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Multi-frequency identification method in signal processing

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ABSTRACT

Virtually vibration signals are always composed of many frequency components. Using the least squares method, a new multi-frequency identification algorithm has been proposed to identify the amplitude and phase of each component of a multi-frequency signal, and it will work well as long as the main frequency values are known. Based on this algorithm, two similar optimization procedures have been presented to obtain accurate frequency values for a sine-wave signal and a bi-tone signal, respectively. Assisted with band-pass filters and these optimization procedures, the multi-frequency identification algorithm can successfully identify the multi-frequency components of a signal. The multi-frequency identification method can be used to identify oil-film coefficients of journal bearing. And some reliable oil-film coefficients have been reached.

1. Introduction

One of typical problems in the vibration analysis of rotating machinery is how to precisely identify the various frequency components of signals. Despite the development of parametric analysis, the windowed discrete Fourier transform (DFT) remains the most useful tool in this field because of its quick and easy implementation through fast Fourier transform (FFT) [1]. Due to the spectrum granularity effect (also known as leakage) caused by a finite number of processed samples, the estimations resulting from the DFT are normally different from the real ones. It is well known that there is no spectral leakage in the DFT of a finite synchronously sampled periodic signal sequence, in which an integer multiple of periods is measured. However, in practical situations, it is impossible for the sampling procedure to be accurately synchronized with every component of a general multi-frequency signal. So in many cases DFT algorithm will produce considerable power leakage error, and some errors will be inevitably introduced in the estimations for the parameters, i.e., amplitude, frequency and phase of each component of a multi-frequency signal. It is possible to obtain high-accuracy frequency estimations through an increase in computational cost. To overcome the leakage problems and receive high-accuracy frequency estimations several techniques have been proposed. Most of them are based on the FFT algorithm, for example, some are relying on interpolating the FFT samples [2–4]; the others are relying on some types of weighted linear regression of phase data [1,4–6]. These methods are very computationally intensive, and the increases in computational cost are always high.

On the other hand, the least squares method has been applied with much success in solving many challenging problems found in signal processing [7]. For example, one of the recommended test methods in Analog to Digital testing standards is based on least square sine-fitting algorithm [4,8,9], it can also be applied to the envelope detection for the vibration signal [10].

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Nomenclature

A_i	amplitude of a sine-wave signal
θ_i	phase of a sine-wave signal
a_i, c_i, q_i, u_i	coefficients of the sine terms
b_i, d_i, r_i, v_i	coefficients of the cosine terms
c_0	constant of the signal
COD	coefficient of determination
f_i	main frequencies of the signal
f_0, f_{01}, f_{02}	initial estimated frequency values
f', f'_1, f'_2	accurate frequency values
f_s	sampling frequency
f_1, f_2	excitation frequencies
Δf	frequency resolution
$F(k)$	exciting force signal
$\hat{F}(k)$	identified exciting force signal
F_y	load parameter of journal bearing
M	number of samples
n	number of main frequencies
$s(t), s(k)$	continuous and discrete simulated signal
$\bar{s}$	mean value of $s(k)$
$s_n(t), s_n(k)$	continuous and discrete signals containing Gaussian white noise
$\hat{s}(k)$	identified discrete signal
t_k	sampling time
T_s	sampling period
σ	root-mean-square value of Gaussian white noise
$\varepsilon(t), \varepsilon(k)$	continuous and discrete Gaussian white noise signal
$\varepsilon^2, \varepsilon_i^2, \varepsilon_{1,2}^2$	sum of squares of the deviation
$\Delta F_x, \Delta F_y$	dynamic oil-film forces
$\Delta X, \Delta Y$	dimensionless relative displacements
$\Delta\dot{X}, \Delta\dot{Y}$	dimensionless relative velocities
X_1, Y_1	dimensionless displacements of bearing house
$y(k)$	displacement signal
$\hat{y}(k), \hat{y}_{1,2}(k)$	identified displacement signal
$K_{XX}, K_{XY}, K_{YX}, K_{YY}$	dimensionless stiffness coefficients of journal bearing
$D_{XX}, D_{XY}, D_{YX}, D_{YY}$	dimensionless damping coefficients of journal bearing

In fact, as shown in this paper, the least squares method and Fourier transform are not competing methods for doing the same thing, but complementary methods. They can be used in different parts of the calculation. If the main frequency values of a multi-frequency signal are known beforehand, the amplitude and phase of each component of the multi-frequency signal can be derived by the least squares method. In the second part of this paper, a new multi-frequency identification algorithm is proposed to cope with this problem. Using Fourier transform and some band-pass filters, the multi-frequency signal can yield a series of simple signals, whose frequency values are easily estimated based on the multi-frequency identification algorithm. Taking some experimental signals for example, the third part of the paper had addressed how to identify the frequency values for a sine-wave signal and a bi-tone signal. And two similar optimization procedures have been presented. In the fourth part of this paper, the multi-frequency identification method has been successfully used to identify a displacement signal.

In the fifth part of this paper, the multi-frequency identification method has been used to identify the oil-film coefficients of journal bearing. Though the oil-film forces of journal bearing are greatly nonlinear [11–13], the linear theory, which approximates the oil-film forces by a linear combination of displacements and velocities using eight oil-film coefficients, is still widely used to predict the stability and trajectories of journal in bearing systems because of its simplicity [13]. The determination of the eight oil-film coefficients has been the goal of several experimental studies of journal bearing. One of the typical techniques to determine eight oil-film coefficients is based on the responses of journal bearing to sinusoidal excitations [14,15]. For the existence of machining error or asymmetry material distribution, the rotor has unbalanced mass unavoidably. The system responses are always multi-frequency signals, whose main frequency components include the synchronous excitation response, the unbalance response and some other frequency components. It is necessary to accurately identify the excitation frequency component (i.e., the most significant component) from the testing signals in order to derive the reliable oil-film coefficients, especially when the excitation frequency is near to other component frequency. The multi-frequency identification method can be efficiently used here. And some reliable oil-film coefficients have been achieved.

2. Multi-frequency identification algorithm

On the assumption that the main frequency values of a signal are known beforehand, these frequency components can be identified by the least squares method. The signal can be assumed to be

$$\hat{s}(t) = c_0 + \sum_{i=1}^{n}\left[a_i \sin(2\pi f_i t) + b_i \cos(2\pi f_i t)\right], \tag{1}$$

where f_i is one of the main frequencies of the signal, $i = 1$–n. According to the sampling frequency f_s, the discrete signal can be expressed as follows:

$$\hat{s}(k) = c_0 + \sum_{i=1}^{n}\left[a_i \sin(2\pi f_i t_k) + b_i \cos(2\pi f_i t_k)\right], \tag{2}$$