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Empirical decomposition method for modeless component and its application to VIV analysis

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ABSTRACT: *Aiming at accurately distinguishing modeless component and natural vibration mode terms from data series of nonlinear and non-stationary processes, such as Vortex-Induced Vibration (VIV), a new empirical mode decomposition method has been developed in this paper. The key innovation related to this technique concerns the method to decompose modeless component from non-stationary process, characterized by a predetermined 'maximum intrinsic time window' and cubic spline. The introduction of conceptual modeless component eliminates the requirement of using spurious harmonics to represent nonlinear and non-stationary signals and then makes subsequent modal identification more accurate and meaningful. It neither slacks the vibration power of natural modes nor aggrandizes spurious energy of modeless component. The scale of the maximum intrinsic time window has been well designed, avoiding energy aliasing in data processing. Finally, it has been applied to analyze data series of vortex-induced vibration processes. Taking advantage of this newly introduced empirical decomposition method and mode identification technique, the vibration analysis about vortex-induced vibration becomes more meaningful.*

KEY WORDS: Empirical decomposition; Modeless component; Modal identification; Vortex-induced vibration**.**

INTRODUCTION

With the development of modern marine and offshore engineering, various cylindrical structures, e.g., flexible risers, pipelines, mooring lines and underwater cables have been widely adopted in deepwater oil production and offshore wind energy utilization industries. Those flexible risers/pipes are easily subject to shear or oscillatory flows. When the frequency of vortex shedding in the wake approaches any natural/intrinsic frequency of marine risers/pipelines, the structural vibration easily takes control of the vortex shedding process, causing the vortices to shed at a frequency very close or even equal to the structural frequency. Subsequently, the phenomenon of 'lock-in/synchronization' emerges. For current and wave are often characterized by high degree of complexity, considerable intensity and multi-direction along water depth, the observed Vortex-Induced Vibration (VIV) processes are usually more intricate than our estimation.

As it is well known, the vibration response of rigid cylinder mounted on spring support is usually of a mono-modal process, and the natural frequency of the riser system is not sensitive to its finite length. On the other hand, the vibration response of flexible riser/pipe system shows different profile, several vibration modes, including some natural modes and arbitrarily excited random modal candidates, may be excited at the same time, whether 'lock-in' takes place or not (Kaasen et al., 2000; Trim et al.,

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2005; Lie and Kaasen, 2006; Kleiven, 2002).

Contrasting to great interesting about the vibration processes relating marine (or offshore) structures, such as VIV, data analysis has seldom attracted much attention. In fact, it is a necessary part concerning naval architecture and ocean engineering, either in theoretical research or in practical application. Palpable as some data might be, they represent the reality sensed by us. Generally speaking, data analysis achieves two purposes: to determine the critical parameters needed to construct the necessary model, and to confirm the model we constructed to represent the phenomenon (Huang et al., 1998). Sometimes, the attempt to develop an effective method to analyze phenomena is more important than the phenomena interpretation themselves. In the field of vibration process concerning VIV, the important thing left to us is how to reveal the myth secreted behind them by a proper analysis method.

Since VIV may cause increase of drag and lift forces onto riser/pipe systems and subsequently attenuates their life span, it is necessary to have deep comprehension about this phenomenon. Particularly, in the case of raw data being provided, the intrinsic characteristics concerning it, such as nonlinearity, should be paid much attention. As one of important analytical tools to theoretic research and practical engineering application concerning VIV of marine risers, a well-performed data processing method may accurately evaluate the efficiency of data series. Subsequently, it might highlight the observation of experiment or numerical simulation.

Most observed data in nature, like the data series of VIV processes from field measurement or numerical simulation, most likely have one or more of the following imperfect problems: (a) the data are non-stationary characterized by a unique component to manifest the deflection trend from its equilibrium position; (b) the total data series is commonly long enough, but have a time-varying instantaneous amplitude and frequency, especially in case of mode jump and vortex shedding modal transition taking place; and (c) the data are difficult for intrinsic mode identification and further estimation relating vibration energy (Huang et al., 1996; Michael, 2008). So complicated as VIV is, the demand for accurate modal analysis is indispensable. When 'Lock-in/synchronization' taking place, the VIV concerning large-scale flexible risers/pipes is indeed a multi-modal process, instead of a mono-modal one, whether in In-Line (IL) or Cross-Flow (CF) direction. In addition, some arbitrary vibration modes, which are randomly excited, can be subsequently aggravated during vibration processes. Since VIV is usually characterized by transience and unsteady, it becomes insufficient to analyze the vibration properties concerning it when using Fourier power spectrum with data unprocessed.

Referring to the common characteristics of vibration process, a generally nonlinear and non-stationary data series might be divided into two major parts, a modal component and a modeless one, respectively. The former is indeed of a composite signal consisting of a series of natural or randomly induced modes, while the latter represents the apparent non-stationarity of a vibration process. In this paper, two kinds of decomposition methods for modeless component would be introduced. The first one relates to a decomposition scheme in which the band-pass and empirical mode decomposition techniques has been adopted (Chen, 2010). The obtained modeless term is indeed of a special signal component defined by low-pass filtering. Another one is newly developed in this paper, which is characterized by 'maximum intrinsic time window' and cubic spline line. Finally, the new modeless decomposition method for modeless component has been applied to analyze the characteristics of three kinds of data series, i.e., self-excited VIV data from different experiments, and some inspiring results and new insights have been obtained.

Before introducing this technique in detail, brief introduction about data characters and their processing methods should be introduced first.

DATA CHARACTER AND IMPERFECTION OF ANALYSIS METHOD

Imperfection of fourier transform

Historically, Fourier spectral analysis has provided a general method for examining the global frequency-energy distributions. As a result, the term 'spectrum' has become almost synonymous with the Fourier transform of the data, and has been applied to all kinds of data. Partially attributing to its efficiency and partially to its simplicity, Fourier analysis has dominated the data analysis field soon after its introduction. Other than stationarity, Fourier spectral analysis also requires linearity. Although many natural phenomena can be approximately regarded as linear systems, they also have the tendency to be nonlinear whenever their variations become finite in amplitude. The imperfection of strain gauge probes or numerical schemes usually makes these complications serious. Therefore, the available data are frequently of finite duration, non-stationary and nonlinear, either intrinsically or through interactions with the imperfect probes or numerical schemes. In case of those conditions, Fourier spectral analysis is of limited use. The uncritical use of Fourier spectral analysis and the insouciant adoption of the stationary and linear assumptions may give misleading results.

The Fourier components could make mathematical sense, but can not really make physical sense at all. Fourier spectral analysis uses linear superposition of trigonometric functions. Therefore, it needs additional harmonic components to simulate some deformed wave-profiles, e.g. some inharmonic components. Similar with the way to define harmonic component globally, it needs many additional harmonic components to simulate non-stationary data which are non-uniform globally. As a result, it spreads the energy over a wide frequency range. Both non-stationarity and nonlinearity may induce spurious harmonic components, causing energy diffusion subsequently.

As it is well known, Fourier series decomposes a periodic function into a sum of simple oscillating functions, namely sins and cosines. There would be some difference between the original signal $x(t)$ and the transmutation $[x(t)]_{F\text{-}IF}$ (namely $IF\{F[x(t)]\}$) which represents the inverse Fourier transform of the Fourier transform $F[x(t)]$. If X_0 represents the mathematical expectation $E[x(t)]$ of $x(t)$, the following equation may be obtained, for the harmonic signal component can not provide any nonzero absolute value.

$$x(t) = E[x(t)] + [x(t)]_{F-IF} \tag{1}$$

For practice application, even if we have some measure to make compromise, for instance, subtracting the mean value from original signal and regarding it as a new data set. Data sets which have asymmetrical trendline may still not satisfy the requirements for harmonic decomposition.

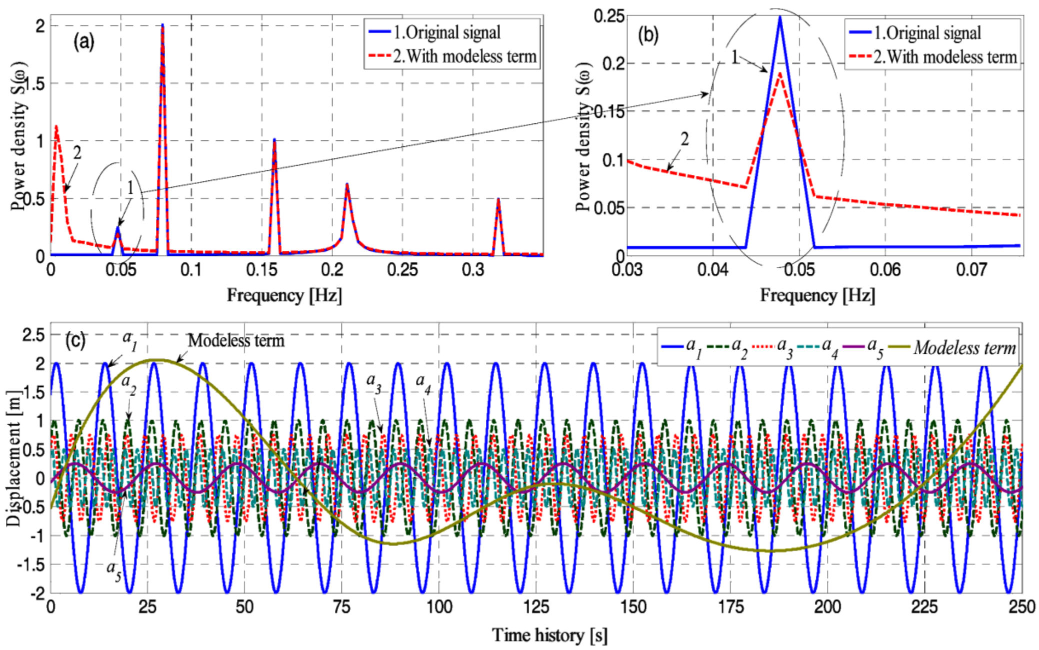

Fig. 1 (a) The power spectral comparison between a composite modal signal and a complex one imbedded a typical modeless component; (b) The locally enlarged power spectra related to the energy diffusion especially to low frequency vibration component resulting from Fourier transform; (c) A typical modeless component and a composite signal composed of several harmonic components.

In order to clearly demonstrate the effect of non-stationarity on Fourier power spectrum, an example is shown in Fig. 1. The solid (No.1) and dotted (No.2) lines shown in subplot Fig. 1(a) respectively denote the power spectra for composite signal $S_1(t)$ and another composite signal which is composed of $S_1(t)$ and a modeless component. They agree well, with regard to spectral density estimation relating high frequency domain. However, the phenomenon of energy diffusion resulting from non-stationarity becomes remarkable around the lowest mode component, shown by enlarged illustration in Fig. 1(b). Even though the dominant frequency of non-stationary term is an order of magnitude lower than that of the original signal, the effect attributing to it is still considerable. Since its corresponding apparent spectral density is considerably large, it subsequently leads to the undervaluation of amplitude, as well as the vibration power and intensity according to Eq. (5). Vibration modal transition or jump in cross-flow and in-line usually happens during acceleration and deceleration processes, and this is the very phenomenon we should pay much attention. For the sake of meaningful frequency-energy analysis, it is important to get the non-stationary/modeless term rid off actual vibration composite signals.

In the case of VIV processing, the obtained data is often characterized by non-stationarity and nonlinearity, for the risers/pipelines deflect attributing to drag force or other factors. Therefore, the expected value in Eq. (1) is not a constant any longer. On the other hand, the composite oscillation data sets which are composed of modal terms can be regarded as linear superposition of trigonometric functions, for some natural and random vibration modes may be excited at the same time when the reduced velocity is fairly large and the aspect ratio is relatively large (or big). Therefore, similar with Longuet-Higgins' model, the data series of VIV process may also be expressed as follows:

$$\zeta(t) = \sum_{n=1}^{\infty} a_n \cos(\omega_n t + \varepsilon_n) \tag{2}$$

where a_n is amplitude of vibration component waveform; ω_n is the angular frequency; and initial phase ε_n is distributed uniformly over $(0, 2\pi)$. The correlation function $R(\tau)$ of $\zeta(t)$ is related to time interval τ, show as follows:

$$R(\tau) = \sum_{n=1}^{\infty} \frac{1}{2} a_n^2 \cos(\omega_n \tau) \tag{3}$$

If set $\tau = 0$, we could obtain the relationship between amplitude a_n and power spectrum:

$$\int_0^{\infty} S(\omega) d\omega = R(0) = \sum_{n=1}^{\infty} \frac{1}{2} a_n^2 \tag{4}$$

and then

$$\int_{\omega}^{\omega+\Delta\omega} S(\omega) d\omega = \sum_{\omega}^{\omega+\Delta\omega} \frac{1}{2} a_m^2 \qquad m \in (1, 2, \cdots n) \tag{5}$$

The symbol $\sum_{\omega}^{\omega+\Delta\omega}$ denotes the total energy of wave components whose angular frequencies are located in the range $(\omega, \omega+\Delta\omega)$. For any composite signal whose ensemble average of displacement/elevation over whole time domain is just equal to that of local finite time domain, namely zero, the expression in Eq. (5) is exactly right. However, it will face predicament, if the non-stationarity is apparent.

Definition of modeless component

The apparent non-stationary term mentioned above has been named modeless component in this paper, in order to distinguish it from the intrinsic vibration modal term. Although the decomposition order and criteria are entirely different, it has similar meaning with the residual term denominated by Huang et al. (1998) and Chen (2010). As it is shown in Fig.1-c, the solid-line marked as 'modeless term' is a typical modeless component attached to the composite modal signal. The particular modeless component here represents the non-modal vibration term imbedded in oscillation process, completely different from intrinsic modal vibration term. It is neither a monotonic function, nor a constant. It is indeed the apparent visualization of non-stationarity concerning nonlinear and non-stationary vibration process, manifesting the tendency of a vibration progressing process.

In the case of VIV, the modal term does not only consist of vibration components induced by some natural modes, but also some randomly excited modes. Otherwise, the so-called modeless term usually represents the temporal accumulated deflection of flexible riser/pipe structures, during the data collection of whole vibration process. Basing upon this viewpoint, it can be regarded as a very long-term signal component whose period is just the measuring interval (from beginning to end), or close to this value. The modeless term usually follows with large distance from zero equilibrium position but without any efficient vibration power and the mean value of residue regarded as the original signal subtracting the modeless component, i.e., local vibration, is zero. If we ignore the meaning of power spectrum concerning non-stationary vibration process anyhow, the apparent dominant vibration frequency and its corresponding power spectral density related to non-stationarity would be processed too. Due to its unpredictable large distance from zero equilibrium position, it might result in a particular emergence that the frequency of the modeless term is at least an order of magnitude less than that of the adjacent identifiable natural mode in general. On the other hand, its apparent power spectral density function may be an order of magnitude larger than that of identifiable intrinsic frequency concerning in-line VIV especially.

From the viewpoint of data series decomposition mentioned above, the original signal concerning non-stationary vibration process can be regarded as the synthesis of some simple harmonic components (S_m , resulting from some intrinsic vibration modes or some randomly excited steady vibration modes belonging to flexible riser/pipe system) and an inharmonic modeless term tendency (S_{ml} , resulting from the non-stationarity of vibration process). In general, for a non-stationary data series $S(t)$, e.g., vibration process, it may be described as below Eq. (6).

$$S(t) = S_m(t) + S_{ml}(t) \tag{6}$$

REQUIREMENT FOR MODELESS COMPONENT DECOMPOSITION

The example shown above primarily interprets the restrictive conditions for modal and modeless identification. In fact, much more efficient and applicable methods should be looked for to decompose the special term, so that the composite signal series can be correctly processed by Fourier transform or other data analysis method related to Fourier technique. According to the physical analysis, each modal data series (e.g., VIV in this paper) which can be processed by Fourier analysis should have the following two characters:

1) The signal series is periodic or approximately periodic with regard to the local zero equilibrium position;
2) The minimum significative frequency that we can observe in oscillation system is just the very one related to the first intrinsic vibration mode.

Only when the data series satisfying the above critical conditions, Fourier transform and modal identification of those kind data might be meaningful. Based on these predeterminations related to single VIV component signal, we propose a class of functions denominated as ‘intrinsic vibration composite signal’ here, characterized with the following formal definitions:

1) The composite signal is composed of some harmonic waveforms resulting from natural vibration mode and some steady vibration waveforms resulting from random vibration modes of flexible riser/pipe system. The expected value of each intrinsic vibration component should be of zero. That is to say that the final composite data signal are symmetric (or approximately symmetric) and periodic with respect to the local zero mean in a finite time window.
2) There is no any component waveform whose frequency is less than the first natural frequency of the flexible riser/pipe system considering the added mass in high density fluid. It means that the modeless component should have been extracted from original vibration process entirely. Mean value the final composite signal consisting of intrinsic vibration components during a considerably long time window should be of zero.

The first condition is obvious. It assures that the zero mean value premise for traditional Fourier transform, as well as the accurate vibration power estimation in the form of decreasing energy dissipation when using spurious harmonic components to form the modeless term with large vibration displacement. Because there would be many intrinsic and few randomly induced steady vibration modes taking place simultaneous in any VIV process, the local zero mean constraint should be efficient in a finite time window scale.

The second restriction is also an indispensable idea. It modifies the classical global requirement to a local one. Due to the unwanted very low frequency fluctuations induced by extremely asymmetric wave profiles, the instantaneous amplitude associated with Hilbert transform and power spectrum from Fourier transform will be meaningless. Ideally, the requirement should be the local mean of the data being zero. Huang et al. (1998) used the local mean of the envelopes defined by the local maxima and the local minima to force the local symmetry instead. This is a necessary approximation to avoid the definition of a local averaging time scale. However it will introduce an alias in the instantaneous frequency for nonlinearly deformed vibration wave profiles and the effects of nonlinearity are notable in comparison with non-stationarity as we encountering in VIV data process. It is worth noting that the spline line in that method indeed attenuates oscillation energy of some intrinsic modes belonging to pipe system.

As a surrogate, for component decomposition of non-stationary data, the technique using 'local time scale' to define 'local mean' aiming at computing the mean, has been proposed in this paper. Therefore, the requirement for local time scale is manifested. How to determine the scale of local mean or finite time window becomes the principal problem that we should focus on, in the case of VIV data processing.

EMPIRICAL DECOMPOSITION METHODS FOR MODELESS COMPONENT

Modeless component decomposition by low-pass filter technique

In the newly developed empirical mode decomposition by virtue of 'band pass filter' technique and fast Fourier transform principle, Chen (2010) had proposed some constraints to define the modeless component too. The so-called modeless component in that thesis, consisting with the description performed above, is indeed a term with very long period, but the energy has been weakened by the Fourier transform. That modeless component is a resultant signal component of 'low-pass filter' term by means of Fourier analysis.

A low-pass filter is designed to pass low-frequency signals, but to make zero the signals with frequencies higher than the cut-off frequency. An ideal low-pass filter completely eliminates all frequencies above the cut off frequency while passing those whose frequency responses are large than cut off frequency unchanged. However, the ideal filter is impossible to realize without having signals of infinite extent in time, and so generally needs to be approximated for real ongoing signals, because the sinc function's support region extends to all past and future times. The filter would therefore need to have infinite delay, or knowledge of the infinite future and past, in order to perform the convolution with its impulse response. It is effectively realizable for pre-recorded digital signals by assuming extensions of zero into the past and future, or more typically by making the signal repetitive and using Fourier analysis.

Real filters for real-time applications approximate the ideal filter by truncating and windowing the infinite impulse response to make a finite impulse response; applying that filter requires delaying the signal for a moderate period of time, allowing the computation to see a little bit into the future. This delay is manifested as phase shift. Greater accuracy in approximation requires a longer delay.

The Whittaker–Shannon interpolation formula describes how to use a perfect low-pass filter to reconstruct a continuous signal from a sampled digital signal. Real digital-to-analog converters use real filter approximations. An ideal low-pass filter results in ringing artifacts via the Gibbs phenomenon. These can be reduced or worsened by choice of windowing function, and the design and choice of real filters involves understanding and minimizing these artifacts. For example, simple truncation causing severe ringing artifacts in signal reconstruction, and to reduce these artifacts one uses window functions which drop off more smoothly at the edges.

In the above reference (Chen, 2010), an empirical mode decomposition based on FFT technique had been developed. The untreated non-stationary vibration data series had been decomposed into a series of intrinsic mode functions and a residue: modeless component which has no modal characteristics. Since the FFT technique had been adopted to define the intrinsic mode functions by means of 'band-pass' filter, the obtained modeless component can be regarded as a residue determined by 'low-pass' filter. Facilitating as the 'low-pass' filter to define the modeless component, there are still some problems left unsolved, such as the definition of long time window scale varying with each individual and the subsequent ringing artifacts. The selection of bandwidth is severely based upon the experience of data processing performer and the criterion of intrinsic mode function, rather than the intrinsic characteristics of data themselves.

According to the particular characteristics of VIV concerning flexible riser/pipe system, a new modeless component decomposition method characterized by cubic spline curve and specially defined time window scale has been developed in this paper.

Modeless component decomposition by cubic spline method

In the field of VIV data analysis, it seems that the signal decomposition attempt to use local mean and the spline method to restructure a curve is more practicable, for the observed VIV data can be regarded as composite signal consisting of many intrinsic modal vibration signals and a modeless component resulting from the accumulated deflection of riser/pipe system.

In this paper, the attempt to decompose the modeless component from extremely nonlinear and non-stationary signals was actualized by applying specifically defined finite time window scale to segment the vibration signal and then using cubic spline line to connect the segmented sections subsequently.

In this new method, some local mean can be obtained by successively sliding a well-designed window along the time axis, and then we can achieve a spline curve by connecting those values with cubic spline method. The 'local mean' involves a 'local time scale' to compute the mean, so the demand for local time scale is urgent. Therefore, how to determine the scale of local time or 'finite time window' becomes the principal problem that we encounter.

The essence of the modeless component decomposition method is to empirically identify it from intrinsic oscillatory modes, by defining some characteristic time scale imbedded in the data. Although we will still adopt cubic spline curve to estimate the special modeless term in this method, the main innovation superior to others is the introduction of new local time scale definition.

Two kinds of typical trendline candidates to present the modeless component which visualizes the non-stationarity of a vibration process are shown in Fig. 2. Both of them can be regarded as the apparent tendency of the nonlinear and non-stationary data series according to different time window scale. Therefore, the key step to decompose the uncertainty of the non-stationary data is to determine the time window scale first.

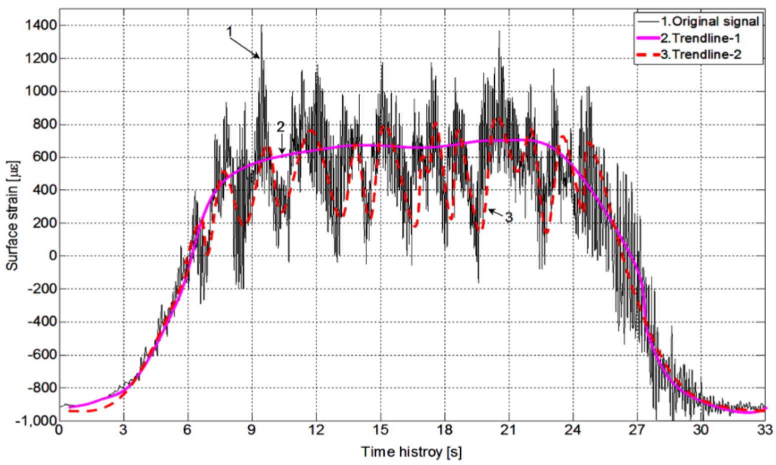

Fig. 2 Two kinds of candidate trendlines to present the non-stationarity.

CALIBRATION OF TIME WINDOW SCALE

In this paper, the main improvement against other methods is the introduction of 'local time window scale' redefinition. Once the special local time window scale is identified, the expectative modeless component can be expressed as the cubic spline line defined by the local mean values. According to Drazin's viewpoint (1992), the first step of data analysis is to examine the data by eye.

According to sampling theorem, aliasing can be avoided if the Nyquist frequency is greater than the bandwidth, or maximum component frequency of the signal being sampled. Strictly speaking, the Nyquist rate is the minimum sampling rate required to avoid aliasing, equal to twice the highest frequency contained within the signal.

$$f_N = 2f_B \tag{7}$$

where f_B is the highest frequency at which the signal has nonzero energy. In practice, to avoid aliasing absolutely, the sampling rate must exceed the Nyquist rate:

$$f_S \geqslant f_N \tag{8}$$

It means that the bandwidth is considered to be the upper frequency limit of a baseband signal. Bandpass sampling signals must be sampled at least twice the frequency of the highest frequency component of the data series. However, it is typical to use aliasing to advantage, allowing sampling of band pass signals at rates as low as $2f_B$.

The constraint used to decompose the modeless term should separate the spurious modeless vibration component characterized by very low frequency and nonzero apparent energy. At the same time, this task should not give any disoperation to the vibration power of the modal vibration wave forms located at the range of lower frequency. Take advantage of sampling theorem, the scale of local 'finite time window' T_f should be ranged as follows: $T_{fst} \leqslant T_f \leqslant T_{ml}/2$, where T_{fst} is the period of the pipe first natural mode and T_{ml} represents the apparent period according to the dominant frequency of modeless component. Although the direct power spectrum analysis about original vibration signals is meaningless for most non-stationary signals, it still provides some relatively formal dominant frequency information even to the modeless component. Generally speaking, the order of magnitude discrepancy between T_{fst} and T_{ml} is at least larger than one in the filed of VIV, or the observed data will be useless if the virtual length of the first natural vibration mode was less than its twice intact period. Therefore, the prior range for the scale of local 'finite time window' T_f is acceptable and logical. For the sake of an accurate power estimation with sufficient sampling point for the first mode and eliminating negative effects from modeless component as much as possible, the scale of local 'finite time window' should be made more rigorous.

The wave profiles are generally symmetric even in the case of low natural vibration modes. Therefore, the sampling period used for modeless component extraction can be as low as T_{fst} (namely, the sampling frequency can be as high as f_{fst}, where f_{fst} means the frequency of the first vibration mode). In this condition, the modal terms can be well high-pass sifting and modeless term left filtered. The filtering would be better to avoid energy dissipation, if T_f could be n times of T_{fst} , where n is a natural number. Time lapse nT_{fst} as the magnitude of time window scale for the principal decomposition criteria has been adopted here. This method does not only give a much finer filtering to the modeless component, but also can bring visible energy reconstruction to vibration modes. On the other hand, n can not be as large as to its upper limit $T_{ml}/2T_{fst}$, or some aliasing resulting from modeless component would be unavoidable. Some compromise ought to be made. Taking advantage of the fact that the RMS displacement and RMS instantaneous amplitude is not consistent if the observed signals are apparently non-stationary (Longuet-Higgins, 1957), an efficient sampling period should be selected, i.e., the proper maximum sampling period. The predetermined value of multiple n usually starts from 1 (depending on the model test style determined by ocular estimation), and successively to larger ones. The upper threshold $n_{\max}$ to end this sifting process is determined as follows: $n_{\max}$ should be a natural number which is large enough to keep the ratio of RMS instantaneous amplitude M_1 against RMS displacement M_3 equals to or very close to $\sqrt{2}$, and this relationship will be broken permanently if n is equals to or larger than $n_{\max}+1$. We named $n_{\max}$ as the 'maximum multiple' of T_{fst}.

In order to process accurate power estimation with sufficient sampling point for the first mode and eliminate negative effects from modeless component as much as possible, the scale of local finite time window should be made more deliberate. Here, the critical constrain for $n_{\max}$ determination has deduced based on the consistency between RMS instantaneous amplitude M_1 against RMS displacement M_3. Because M_1/M_3 is a specific value, it is suitable to express any data with consistent measurement unit. A parameter named R_r was introduced to express the close relationship between M_1 and M_3.

$$R_r = \left|\sqrt{2} - \frac{M_1}{M_3}\right| \leqslant 1‰ \tag{9}$$

The predetermined constant 1‰ given in advance may satisfy most instances for general VIV processes. For special conditions which non-stationarity plays an extreme role in some observed signal sets, the determination to this constant should be more rigorous. We named $T_{max}\ (= n_{\max} T_{fst})$ as the 'maximum intrinsic time window' of the original untreated data and $n_{\max}$ as the 'maximum multiple' of T_{fst} corresponding to T_{max}.

According to the principle that the mean value of inverse fast Fourier transform equals to zero, the average of any data series should be zeroized in Fourier transform. On the other hand, since the modeless component is indeed a trendline which is defined by the cubic spline curve connecting the mean values demarcated by local maximum intrinsic time window T_{max} continuously, the obtained residual vibration composite signal S_m is undoubtedly characterized by local and total zero mean levels. With physical approach and the approximation adopted here, the modeless decomposition method would always provide a zero mean S_m. It is useful to guarantee a meaningful Fourier transform and perfect instantaneous amplitude under all conditions in VIV signal processing.

In the case of self-exited VIV conditions, the instantaneous characters about the launching section of transverse vibration are often key parts concerning VIV research. This important vibration process often occurs with apparent in-line direction deflection, making mode jump and energy distribution analysis to this field inaccurate and infructuous. The attempt of separating modeless component from original data series would be helpful to give a deep look at those crucial processes.

APPLICATION IN VIV DATA PROCESSING

Empirical modeless decomposition method for VIV

By virtue of rigorous constraints for local maximum intrinsic time window T_{Max}, the whole modeless component decomposition process can be regarded as the trendline defined by the local mean values and connected by a cubic spline line successively. As a general modeless component decomposition method, it could be applied to most fields which have extremely strong non-stationarity and some intrinsic local vibration terms throughout the whole signal simultaneously. Here, specially, we introduce the unique application to analyze the vibration characters related to vortex-induced vibration data. This decomposition process was shown as follows in detail:

Read the values of T_{fst} and T_{ml}. Fourier spectral analysis for untreated vibration data should be processed first of all. In general, the order of frequency magnitude between T_{fst} and T_{ml} is at least larger than one in the field of VIV. Because of the imperfection of Fourier transform, it will attenuate the power spectral density of eigenmodes located in low frequency domain, but the value of frequency can be predicted exactly. The 'apparent' period of modeless component T_{ml} and the weakened first intrinsic vortex-induced vibration T_{fst} may be exactly estimated from the Fourier spectrum of raw data.

Visualize the modeless component from the raw data. The essence of this decomposition method is to identify the intrinsic modeless component by its characteristically finite time scales of the vibration data series empirically, and then decompose the data subsequently. A proper threshold for $n_{\max}$ determination should be selected, such as 1‰, according to different non-stationarity of any observed data and accuracy requirement that the user predetermines. The RMS values of instantaneous amplitude $M_1^{'}$ and displacement $M_3^{'}$ of obtained residual signal should be calculated subsequently. By virtue of the constraint expressed in Eq. (9) and increasing the multiple n one by one, it would be easy to find the maximum multiple $n_{\max}^{'}$. Once the maximum multiple $n_{\max}^{'}$ has been determined, a cubic spline line could be obtained when connecting a series of local mean values in the maximum intrinsic time window $T_{m\,\mathrm{ax}}^{'}$ successively as the whole tendency of the non-stationary vibration process. This is only a preliminary visualization of modeless component $S_{ml}^{'}$. Some rectification should be done to confirm its validity.

By subtracting S'_{ml} from original signal S, the primary composite signal of vortex-induced vibration terms S'_{lv} could be obtained. Fourier spectral analysis for treated vibration data S'_{lv} should be done again. If there is any evidence that some considerable energy residua exists in the very low frequency domain (lower than the first intrinsic mode) from the Fourier transform of S'_{lv}, a proper threshold for R_r should be selected and then do the step 2) again. The sifting for modeless component should not stop until the apparent vibration spectral density concerning very low frequency is distinctly lower than frequency of the first (for low reduced velocity) or other dominant vibration mode (for high reduced velocity). Then we regard $n'_{\max}$ as $n_{\max}$, $T'_{m\text{ax}}$ as T_{max}, and S'_{ml} as S_{ml} consequently.

Decompose the final modeless component and residual composite signal of vortex-induced vibration, respectively. The finally obtained tendency envelope defined by the maximum intrinsic time window T_{max} is the so-called modeless component. The composite signal of vortex-induced vibration terms S_{lv} could be obtained by the equation show as follows:

$$S_{lv} = S - S_{ml} \tag{10}$$

Calculate the instantaneous amplitude RMS and true power spectra of vibration process. By Hilbert and Fourier transforms of S_{lv}, we may get the instantaneous amplitude and power spectrum of S_{lv}. Further vibration modal analysis might be performed.

The key innovation for this empirical mode decomposition method is that the step to decompose modeless component has been done firstly, completely different from other modal analysis methods. If the modeless component decomposition was performed in the end, the energy of modal term may be weakened by the Fourier transform. Even some fragmentary inharmonic signal components which are located very close to the apparent frequency of the real modeless component might be mistakenly regarded as harmonic signal component of the last several intrinsic mode functions by means of very low 'band-pass' filter. This means that non-stationarity maybe easily leads to spurious harmonic components and distort the oscillation energy distribution finally.

In the case of raw data consisting of may impulse signals, the decomposed modeless component may be different from the theoretical local mean, similar with the sifting process adopted by Huang et al. (1998). Consequently, some asymmetric wave forms may still exist in the residue signals. However, it is indeed competent to produce a true local mean estimation to any VIV processes, for almost all the obvious oscillation components are dominated by eigenmodes.

Efficiency validation

In this section, we will demonstrate the efficiency validation of the newly developed empirical modeless decomposition to VIV data processing via a number of examples.

Although empirical mode decomposition methods with different criteria have been adopted for the sifting process of intrinsic mode function (Huang et al., 1996; Chen, 2010), the decomposition purpose is consistent, that is, generally from higher to lower frequency domains. In the empirical mode decomposition method developed by Huang, the sifting process stops, when the so-called 'residue' (namely modeless component in this paper) becomes so small that it is less than the predetermined value of substantial consequence, or becomes a monotonic function from which no more intrinsic mode function can be extracted (Huang et al., 1996). Since the character of band wide had not been required for single intrinsic mode functions in Huang's method, the comparison between the 'residue' mentioned above and the modeless component defined by this paper is meaningless. As it was mentioned above, the so-called modeless component related to that data decomposition method developed in this paper is indeed a term with very long period.

Here, we compare the resultant modeless components created by the well-known 'low-pass' filter using FFT technique with the one developed in this paper which is characterized by the combination of the maximum intrinsic time window and cubic spline method. Figs. 3~8 illustrate the comparison of the two kinds of modeless component decomposition methods related to the observed data of VIVs. Among those figures, the former four relates to the in-line vibration process of a FRP riser model carried out at KORDI in 2007 (Chen and Kim, 2010), and the latter two concerns the in-line vibration process of a naked pipe model from the VIV experiment carried out MARINETEK (Lehn, 2003). It is worth noting that the selected position for demonstration is approximate located at the very section of maximum in-line deflection.

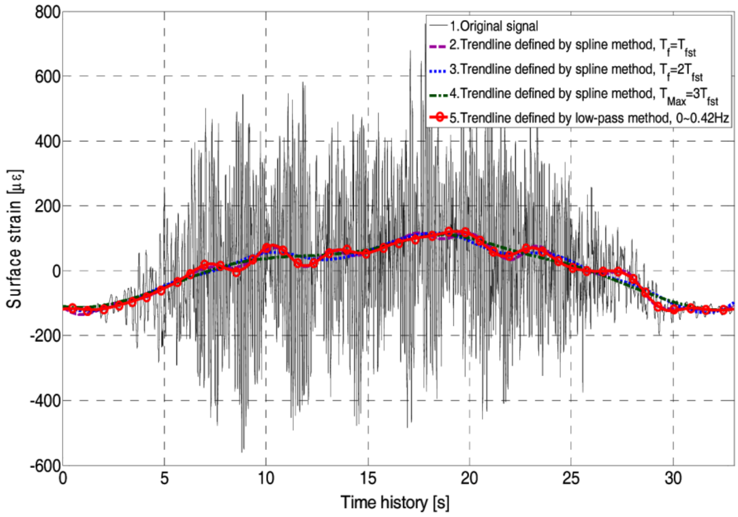

Fig. 3 The comparison of two kinds of modeless component decomposition methods related to the observed data of in-line VIV from experiment, in the case of wake non-stationarity, Data No. 1, T_{fst} =1.14 *sec*.

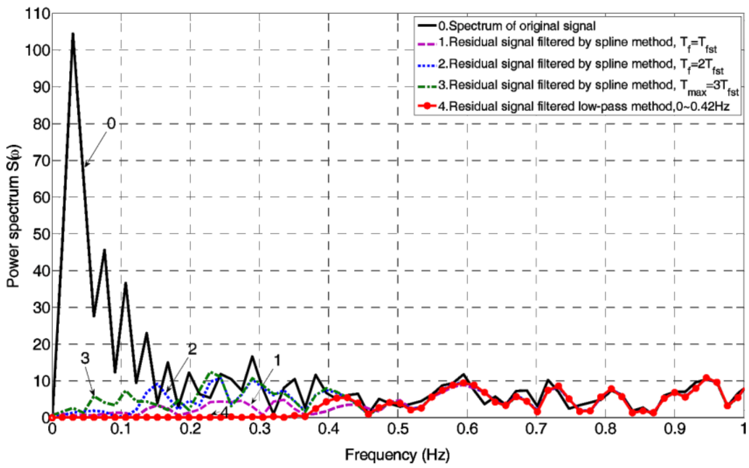

Fig. 4 The comparison of power spectra between decomposition residues by means of two kinds of modeless component decomposition methods in the case of wake non-stationarity, Data No. 1, T_{fst} =1.14 *sec*.

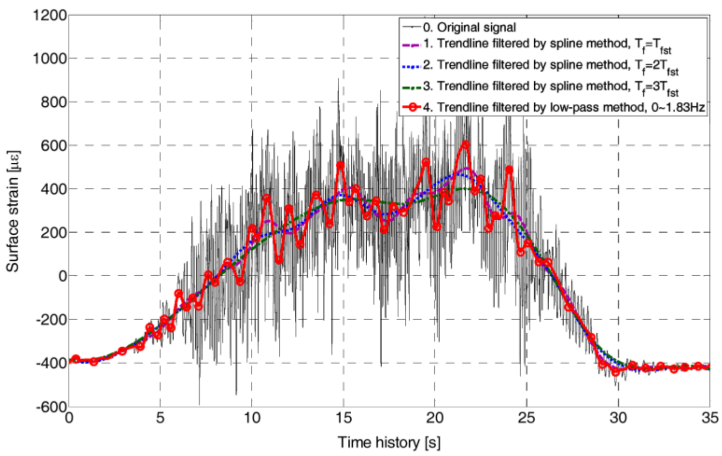

Fig. 5 The comparison of two kinds of modeless component decomposition methods related to the observed data of in-line VIV from experiment, in the case of mild nonstationarity, Data No. 2, T_{fst} =1.14 *sec*.

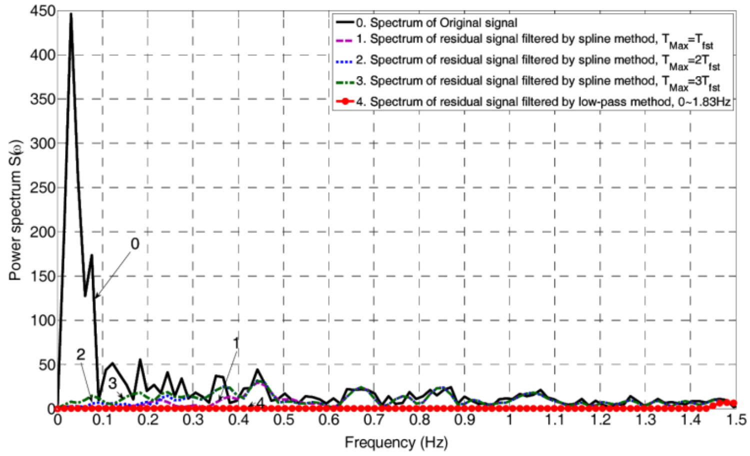

Fig. 6 The comparison of power spectra between decomposition residues by means of two kinds of modeless component decomposition methods in the case of mild non-stationarity, Data No. 2, T_{fst} =1.14 *sec*.

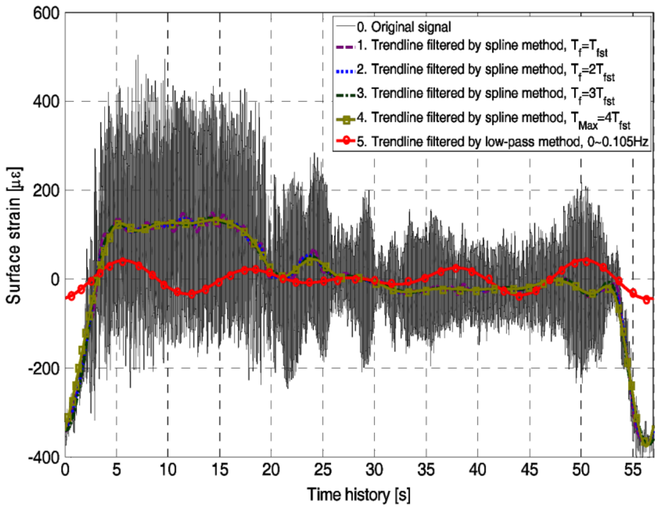

Fig. 7 The comparison of two kinds of modeless component decomposition methods related to the observed data of in-line VIV from experiment, in the case of strong non-stationarity, Data No. 3, T_{fst} =0.48 *sec*.

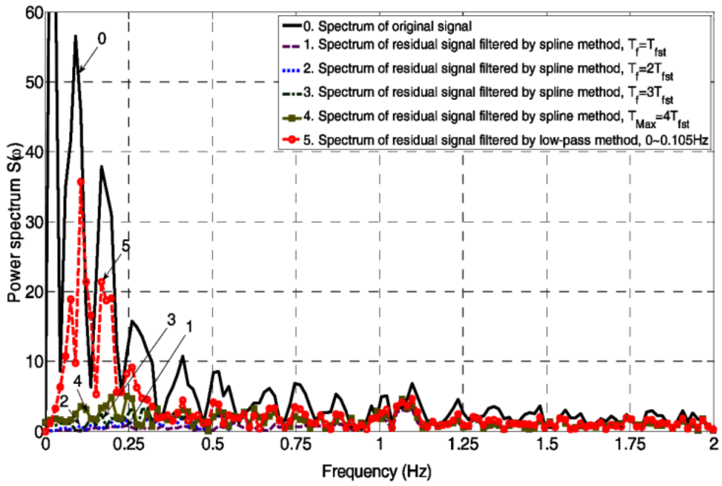

Fig. 8 The comparison of power spectra between decomposition residues by means of two kinds of modeless component decomposition methods in the case of strong non-stationarity, Data No. 3, T_{fst} =0.48 *sec*.

Figs. 3, 5 and 7 demonstrate the comparison of the above two kinds of modeless component decomposition methods related to the observed data of in-line VIV from experiments, in the case of wake, mild and strong non-stationarities, respectively; and Figs. 4, 6 and 8 demonstrate the comparison of power spectra between raw and processed data series related to two kinds of modeless component decomposition methods, in the case of wake, mild and strong non-stationarities, respectively. In order to manifest the effect of finite time window scale definition to the final visualization of modeless component, the trendlines defined by the finite time window scales from T_{fst} to $(n_{\max}-1)T_{fst}$ have also been illustrated in Figs. 3~8.

The attempt to evaluate the efficiency of modeless component method seems difficult, because the qualitative observation of non-stationarity is explicit, while the quantification becomes implicit. Some subjective criteria for judgment should be draft first. The first step of data analysis is to examine the data by eye. The second step should refer to the instantaneous envelope amplitude $\rho(t)$ definition which was deduced from 'narrow-band' signal hypothesis and extend the application to 'real envelope function' of any composite signal composed of harmonic components, according to Longuet-Higgins' wave envelope definition (Longuet-Higgins, 1984). The third step should refer to the quantificational criterion which is expressed by Eq. (9).

It could be found that the trendlines shown in Fig. 3, defined by different modeless component methods and various time window scales agrees well with the approximate development tendency of in-line vibration process which is characterized by wake non-stationarity. The local enlargement visualization shown in Fig. 4 manifests the similar conclusion drawn above. It is obvious that these two kinds of modeless component methods have equivalent efficiency to get rid of the spurious long-term oscillation term characterized by considerable deflection from zero equilibrium position, namely modeless component. The criteria selection for intrinsic mode function decomposition would consequentially contribute the visualization of non-stationarity first.

As it is shown in Figs. 4 and 6, when the apparent power spectral density related to modeless component is significantly 'narrow-banded', the decomposition result of modeless component by 'low-pass' filter is as preferable as the one using newly developed method. On the other hand, in the case of apparent power spectral density is considerable 'wide-banded', shown in Fig. 8, the decomposition result of modeless component by this method becomes terrible. As demonstrated by the dashed hollow-block line (No. 5) in the Fig. 8, the apparent vibration power belonging to the modeless component had been left omitted seriously. Similar imperfection could be found in the dashed hollow-block trendline (No. 5) shown in Fig. 6, although is not severe. Distinct disagreement might be observed at the beginning and end of data series of the vibration process which is characterized by mild and strong non-stationarity. It is just the unique range that the emergence of modal jump, transition phenomena, due to acceleration and deceleration of vibration process.

From the comparison between the trendlines deduced by 'low-pass' filter and the one deduced by the combination of the maximum intrinsic time window and cubic spline method, it has been found that the trendlines defined by the latter method agree fairly well with the development tendency of all kinds of VIV processes. In some situations, the power spectra concerning residual signals filtered by the combination of cubic spline method and finite time windows of $T_f = nT_{fst}$ (where $n < n_{\max}$) are very similar with that related to $T_{\max} = n_{\max}T_{fst}$. However, the trendline defined by the latter manifest the development trend of the whole vibration process superior to the former, keeping the intrinsic vibration characteristic as much as possible.

In this section, the modeless component decomposition characterized by finite time window scale and cubic spline method has been proved to be efficient to manifest the non-stationarity of any vibration processes than 'low-pass' filter technique. The definition of maximum intrinsic time window is helpful to visualize the true non-stationary term with supremacy to manifest the non-stationarity of a vibration process and minimize the effort to attenuate the intrinsic characteristics of natural vibration component.

CONCLUSION

In this paper, we have presented a modeless component identification technique using empirical mode decomposition method. It has been proven to be versatile and robust in analysis of nonlinear and non-stationary data series.

First, a new decomposition method for modeless component from non-stationary process, characterized by cubic spline and a predetermined finite time window has been developed. In order to avoiding the arbitrary selection of time window scale, 'maximum intrinsic time window' based on the properties of intrinsic vibration mode and apparent modeless component has been introduced. The introduction of conceptual modeless component eliminates the requirement of using spurious harmonics to represent nonlinear and non-stationary signals and then makes subsequent modal identification more accurate and meaningful. It neither slacks the vibration power of natural modes nor aggrandizes spurious energy of modeless component. The scale of the maximum intrinsic time window has been well designed, avoiding energy aliasing in data processing, superior to other time-consuming spline procedures. In this way, only one spline fitting is required rather than more some empirical decomposition methods used.

Second, the newly developed techniques have been applied to analyze data series of vortex-induced vibration processes. Taking advantage of this newly introduced empirical decomposition method and modeless identification technique, the vibration analysis about VIV becomes more meaningful.

Finally, although the new innovation relating empirical decomposition makes the modeless component identification method highly effective and physically sound, there are, however, areas needing focusing on. It is suitable for problems where vibration processes were characterized by modal term and remarkable non-stationary. In the case of impulse response, it is easier to implement, but the amplitude averaging effects should be paid much attention when the neighboring instantaneous amplitude are of different magnitudes and the waveform is solitary.

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