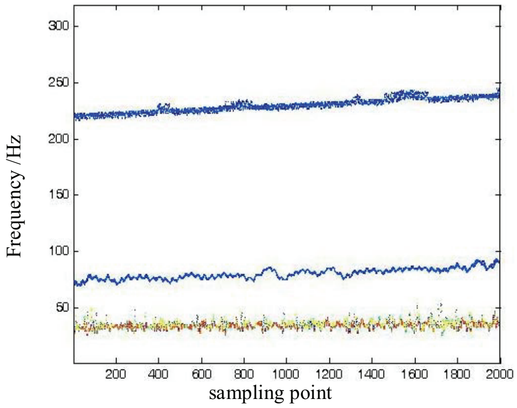

Figure 4. Hilbert-Huang transform after denoising

nonstationary signals and has good time-frequency convergence. Meanwhile, additional denoising operation can be achieved. The computer simulation demonstrates that the proposed method is effective and the MMW Doppler radar is capable of processing echoes which contain multicomponent LFM signals.

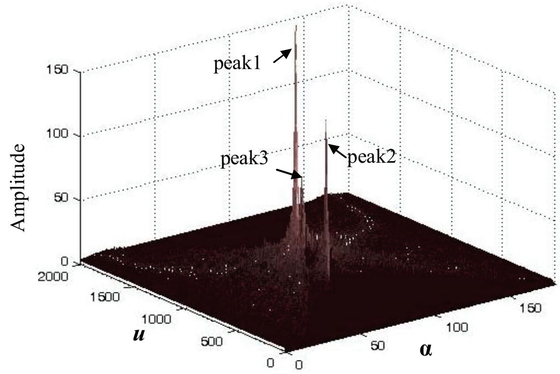

Figure 5. Radon-HHT of the signal

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