Analysis of Time Domain and Frequency Domain of Mechanical Test Signals

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Abstract: Mechanical signal processing is done by transforming some of the measurement signals, weakening the unwanted redundant signals in the mechanical signal, filtering out the mixed noise interference, or turning the signal into a form that is easy to identify in order to extract its eigenvalues. The In this paper, the time-frequency domain processing method of a mechanical signal is introduced. The simulated noisy period signal is constructed by Matlab, and the time-frequency domain is processed. The signal filtering, correlation analysis, power spectrum analysis, and other methods of the characteristics and advantages.

Key words: Mechanical signal; noice interference; time-frequency domain processing

Chapter 1 Introduction

Mechanical signals are dynamic information that varies over time during the operation of the mechanical system, and the data or images picked up and recorded and stored by various test instruments. Mechanical equipment is the basis of industrial production, and mechanical signal processing and analysis technology are important industrial development of basic technology.

With the rapid development of all walks of life and a variety of application requirements, signal analysis and processing technology in the signal processing speed, resolution, functional scope and special treatment will continue to progress, the new processing hormone will continue to emerge The development of the current signal processing is mainly manifested in 1. The emergence of new technologies and new methods; 2. Further improvement of real-time capability; 3. Research on high-resolution spectrum analysis methods.

The development and application of signal processing are complementary, and the demand for industrial applications is the driving force behind the development of signal processing, and the development of signal processing, in turn, extends its application field. Mechanical signal analysis and processing methods from the early simulation system to the digital direction. In almost all mechanical engineering, it has been an important research topic.

Mechanical signal analysis and processing technology is evolving, it is possible to help professionals engaged in fault diagnosis and monitoring from the machine running records to extract and summarize the basic laws of machine operation, and make full use of the current operating conditions and future conditions Understanding and research, comprehensively analyzing and dealing with the possible impact of various interference factors, predicting the state and dynamic characteristics of the machine during future operations, providing the basis for the development of a predictive maintenance system, an extension of overhaul and scientific development of equipment renewal and maintenance plans , So as to more effectively ensure the stable and reliable operation of the machine to improve the utilization of large-scale key equipment and efficiency.

The mechanical signal processing is a process of transforming the measurement signal, weakening the unwanted redundant signal in the mechanical signal, filtering out the mixed noise interference, or turning the signal into a form that is easy to recognize in order to extract its eigenvalue. The basic flow chart of mechanical signal processing is shown in Figure 1.1.

Figure 1.1 the basic process of mechanical signal processing

This article mainly discusses the third and fourth steps.

Chapter 2 Time domain processing of mechanical signals and their analytical methods

2.1 Time domain statistics feature parameter processing

Some of the characteristic parameters that can be obtained by time-domain waveforms are often used for rapid evaluation and simple diagnosis of machinery.

1) Dimensional amplitude parameter

Dimensional amplitude parameters include square root amplitude, mean amplitude, mean square amplitude and peak. If the random process x (t) coincides with the smoothness, the states are conditional, and the mean is zero, let x be the amplitude, p (x) be the probability density function, and the dimension parameter of the dimension can be defined as

Xd ==

Where: xr is the root mean, is the mean, is the mean square value, and is the peak.

Because of the metrological amplitude parameters to describe the mechanical state, not only with its state, but also with the machine's motion parameters (such as speed, load, etc.), so they directly evaluate the mechanical conditions of different conditions cannot be unified The conclusion.

2) dimensionless parameters

The dimensionless parameters have characteristics that are insensitive to changes in mechanical conditions, which mean that, in theory, they are independent of the kinematic conditions of the machine, and they depend only on the shape of the probability density function p (x), so the dimensionless parameter is A better evaluation parameter. In general, it can be defined as

, The formula, you can get some of the following indicators

A. The waveform index $l = 2$, $m = 1$

K =

B. The peak index $l \to \infty$, $m = 2$

C =

C. Pulse index $l \to \infty$, $m = 1$

I =

D. Margin indicator $l \to \infty$, $m = 1/2$

L =

E. Kurtosis index

K =

Where the standard deviation of the signal =

2.2 Correlation analysis methods and applications

The so-called correlation refers to the linear relationship between variables, it is a very important concept. For a deterministic signal, the two variables can be described by a functional relationship, and the two correspond to and determine the value. And the two then variables do not have a definite relationship. However, there is a certain linear relationship between the two variables if there is some uncertainty between the two variables but with an approximate relationship that characterizes their properties. At this time, for a random mechanical signal, the correlation function can be used to describe its degree of change in amplitude at different times.

1. The concept and nature of autocorrelation function

X (t) is a sample function of each state after a random process, x (t +) is x (t) after moving after the sample (Figure 2.6), the correlation coefficient x (t) x (t +) For x (), then there is:

The following are the same as the

If Rx () is used to represent the autocorrelation function, it is defined as:

The nature of the signal is different, and the autocorrelation function has different expressions. Such as the periodic signal (power signal):

Aperiodic signal (energy signal):

Figure 2.7 shows the properties of the autocorrelation function. The autocorrelation function of the sine function is a cosine function with the maximum value at $\tau = 0$. It preserves the amplitude information and frequency information but lost the initial phase information in the original sine function.

2.3 Matlab programming results

1. Structure plus noise cycle signal, time domain feature analysis, autocorrelation function characteristics of the verification, (program 1)

Noise - autocorrelation .jpg

As shown in the figure: The autocorrelation function eliminates a large amount of noise, and the periodic composition becomes very noticeable.

The time domain processing result of the original signal:

Average: 0.0184

Minimal value: -2.8138

Maximum value: 2.8557

Standard deviation: 1.0103

Variance: 1.0207

Peak: 5.6695

Chapter 3 Frequency Signal Processing of Mechanical Signals and Its Application

In signal processing, the Fourier transform resolves a random signal into a sine wave of different frequencies, making the frequency domain analysis of the signal possible. Due to the development of computer technology, it is very convenient to use discrete Fourier transform directly on a microcomputer, which makes frequency domain analysis called common processing method. Commonly used frequency domain analysis methods include self-spectrum, power spectrum, and cepstrum and so on.

3.1 Spectrum analysis method

(1) DFT and FFT

1.1 Discrete Fourier Transform DFT

Fourier transform and its inverse transformation are not suitable for digital computer calculation. To perform numerical calculations and processing, the continuous signal must be discretized, and the infinite data can be limited. This Fourier transform of finite discrete data is called finite discrete Fourier transform, or DFT (Discrete Fourier Transform).

1.2 Fast Fourier Transform FFT

1965 J.W. Cooley and J.W.Tukey studied a fast algorithm for DFT called Fast Fourier Transform, referred to as FFT (FastFourier Transform). The rapid development of FFT, digital spectrum analysis has made a breakthrough. According to the FFT rapid transformation of the guiding ideology, you can compile the FFT calculation program. Time series from the time domain to the frequency domain to use FFT transform, from the frequency domain to the time domain to use inverse transformation IFFT, FFT and IFFT formula can be unified.

(2) Physical meaning of the power spectral density function

Sx (f) and Sxy (f) are frequency domain description functions of random signals. Sx (f) represents the distribution of the power density of the signal along the frequency axis, so called Sx (f) is the power spectral density function.

3.2 Power spectrum method and application

The power spectrum is defined as

If X (Ω) = DFT [x (m)], x (n) is an N-point sequence. then

X (Ω) = DFT [x (-m)]

And thus DFT [R (M)] = DFT [x (m)] DFT [x (-m)]

(Ω) = X (Ω) X (Ω) = | X (Ω) | ^ 2

In summary, the first use of FFT to find the random discrete sequence DFT, and then calculate the amplitude and frequency characteristics of the square, and then divided by N, that is, the random signal power spectrum estimation.

3.3 Cepstrum analysis method

The cepstrum is a Fourier transform of the frequency domain signal or 'Fourier transform of the frequency domain signal.' The purpose of taking the logarithm of the power spectral density function is to make the energy of the signal more concentrated after the transformation. The cepstrum can analyze the periodic components of the complex spectrum, separating and extracting the components in the dense pan-frequency signal. For the same family of harmonic and alien harmonic and other complex signal analysis, the effect is very good. The cepstrum is useful for the measurement and detection of speech tones in speech analysis, the detection and diagnosis of harmonic components in mechanical vibration spectra, and the elimination of echoes.

(1) Mathematical description of cepstrum

The mathematical expression of CF (q) (power cepstrum) is:

CF (q), also known as power cepstrum or called the power spectrum of the log spectrum. Engineering is commonly used in the formula (2.67) of the prescription form, namely:

C0 (q) is called amplitude cepstrum, sometimes referred to as cepstrum.

The physical meaning of the inverse spectrum q

In order to make the definition more clear, you can also define:

That is, the cross spectrum is defined as the signal of the bilateral power spectrum logarithmic weight, and then take its inverse

Fourier transform, contact the signal autocorrelation function:

It is shown that this method is very similar to the autocorrelation function, and the variable q is the same in dimension.

In order to reflect the phase information, after the separation can restore the original signal, but also proposed a complex spectrum of the calculation method. If the Fourier transform of the signal x (t) is X (f):

The cepstrum of x (t) is denoted by:

Obviously, it retains the phase information.

The cepstrum is only logarithmic weighted on correlation function, with the aim of concentrating the signal energy after the transformation and expanding the spectral range of the dynamic analysis and improving the accuracy of the re-transformation. It can also deconvolution (convolution) components, easy to separate the original signal and identification.

3.4 Refinement spectrum analysis method

The refined spectral analysis is to increase the spectral part of the resolution of the method, that is, 'local amplification' approach. The so-called refinement analysis room only to a fixed narrow band to enlarge, as the camera will be the same part of the photo zoom so that the dynamic range and resolution are improved.

In the process of refinement, we first obtain the N-point discrete sequence {xn} by sampling the sampling frequency fs = 1 / h as in the usual FFT practice. Suppose that we are interested in a narrow band f, And then multiply a new N-point discrete sequence of {xn} by a complex sine sequence (unit rotation vector) exp [-j2fknh]. According to the frequency shift theorem, the frequency origin is effectively moved to the frequency fk (i.e., complex modulation). Fk becomes the new frequency coordinate origin. Positive and negative sampling frequencies fs also move a quantity fk. A low-pass filter to get the {gm} sequence retained by the narrow band if the total bandwidth after filtering is less than 1 / D times the sampling frequency, it is possible to reduce the sampling frequency to 1 / D, and no new The frequency near the Qwest frequency is aliased. And then re-sampling, with fs2 = fs / D frequency to sample, that is, to reduce the sampling frequency. From the sampling theorem, it can be seen that the frequency resolution is also increased by D times when the sampling frequency is reduced, and the same sampling point N is maintained, which is equivalent to the total time window. Therefore, the complex discrete sequence {rm} obtained after resampling is subjected to complex FFT calculations to obtain the refined lines, which represent the refinement spectrum between a narrow band f with a center frequency of fk.

3.5 Matlab programming results

1. Generate a group of 60Hz and 150HZ sinusoidal signal and random noise composed of the signal; observe the time domain waveform and spectrum. (Procedure 2)

Figure 3-1 Time-domain waveform of the original signal

Figure 3-2 Spectrum of the original signal

Figure 3-2 can be seen to see that there are two spikes at frequencies of 60 Hz and 150 Hz, which are the two frequency components of the signal.

2. Power spectrum estimation (periodic graph method):

1. Using the amplitude of the result of the Fourier transform of the noisy original signal in the above figure, the amplitude of the power spectrum is obtained by the square of the amplitude (Welch method)

Figure 3-3 Estimated power spectrum when sampling points are 1024

Figure 3-4 Estimated power spectrums when sampling points are 256

As can be seen from Figure 3-3 and 3-4:

2. To improve the smoothness of the periodic graphs, the signal is segmented and averaged to reduce the covariance of the power spectrum estimate, resulting in an average periodogram.

Figure 3-5 Three-stage average estimated power spectrums

Figure 3-6 Six-segment average estimated power spectrums

From Figure 3-5 and 3-6 see: sub-averaging method to improve the smoothness of the power spectrum, the more the number of segments, the better the smoothing effect, the signal details more easily lost.

3. Data segmentation plus non-rectangular shape to correct the power spectrum estimation method:

Figure 3-7 Estimated power spectrum of the Hahan window

Since the window is zero at its edge, this reduces the dependency of the segment on aliasing. Using the appropriate window function, the aliasing rate of half the length of the segment can greatly reduce the estimated covariance.

3. Cepstrum analysis:

Figure 3-8 real cepstrum

Figure 3-9 Complex cepstrum

Sinusoidal signal, the first power spectrum is converted into a pulse, filtered into the second power spectrum conversion, the output is a very low amplitude of the triangular wave output, and thus cannot detect its existence.

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4. Refined spectrum analysis:

Figure 3-10 Original signals FFT

Figure 3-11 ZOOM-FFT

Program list

Program 1. Construction plus noise cycle signal, time domain characteristics analysis, autocorrelation function characteristics of the verification

```
Fs = 1000;
T = 0: 1 / fs: (1-1 / fs);
Maxlag = 100;
X = randn (1, fs);
```

[C, maxlags] = xcorr (x, maxlag); % The autocorrelation of white noise

Z = cos (2 * pi * 20 * t) + 0.7 * randn (1, 1000); % plus white noise

M = mean (z); disp (m);% Calculate the mean

Mi = min (z); disp (mi);% minimum

Mx = max (z); disp (mx);% max

St = std (z); disp (st);% standard deviation

Fc = st. ^ 2;% variance

Figure (1)

Subplot (2,2,1)% 2 * 2 first picture

Plot (t, x)% image area size

Xlabel ('t'); title ('white noise');%

Subplot (2,2,2)

Plot (maxlags / fs, c)

Xlabel ('t'); title ('white noise autocorrelation');

[C, lags] = xcorr (z, maxlag);% cosine correlation with white noise

Subplot (2,2,3)

Plot (t, z)

Xlabel ('t'); title ('raw signal');

Subplot (2,2,4)

Plot (maxlags / fs, c)

Xlabel ('t'); title ('autocorrelation');

Program 2: Generates a set of signals consisting of 60HZ and 150HZ sinusoidal signals and random noise, comparing them with spectral analysis, cepstrum analysis, and several power spectral estimation methods.

% 1. (Spectrum analysis) produces a set of signals consisting of 60HZ and 150HZ sinusoidal signals and random noise to observe their time domain waveforms and spectra.

Fs = 1000;

N = 1024;

T = (0: N-1) / fs;

F1 = 60;

F2 = 150;

S1 = sin (2 * pi * f1 * t) + sin (2 * pi * f2 * t);

S2 = 2 * randn (size (t));

X = s1 + s2;

Figure (1)

Subplot (2,1,1)

Plot (t, x)

X = abs (fft (x));

F = (0: N / 2-1) * fs / N;

Subplot (2,1,2)

Plot (f (1: N / 2), X (1: N / 2))

% Creep analysis

D = rceps (x);% real cepstrum

Figure (2)

Subplot (2,1,1)

Plot (t, D)

E = cceps (x);% complex cepstrum

Subplot (2,1,2)

Plot (t, E)

% 3.1 power spectrum estimation (Welch method)

Pxx = abs (fft (x, N)). ^ 2 / N;% The number of sampling points is 1024

Pxx_short = abs (fft (x, 256)). ^ 2/256;% Sampling points are 256

Figure (3)

Subplot (2,1,1)

Plot ((0: N-1) / N * fs, 10 * log10 (Pxx))

Subplot (2,1,2)

Plot ((0: 255) / 256 * fs, 10 * log10 (Pxx_short) * 10)

% 3.2 The signal is segmented and averaged to reduce the covariance of the power spectrum estimate, resulting in an average periodogram.

P 2 = abs (f (x (5: 125))) ^ 2 + abs (fft (x (513: 768))) ^ 2 + abs) / 256/3;

Figure (4)

Plot ((0: 255) / 256 * fs, 10 * log10 (Pxx))

% 3.3 divides the signal into six segments for power spectrum estimation and averaging.

P 2 = abs (f (x (25: 38))) ^ 2 + abs (fft (x (25: + 2 (absent (x (641: 768))) ^ 2 + abs (fft (x (641: 768))) ^ 2 + 256/6;

Figure (4)

Plot ((0: 127) / 128 * fs, 10 * log10 (Pxx))

% 3.4 on the data segmentation of non-rectangular shape of the modified cycle of the law. The window is zero at its edge, which reduces the dependency of the segment on aliasing. With the appropriate window function (such as Hamming window, Hanning window), the use of half the length of the aliasing ability

% Greatly reduces the estimated covariance. Hanning:

W = hanning (256) ';

(2) (2):) ^ 2 + abs (fft (w. * X (385: 640))) ^ 2 + abs (fft (w. * X (513: 768))) ^ 2 + abs Fft (w. * X (641: 896))) ^ 2) / (norm (w) ^ 2 * 6);

Figure (5)

Plot ((0: 255) / 256 * fs, 10 * log10 (Pxx))

Procedure 3:

% ZOOM-FFT

Fs = 200;

N = 1024;

N = 0: N-1;

T = n / fs;

F = (0: N-1) * fs / N;

F1 = 7; f2 = 7.2; f3 = 8;

S1 = sin (2 * pi * t * f1);

S2 = sin (2 * pi * t * f2);

S3 = sin (2 * pi * t * f3);

X = s1 + s2 + s3;

Load zoomfftdata;

Fi = 6;% minimum refinement cutoff frequency

Np = 10;% magnification

Nfft = 512;% fft length

Nt = length (x);

Fa = fi + 0.5 * fs / np;% maximum refinement cutoff frequency

Nf = 2 ^ nextpow2 (nt);% The

Na = round (0.5 * nf / np + 1);

% Frequency shift

N = 0: nt-1;

B = n * pi * (fi + fa) / fs;% Determine the rotation factor

```
Y = x. * Exp (-i * b);
B = fft (y, nf);% fft transform
(1: na) = b (1: na);% Positive frequency The assignment of elements within the band pass
B = ifft (a, nf);% Negative frequency The assignment of elements within the band pass (nf-na + 1: nf) = b (nf-na + 1: nf)
C = b (1: np: nt);% resampling
A = fft (c, nfft) * 2 / nfft;% for ZOOM-FFT (nfft what stuff)
% Conversion results reordering:
Y2 = zeros (1, nfft / 2);
Y2 (1: nfft / 4) = a (nfft-nfft / 4 + 1: nfft);
Y2 (nfft / 4 + 1: nfft / 2) = a (1: nfft / 4);
N = 0: (nfft / 2-1);
F2 = fi + n * 2 * (fa-fi) / nfft;
% FFT transform
Y1 = fft (x, nfft) * 2 / nfft;
F1 = n * fs / nfft;
Ni = round (fi * nfft / fs + 1);
Na = round (fa * nfft / fs + 1);
% Output waveform
Subplot (2,1,1)
Plot (t, x);
Subplot (2,1,2)
Nn = ni: na;
Plot (f1 (nn), abs (y1 (nn)), ':', f2, abs (y2));
% Store ZOOM-FFT results
Save afterzoomdata f2 y2
```

Conclusions

Through this nearly a week and a half of the digital signal processing course design, I first in the library to find the relevant books, such as MATLAB class programming books, books and other types of data processing books and mechanical vibration class, that is rich to their knowledge, but also with their own knowledge has a deeper understanding and understanding, but also its application has a general understanding. This will be more motivating me to learn the relevant knowledge, and constantly use the knowledge to practice. In practice to firmly grasp it.

In the design process, I also recognized the lack of knowledge they have learned. This also makes me once again realize that knowledge is endless, and only continue to enrich themselves, improve their knowledge theory system, can better qualify for their future work. The lack of knowledge in the design process also made me more determined to study for life.

In the design process, I also got the members of our design team and a lot of classmates. This also strengthens my ability to work with other students. Find the information in the process I also enhance their ability to learn, which will allow me in the future study, life, and work to benefit.

In short, for such a curriculum design activities, I harvest a lot of things, will also make me in the future study, and work more easily and actively. This is the purpose and meaning of participating in this event.

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