Time-Frequency Distribution of Encountered Waves Using Hilbert-Huang Transform

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Abstract— Time-frequency distribution (TFD) of signals gains increasing applications in various areas of sciences and engineering for processing non-stationary signals and nonlinear signals. This paper presents our work of TF analysis of encountered wave signal in ship science using the Hilbert-Huang transform (HHT). The results in this paper exhibit that the HHT based TFD of encountered wave signal has better resolution in comparison with those resulted from the traditional methods, such as short-time Fourier transform (STFT), wavelet transform (WT) TFD, and Choi-Williams TFD.

Keywords— Time-frequency distribution, encountered waves, Hilbert-Huang transform, wavelet transform, short-time Fourier transform.

I. INTRODUCTION

TIME-frequency (TF) description of nonstationary and or nonlinear signals is important for structural mechanics, see e.g. [1-3]. Spectral structure of encountered waves exerting on a ship hull plays a role in the optimal design of ship structures, see e.g. Troesch [32,33], Jensen [34], Gu et al. [35]. Hence, TF distribution (TFD) of encountered wave signal in good quality is greatly desired in ship mechanics (Gu et al. [35], Xu and Gu [36]).

The power spectrum density (PSD) of a non-stationary signal is time varying. That is, it is also a function of time in addition to frequency. More precisely, the PSD of a non-stationary process $\{x(t)\}$ should be expressed by $S_{xx}(t,\omega)$, which is called evolutionary spectrum. In the field of signal processing, it is usually termed TFD. By analogy with stationary processes, the PSD of a non-stationary process is defined as

$$S_{xx}(t,\omega) = \mathrm{F}\left[r_{xx}(t,\tau)\right] = \int_{-\infty}^{\infty} r_{xx}(t,\tau)e^{-j\omega\tau}d\tau, \qquad (1)$$

where $r_{xx}(t,\tau)$ is the autocorrelation function of $x(t)$ and F the operator of the Fourier transform. Eq. (1) implies that the PSD of a non-stationary process should be analyzed in a TF plane.

Some early work regarding the mathematical properties of TFD was reported by Priestley [4], Loynes [5], Mark [6], Shinozuka [7]. There are several types of methods that are commonly used in engineering to describe $S_{xx}(t,\omega)$, such as Priestley's evolutionary spectrum [4], Mark's physical spectrum [6], short-time Fourier transform (STFT) [8,9], TFDs in the Cohen class [10] (e.g., Chio-Williams distribution (CWD)), and wavelet-based TFD [11]. Recently, Huang and et al. introduced a new type of TFD based on the Hilbert-Huang transform (HHT) [12,13]. Its applications in practice are noticeable, see e.g. Du and Yang [14], Yang and Gao [15]. This paper aims at presenting our TF analysis of encountered wave signal using HHT in ship mechanics and demonstrating the resolution comparison with the TFDs based on STFT, WT, and CWD. The results imply that the HHT based TFD for encountered wave signal has higher resolution than other three.

The rest of paper is organized as follows. In Section 2, the environment of signal measurement is briefed. We demonstrate the TFD comparisons in Section 3 together with the brief description of each computational method. Section 4 concludes the paper.

II. ENVIRONMENT OF SIGNAL MEASUREMENT

The signal was measured during a model test of a large-scaled oil tanker in the seakeeping test basin in the China Ship Scientific Research Center. It is in the size of 69m(length)×46m(width)×4m(depth) (Fig. 1).

Fig. 1. Profile of the basin for model test.

The wave-height gauge was mounted at the point 2 meters away in front of the prow. The recorded data history of the encountered waves is indicated in Fig. 2. We shall discuss its TFD in the next section.

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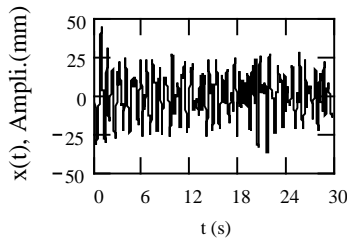
Fig. 2. Encountered waves: signal to be processed.

III. TFDs of Encountered Waves with Comparison Demonstrations

In this section, the TFDs of the encountered waves in Fig. 2 are discussed based on STFT, WT, CWD, and HHT in turn.

A. STFT of Encountered Wave Signal

Linear transforms were first introduced by Gabor [16]. The basic idea behind Gabor regarding TF description of a signal is to obtain a TFD of the signal by performing Fourier analysis on the signal as it is when observed through a set of identical windows that are translated with respect to each other in time. The functionality of windows is to localize the signal in TF plane. The window function Gabor suggested is Gaussian.

STFT is a kind of linear transforms. It is an extension of Gabor's transform [17]. Denote $S_x(t, \omega)$ the STFT of $x(t)$. Then,

$$S_x(t, \omega) = \int_{-\infty}^{\infty} x(\tau)h(t - \tau)e^{-j\omega\tau}d\tau, \qquad (2)$$

where $h(t)$ is a window function. Using the Hamming window of the window size 127, we obtain the STFT based TFD of the encountered wave signal $x(t)$ in Fig. 2 as that indicated in Fig. 3.

Note that STFT stands for a set of methods. Different methods use different window functions. To select a window function so that it is optimally suitable for the signal to be processed may be an uneasy task in practice. In addition, the bandwidth of the analyzing functions is a constant that is independent of center frequency. Similarly, the time duration or window size of the analyzing functions is also a constant. To choose concrete values of the bandwidth and the time duration so that they are optimally suitable for the signal to be processed when a window function is given appears a hard problem.
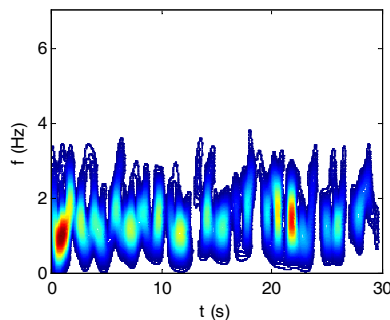

Fig. 3. STFT based TFD of the encountered waves.

B. CWD of Encountered Wave Signal

Different from STFT, a class of TFDs is discussed by Cohen [10,18]. TFDs in the Cohen class are generalizations of the Wigner-Ville distribution that was first introduced by Wigner [19] in 1932 in quantum mechanics and Ville [20] in 1948 for TF analysis.

Denote $WD_x(t, \omega)$ the Wigner distribution (WD) of a real-valued signal $x(t)$. Then,

$$WD_x(t, \omega) = \int_{-\infty}^{\infty} x\left(t + \frac{\tau}{2}\right)x\left(t - \frac{\tau}{2}\right)e^{-j\omega\tau}d\tau. \qquad (3)$$

The main unsatisfactory point of WD in practice is that it produces cross-terms. In fact, using the Fourier series, one has $x(t) = \sum A_n \cos(n\omega_1 t + \varphi_n)$, where A_n and φ_n are the amplitude and the initial phase of the nth harmonic of $x(t)$, respectively. Thus,

$$x(t + \tau/2)x(t - \tau/2)$$
$$= \sum A_n \cos[n\omega_1(t + \tau/2) + \varphi_n]\sum A_n \cos[n\omega_1(t - \tau/2) + \varphi_n].$$
$$(4)$$

The above clearly interprets why there exist cross-terms in a WD.

In order to suppress cross-terms and to obtain auto-terms as many as possible, a kernel is utilized in the Cohen class. Denote $\Phi(u, \tau)$ a kernel function. In the general sense, we denote a TFD in the Cohen class by GTFD(t, ω), which is written by

$$GTFD(t, \omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x(t + \tau/2)x(t - \tau/2)$$
$$\Phi(u, \tau)e^{j(ut - \tau\omega - ut)}dtd\tau du, \qquad (5)$$

where $\Phi(u, \tau)$ satisfies the conditions mentioned in [10].

The literature regarding kernel design is rich. Several commonly used kernels are Gaussian function discussed by Choi and Williams [22], Bessel function studied by Guo and et al. [23], corn-shaped kernel explained by Oh and Marks [21], and others [10]. The Gaussian function used in CWD is given by

$$\Phi_{CWD}(u, \tau; \sigma) = e^{-\frac{u^2\tau^2}{\sigma}}, \qquad (6)$$

where σ is a scaling factor to control its attenuation rate. Fig. 4 shows the CWD of the encountered waves for $\sigma = 1$.
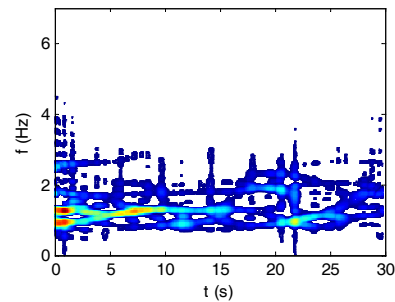

Fig. 4. CWD of the encountered waves for $\sigma = 1$.

Note that to select the optimal kernel for a signal being processed may be difficult since kernel selection is signal dependent (Baraniuk and Jones [24,25]).

C. WT Based TFD of Encountered Waves

WT of a signal $x(t)$ is defined by

$$\mathrm{WT}_x(t;a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(\tau) g^* \left(\frac{\tau - t}{a} \right) d\tau, \qquad (7)$$

where $g(t)$ is the basic wavelet or the mother function, $*$ represents the complex conjugate, $a > 0$ is a scalar. The constant $1/\sqrt{a}$ is used for energy normalization. Different values of a and t cause the property of multiresolution.

Note that $g(t)$ in (7) can be taken as an impulse function of a linear system. Denote f_0 the central frequency of the analysis system. Then, the scalar a can be expressed by

$$a = \frac{f_0}{f}. \qquad (8)$$

Hence, WT is a tool for TF analysis of signals with the local frequency $f = af_0$, see e.g. Rioul and Vetterli [26], Strang and Nguyen [27].

There are a number of mother functions in the field, such as Daubechies's 4-coefficient wavelet, Haar wavelet, Morlet wavelet, and so on. We use the Morlet wavelet to obtain WT based TFD of the encountered wave signal $x(t)$ as indicated in Fig. 5.
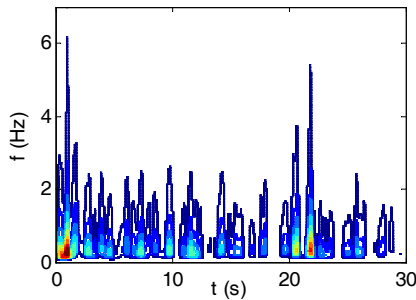

Fig. 5. WT based TFD of the encountered wave signal.

Note that the selection of the optimal mother function for a signal being processed may be a hard issue.

D. HHT Based TFD of Encountered Waves

By using HHT, a signal being analyzed can be represented in TF domain by combining the empirical mode decomposition (EMD) with the Hilbert transform (Huang and et al. [12,13]). Different from three approaches mentioned previously, EMD is adaptively data-driven, see e.g. Flandrin and Gonçalvès [29,30].

Denote H the operator of the Hilbert transform (HT). Then, $\mathrm{H}[x(t)]$ is given by

$$\mathrm{H}[x(t)] \triangleq y(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau. \qquad (9)$$

As any analytic signal $z(t)$ can be expressed by the sum of its real part $x(t)$ and the imaginary part $y(t)$ that is the Hilbert transform of the real part (Papoulis [31, Chap. 7]), one has

$$z(t) = x(t) + jy(t). \qquad (10)$$

In the polar coordinate system, the above can be written by

$$z(t) = a(t)\exp[j\vartheta(t)], \qquad (11)$$

where $a(t) = [x^2(t) + y^2(t)]^{0.5}$ and $\vartheta(t) = \tan^{-1}[y(t)/x(t)]$ are the instantaneous amplitude and the instantaneous phase of $z(t)$, respectively. Thus, $x(t)$ can be recovered from $z(t)$ by

$$x(t) = \mathrm{Re}[z(t)] = \mathrm{Re}\{a(t)\exp[j\vartheta(t)]\}. \qquad (12)$$

Based on HT, therefore, the instantaneous frequency $\omega(t)$ is expressed by

$$\omega(t) = \frac{d\vartheta(t)}{dt} = \frac{\dot{y}(t)x(t) - y(t)\dot{x}(t)}{x^2(t) + y^2(t)}. \qquad (13)$$

Note that to assure of the physical meaning of $\omega(t)$ requires that $\vartheta(t)$ must be a single-valued function over time, i.e., a mono-component function. A signal being processed in general, however, may not be mono-component but multi-component. Thus, a method to decompose $x(t)$ into a series of mono-functions is desired. In this aspect, Huang and et al. developed a method called EMD that decomposes $x(t)$ into a series of mono-functions termed intrinsic mode functions (IMFs).

It is noted that, physically speaking, the necessary conditions to define a meaningful instantaneous frequency are that the signal being processed must be symmetric regarding the local zero mean, and have the same numbers of zero crossings and extrema. This implies that, in an IMF, the number of extrema and the number of zero crossings must be either equal or different at most by one in the whole data set, and the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at every point. Those conditions are strict such that the resulting IMF may not satisfy them exactly in general. Hence, the result is generally nearly a mono-component function instead of a perfect one. However, this does not matter in practice when one considers that signals to be processed usually include a certain amount of noise or measurement errors in addition to computation errors in signal processing.

The procedure to decompose $x(t)$ into a series of IMFs is as follows.

First, identify all local maxima from $x(t)$ and then connect them with the cubic spline line to form the upper envelope of $x(t)$. Denote the upper envelope of $x(t)$ by $x_{\mathrm{up}}(t)$.

Second, identify all local minima from $x(t)$ and then connect them with the cubic spline line to form the lower envelope of $x(t)$. Denote the lower envelope of $x(t)$ by $x_{\mathrm{low}}(t)$.

Third, compute the mean by

$$m_{11}(t) = [x_{\mathrm{up}}(t) + x_{\mathrm{low}}(t)]/2 \qquad (14)$$

and construct a new signal $h_{11}(t)$ by

$$h_{11}(t) = x(t) - m_{11}(t). \qquad (15)$$

In the ideal case, $h_{11}(t)$ is an IMF since it satisfies all the conditions of IMF. In practice, however, there may exist overshoots and undershoots during processing. This is particular true for processing encountered wave signals in ship mechanics. Those overshoots or undershoots may distort the mean values, accordingly make the envelope mean differ from

the true local mean, and, as a result, make $h_{11}(t)$ asymmetric. To deal with this practical issue, Huang and et al. suggested the fourth step below.

Fourth, repeat the shifting process (15) by taking $h_{11}(t)$ as a new signal. After the *k*th iteration, we have

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t),\qquad(16)$$

where $m_{1k}(t)$ is the mean envelope after the *k*th iteration, and $h_{1(k-1)}(t)$ is the difference between the signal and the mean envelope at the $(k-1)$th iteration. Define $h_{1k}(t)$ as the first IMF component. Express it by

$$c_1(t) = h_{1k}(t).\qquad(17)$$

Fifth, having separated $c_1(t)$ from $x(t)$, one has the residue given by

$$r_1(t) = x(t) - c_1(t).\qquad(18)$$

The criterion for stopping the iteration suggested by Huang and et al. is like this. Given the standard deviation expressed by

$$SD = \sum_{t=0}^{N} \frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)}.\qquad(19)$$

Then, the iteration stops when SD is equal to or less than a predetermined value. Huang and et al. suggested that, typically, $SD \approx 0.2 \sim 0.3$, which is very rigorous limit for the difference between two consecutive iteration.

Sixth, treating $r_1(t)$ as a new signal and the above iteration procedure is repeated to extract the rest of IMFs to the signal $x(t)$ as

$$\begin{cases} r_1(t) - c_2(t) = r_2(t) \\ \qquad\vdots \\ r_{n-1}(t) - c_n(t) = r_n(t) \end{cases}.\qquad(20)$$

Seventh, the signal decomposition procedure ends when $r_n(t)$ becomes a monotonic function or a constant, which implies that no further IMFs can be extracted from $x(t)$.

Replacing (20) into (18), a series of IMFs of $x(t)$ are obtained. Therefore, $x(t)$ can be expressed as the combination of $c_i(t)$ plus the residue $r_n(t)$. That is,

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t).\qquad(21)$$

Now, performing HT on $c_i(t)$ yields

$$a_i(t) = \sqrt{[c_i(t)]^2 + H[c_i(t)]^2},\ \vartheta_i(t) = \tan^{-1}\left\{ \frac{H[c_i(t)]}{c_i(t)} \right\}.\quad(22)$$

The instantaneous frequency is given by

$$\omega_i(t) = \frac{d\vartheta_i(t)}{dt}.\qquad(23)$$

In the polar coordinate system, $x(t)$ is expressed by

$$x(t) = \text{Re}\left(\sum_{i=1}^{n} a_i(t) \exp\left[j\int \omega_i(t)dt \right] \right) + r_n(t).\qquad(24)$$

Ignoring the residue is practically allowed since it is either a monotonic function or a constant. Doing so yields

$$x(t) \approx \text{Re}\left(\sum_{i=1}^{n} a_i(t) \exp\left[j\int \omega_i(t)dt \right] \right).\qquad(25)$$
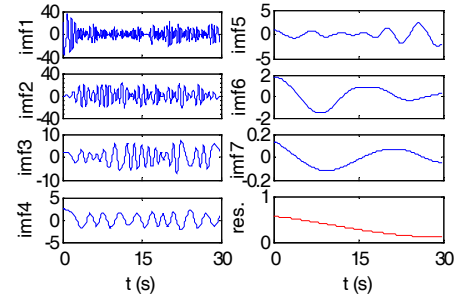

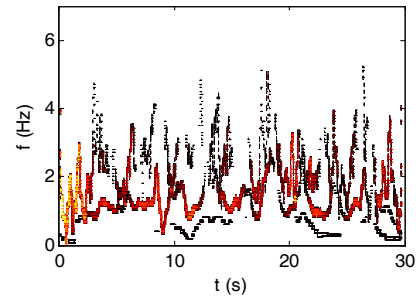Fig. 6. IMFs of the encountered wave signal.

Fig. 7. HHT based TFD of the encountered wave signal.

Let $a_i(t, \omega)$ be the combination of the amplitude $a_i(t)$ and the instantaneous frequency $\omega_i(t)$ of the *i*th IMF. Denote the HHT of $x(t)$ by $\text{HHT}(t, \omega)$. Then,

$$\text{HHT}(t, \omega) = \sum_{i=1}^{n} a_i(t, \omega).\qquad(26)$$

Fig. 6 indicates the IMFs and the residue of the encountered wave signal $x(t)$. Fig. 7 is its $\text{HHT}(t, \omega)$.

E. Discussions

Judging from Figs. 3, 4, 5, and 7, one sees that $\text{HHT}(t, \omega)$ clearly has higher resolution than those with STFT, CWD and WT. As a matter of fact, the basis of HHT is adaptively constructed according to the signal being analyzed while others are not. This advantage makes HHT superior to other three without the limitations caused by those like various window functions in STFT or different mother function in WT or different transform kernels in GTFD. In addition, HHT has no requirement in record length of signal being analyzed since its decomposition accuracy is adaptively satisfied with a given SD expressed in (19). For the Fourier type PSD, however, in order to obtain the desired resolution of PSD of ocean waves, the record length of wave signal is strictly required (Li [37]).

IV. CONCLUSION

We have discussed our TF analysis of the encountered wave signal. The results indicate that the HHT based TFD has high resolution.

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