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Some Worthy Signal Processing Techniques for Mechanical Fault Diagnosis

2002. 5.

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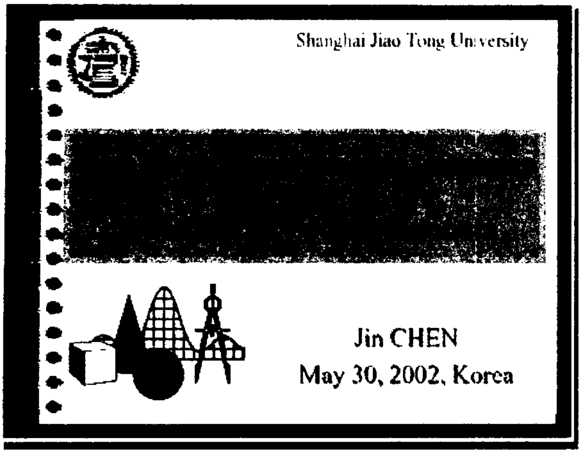
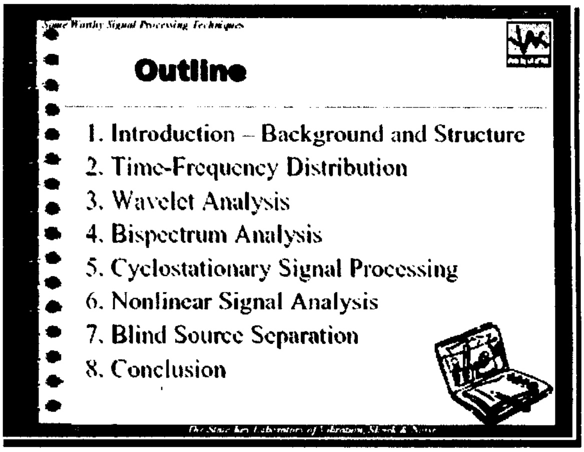


Shanghai Jiao Tong University

Jin CHEN
May 30, 2002, Korea

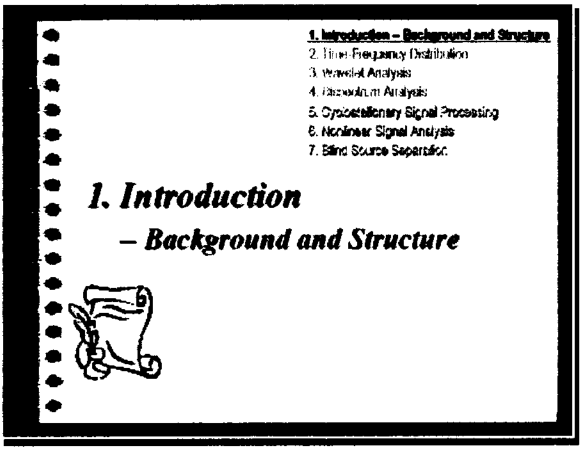


Some Worthy Signal Processing Techniques

Outline

1. Introduction – Background and Structure
2. Time-Frequency Distribution
3. Wavelet Analysis
4. Bispectrum Analysis
5. Cyclostationary Signal Processing
6. Nonlinear Signal Analysis
7. Blind Source Separation
8. Conclusion

The State Key Laboratory of Vibration, Shock & Noise



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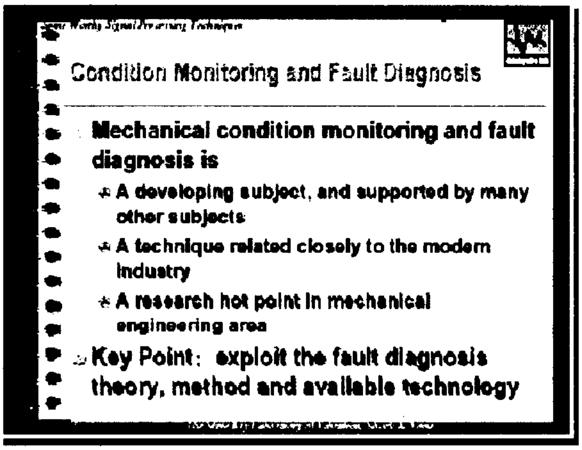
1. Introduction
– Background and Structure

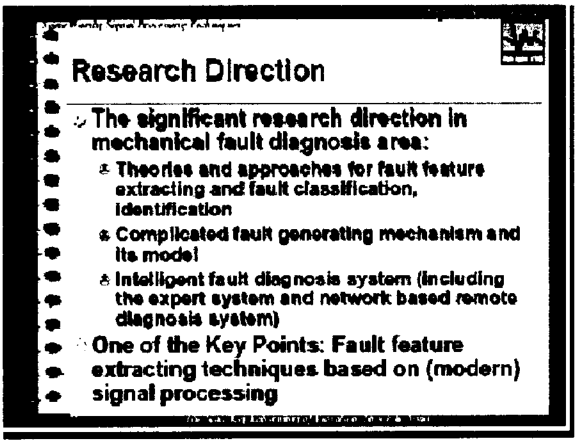


Some Worthy Signal Processing Techniques

Condition Monitoring and Fault Diagnosis

- **Mechanical condition monitoring and fault diagnosis is**
  - **A developing subject, and supported by many other subjects**
  - **A technique related closely to the modern industry**
  - **A research hot point in mechanical engineering area**
- **Key Point: exploit the fault diagnosis theory, method and available technology**

The State Key Laboratory of Vibration, Shock & Noise



Some Worthy Signal Processing Techniques

Research Direction

- **The significant research direction in mechanical fault diagnosis area:**
  - **Theories and approaches for fault feature extracting and fault classification, identification**
  - **Complicated fault generating mechanism and its model**
  - **Intelligent fault diagnosis system (including the expert system and network based remote diagnosis system)**
- **One of the Key Points: Fault feature extracting techniques based on (modern) signal processing**

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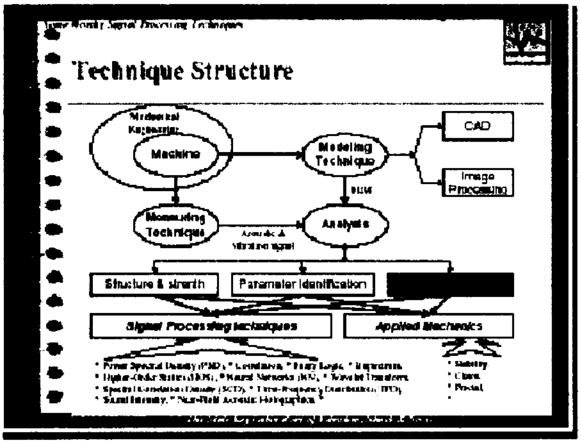

Some Worthy Signal Processing Techniques

Technique Structure

- Power Spectral Density (PSD), * Correlation, * Fuzzy Logic, * Cepstrum
- Higher-Order Statistics (HOS), * Neural Networks (NN), * Wavelet Transform
- Spectral Correlation Density (SCD), * Time-Frequency Distribution (TFD)
- Sound Intensity, * Near-Field Acoustic Holography

- Stability
- Chaos
- Fractal

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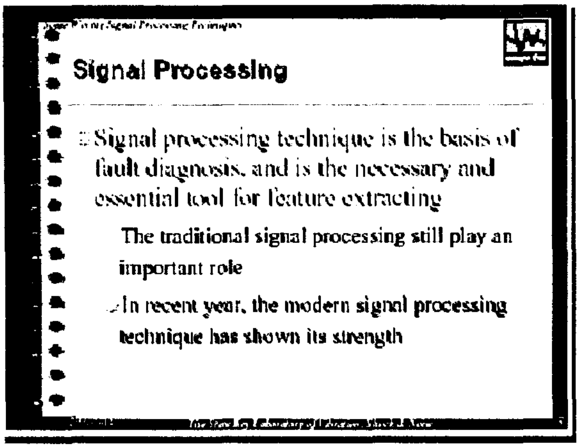
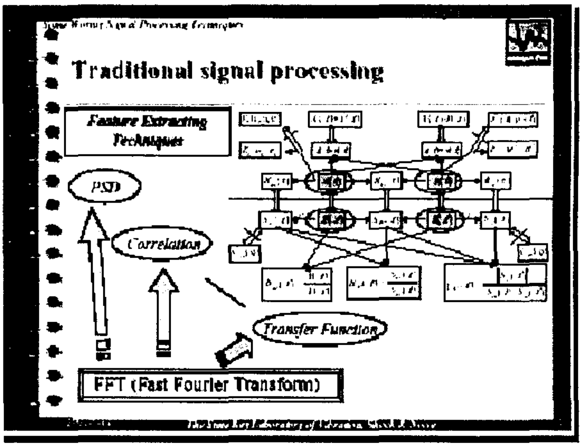
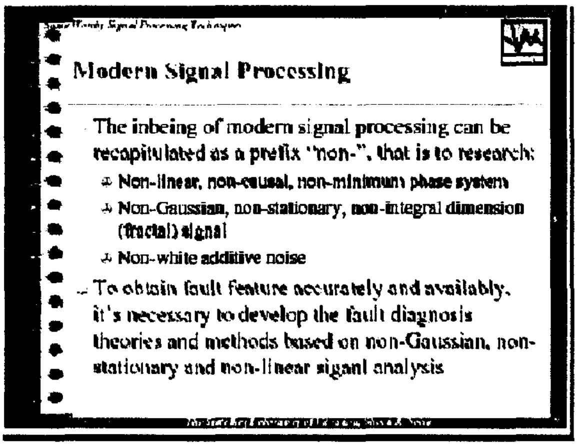


Signal Processing

- Signal processing technique is the basis of fault diagnosis, and is the necessary and essential tool for feature extracting
  - The traditional signal processing still play an important role
  - In recent year, the modern signal processing technique has shown its strength

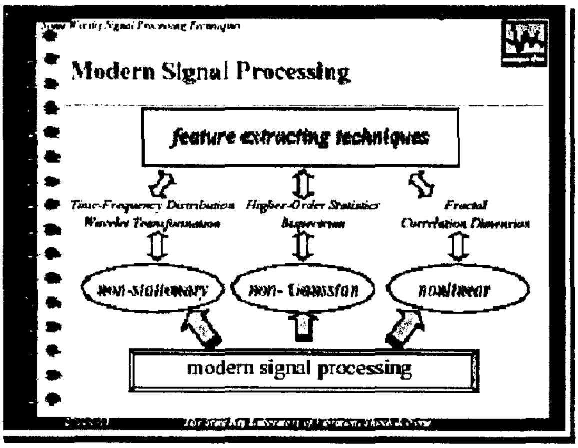


Traditional signal processing

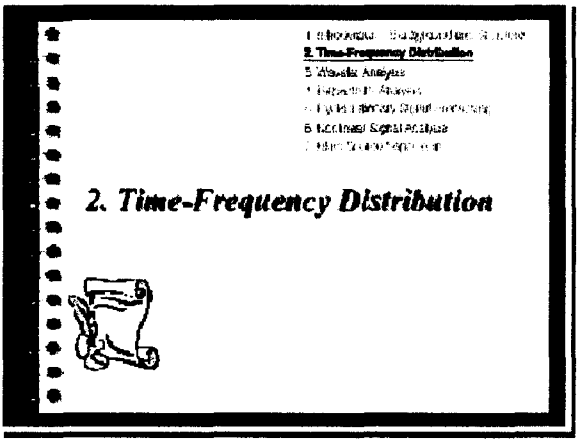


Modern Signal Processing

- The inbeing of modern signal processing can be recapitulated as a prefix "non-", that is to research:
  - Non-linear, non-causal, non-minimum phase system
  - Non-Gaussian, non-stationary, non-integral dimension (fractal) signal
  - Non-white additive noise
- To obtain fault feature accurately and availably, it's necessary to develop the fault diagnosis theories and methods based on non-Gaussian, non-stationary and non-linear siganl analysis



Modern Signal Processing



1 [illegible]
2. Time-Frequency Distribution
3 Wavelet Analysis
4 [illegible]
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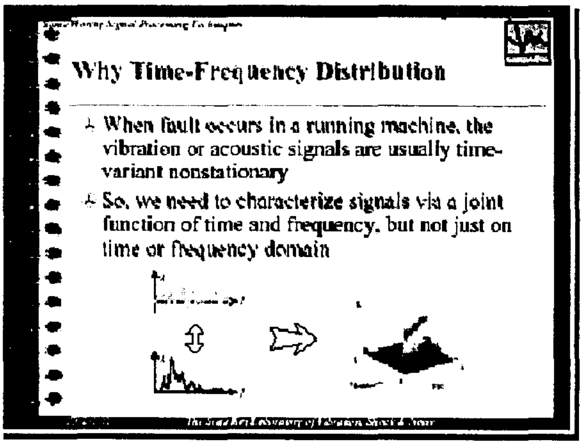
6 Nonlinear Signal Analysis
7 [illegible]

2. Time-Frequency Distribution



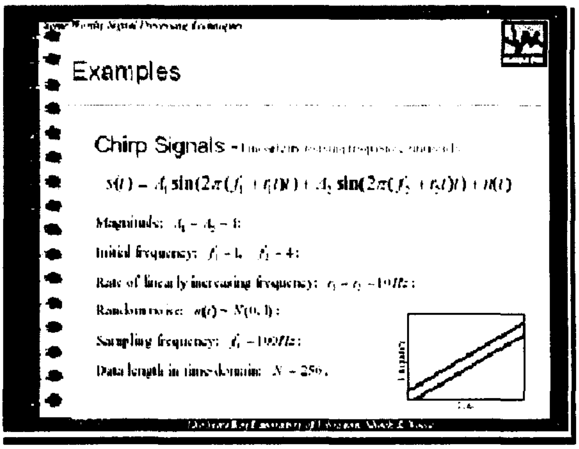
Why Time-Frequency Distribution

- When fault occurs in a running machine, the vibration or acoustic signals are usually time-variant nonstationary
- So, we need to characterize signals via a joint function of time and frequency, but not just on time or frequency domain

Classification of TFD

Linear		Nonlinear		
		Bilinear (quadratic) energy time-frequency distribution		Nonlinear (non-quadratic) time-frequency distribution
Wavelet transform (WT)	Short time Fourier transform (STFT)	Time-frequency shifting invariant (Cohen Class C_t)	Time-scale shifting invariant (Affine Class A)	Radially Gaussian kernel distribution (RGKD)

- Fault condition usually corresponds to the energy change of the measured signal
- For feature extracting, since our purpose is to describe a signal's Time-Frequency (T-F) energy distribution (that is, the instantaneous PSD), while wavelet transform is not in meaning of T-F (but in time-scaling) & don't corresponds to the energy, therefore, the C_t class is selected



Examples

Chirp Signals - Linearly increasing frequency sinusoids

$$s(t) = A_1 \sin(2\pi(f_1 + r_1 t)t) + A_2 \sin(2\pi(f_2 + r_2 t)t) + n(t)$$

Magnitude: $A_1 = A_2 = 1$;

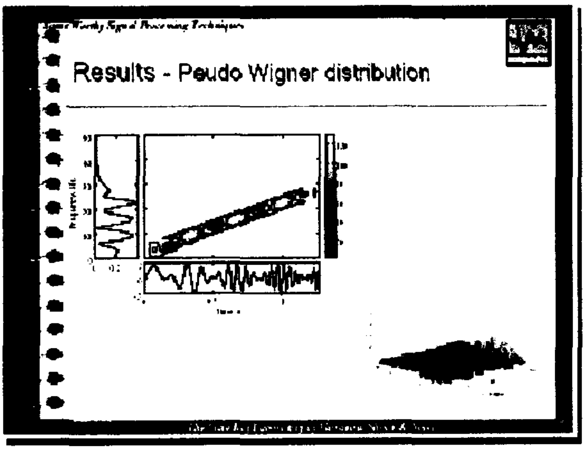
Initial frequency: $f_1 = 1$, $f_2 = 4$;

Rate of linearly increasing frequency: $r_1 = r_2 = 10Hz$;

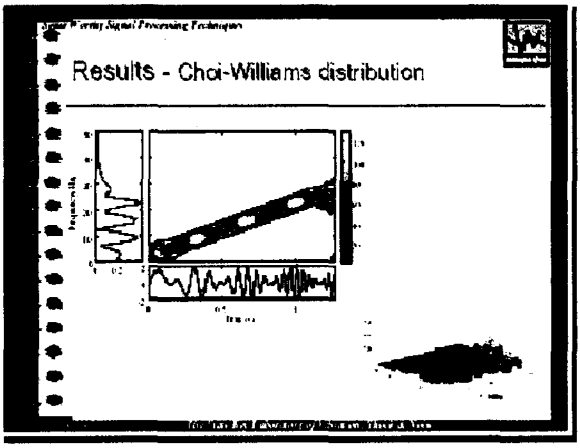
Random noise: $n(t) \sim N(0, 1)$;

Sampling frequency: $f_s = 100Hz$;

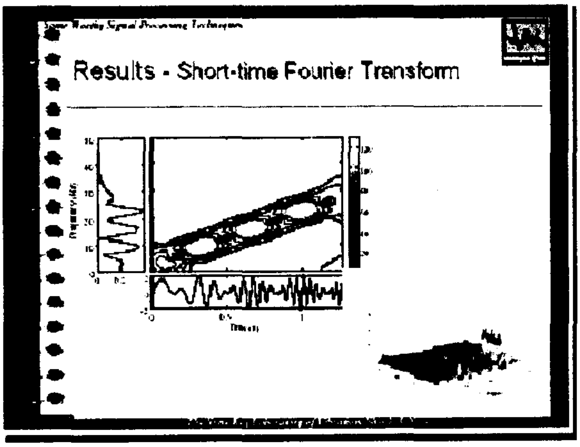
Data length in time-domain: $N = 256$.



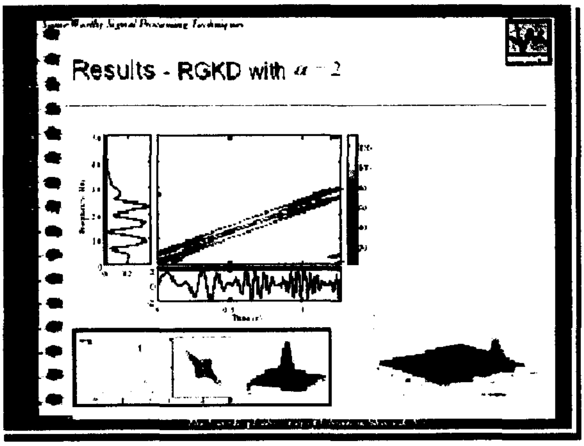
Results - Peudo Wigner distribution



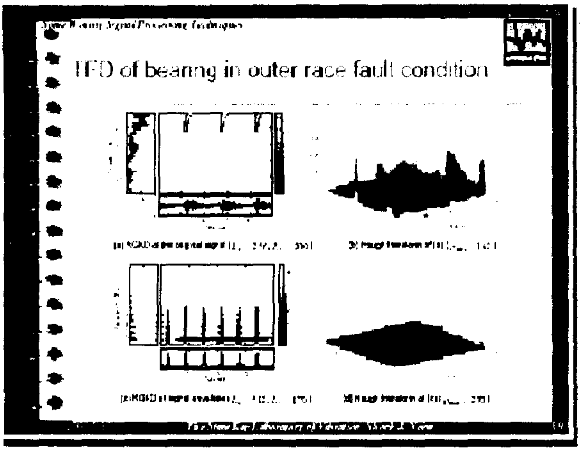
Results - Choi-Williams distribution



Results - Short-time Fourier Transform



Results - RGKD with $\alpha = 2$



Some Modern Signal Processing Techniques

TFD of bearing in outer race fault condition

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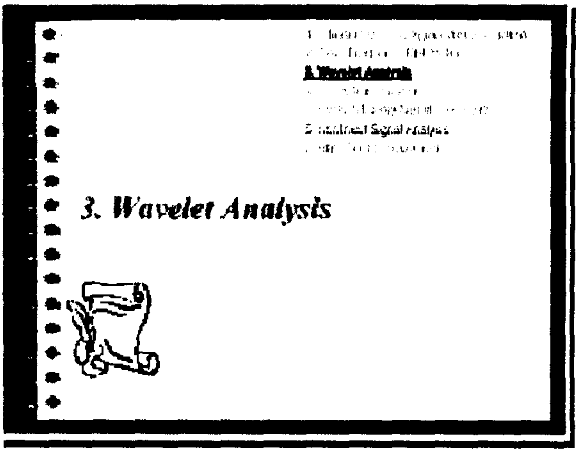

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5. Nonlinear Signal analysis
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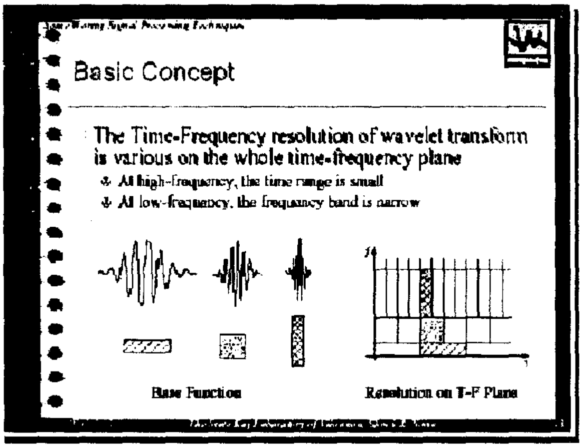
3. Wavelet Analysis



Some Modern Signal Processing Techniques

Basic Concept

The Time-Frequency resolution of wavelet transform is various on the whole time-frequency plane

- At high-frequency, the time range is small
- At low-frequency, the frequency band is narrow

Base Function

Resolution on T-F Plane

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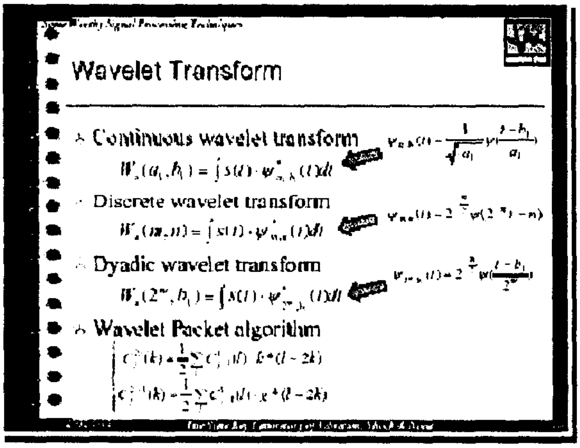

Some Modern Signal Processing Techniques

Wavelet Transform

- Continuous wavelet transform

$$W_s(a_1,b_1)=\int s(t)\cdot\psi^*_{a_1,b_1}(t)dt \quad \psi_{a,b}(t)=\frac{1}{\sqrt{a_1}}\psi\left(\frac{t-b_1}{a_1}\right)$$

- Discrete wavelet transform

$$W_s(m,n)=\int s(t)\cdot\psi^*_{m,n}(t)dt \quad \psi_{m,n}(t)=2^{-\frac{m}{2}}\psi(2^{-m}t-n)$$

- Dyadic wavelet transform

$$W_s(2^m,b_1)=\int s(t)\cdot\psi^*_{2^m,b_1}(t)dt \quad \psi_{2^m,b_1}(t)=2^{-\frac{m}{2}}\psi\left(\frac{t-b_1}{2^m}\right)$$

- Wavelet Packet algorithm

$$\begin{cases} c_j^{2n}(k)=\frac{1}{2}\sum_l c_{j-1}^n(l)\,h^*(l-2k) \\ c_j^{2n+1}(k)=\frac{1}{2}\sum_l c_{j-1}^n(l)\,g^*(l-2k) \end{cases}$$

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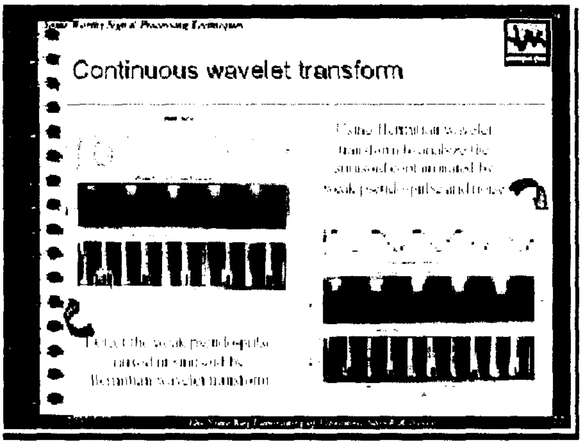

Some Modern Signal Processing Techniques

Continuous wavelet transform

Using Hermitian wavelet transform to analyze the sinusoid contaminated by weak pseudo-pulse and noise

Detect the weak pseudo-pulse caused in sinusoid by Hermitian wavelet transform

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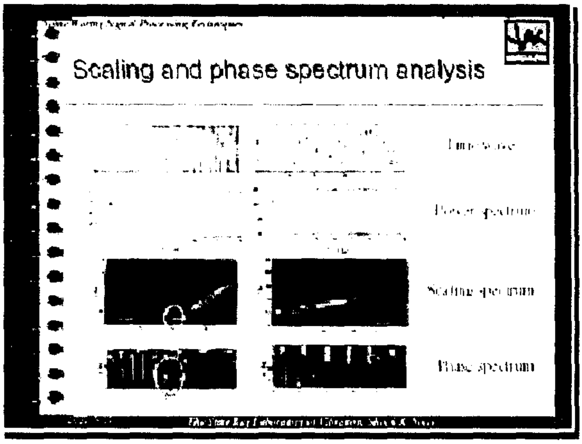

Some Modern Signal Processing Techniques

Scaling and phase spectrum analysis

Time wave

Power spectrum

Scaling spectrum

Phase spectrum

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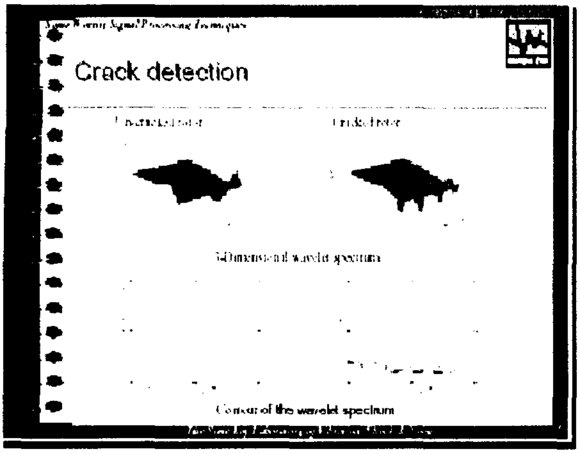


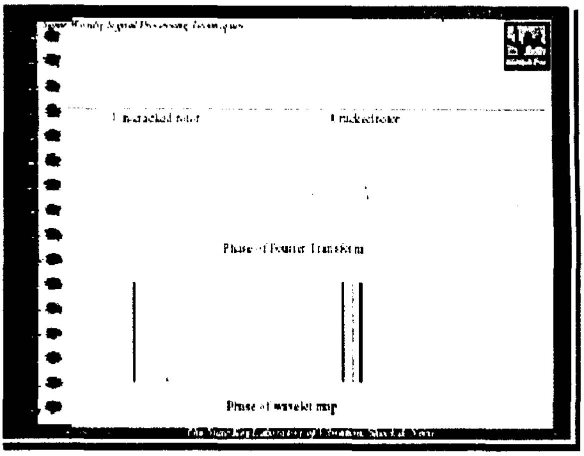
Crack detection

Uncracked rotor

Cracked rotor

3-Dimensional wavelet spectrum

Contour of the wavelet spectrum

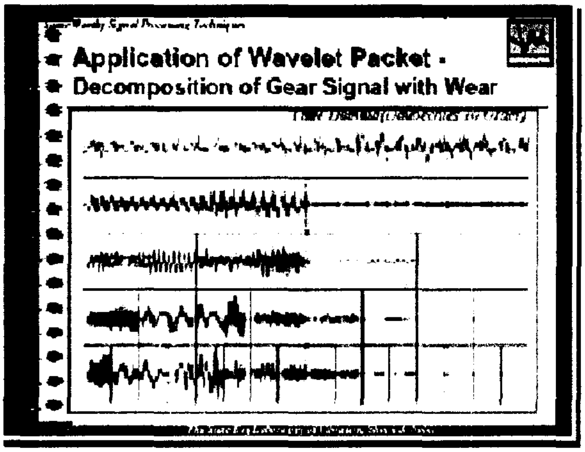


Uncracked rotor

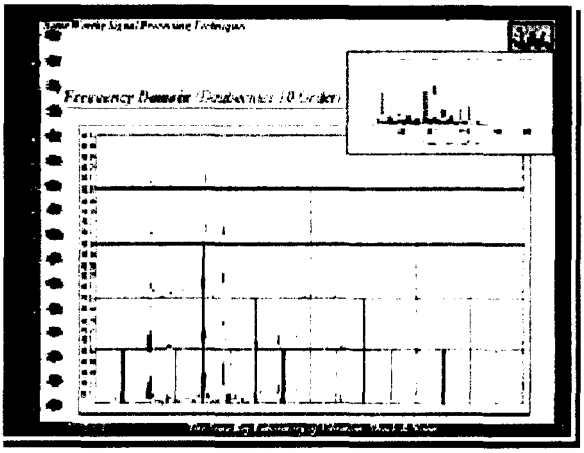
Cracked rotor

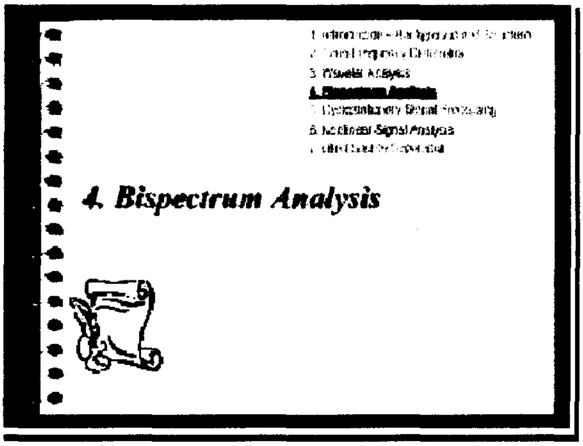
Phase of Fourier Transform

Phase of wavelet map



Application of Wavelet Packet - Decomposition of Gear Signal with Wear



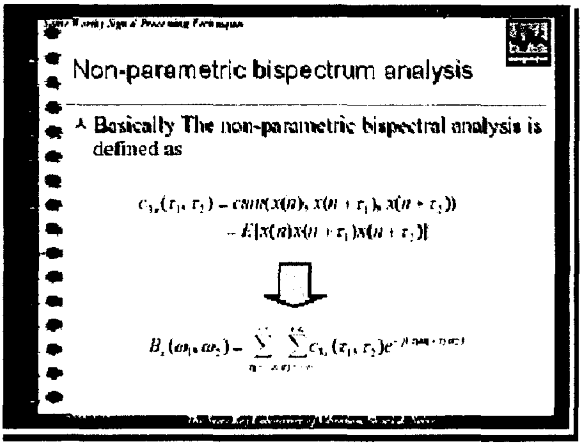


3. Wavelet Analysis

4. Bispectrum Analysis

6. Nonlinear Signal Analysis

4. Bispectrum Analysis



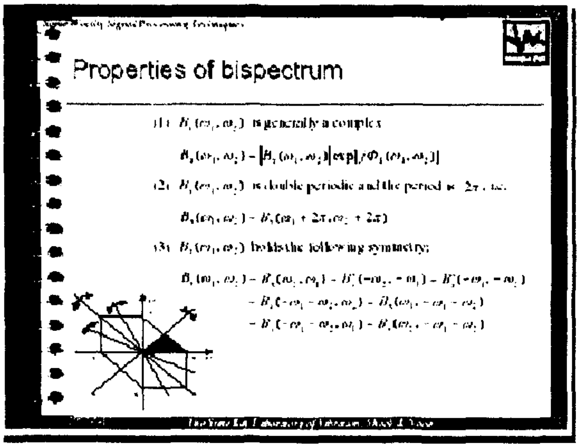
Non-parametric bispectrum analysis

- Basically The non-parametric bispectral analysis is defined as

$$c_{3x}(\tau_1,\tau_2) = cum(x(n), x(n+\tau_1), x(n+\tau_2)) = E[x(n)x(n+\tau_1)x(n+\tau_2)]$$

$$\Downarrow$$

$$B_x(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{+\infty}\sum_{\tau_2=-\infty}^{+\infty} c_{3x}(\tau_1,\tau_2)e^{-j(\omega_1\tau_1+\omega_2\tau_2)}$$



Properties of bispectrum

(1) $B_x(\omega_1,\omega_2)$ is generally a complex

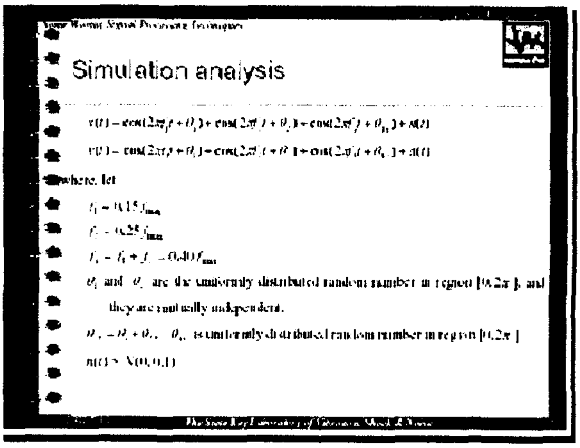
$$B_x(\omega_1,\omega_2)=|B_x(\omega_1,\omega_2)|\exp[j\Phi_x(\omega_1,\omega_2)]$$

(2) $B_x(\omega_1,\omega_2)$ is double periodic and the period is 2π, i.e.

$$B_x(\omega_1,\omega_2)=B_x(\omega_1+2\pi,\omega_2+2\pi)$$

(3) $B_x(\omega_1,\omega_2)$ holds the following symmetry:

$$B_x(\omega_1,\omega_2)=B_x(\omega_2,\omega_1)=B_x^*(-\omega_2,-\omega_1)=B_x^*(-\omega_1,-\omega_2)$$
$$=B_x(-\omega_1-\omega_2,\omega_2)=B_x(\omega_1,-\omega_1-\omega_2)$$
$$=B_x(-\omega_1-\omega_2,\omega_1)=B_x(\omega_2,-\omega_1-\omega_2)$$



Simulation analysis

$$x(t)=\cos(2\pi f_1 t+\theta_1)+\cos(2\pi f_2 t+\theta_2)+\cos(2\pi f_3 t+\theta_3)+n(t)$$
$$y(t)=\cos(2\pi f_1 t+\theta_1)+\cos(2\pi f_2 t+\theta_2)+\cos(2\pi f_3 t+\theta_4)+n(t)$$

where, let

$f_1=0.15f_{\max}$

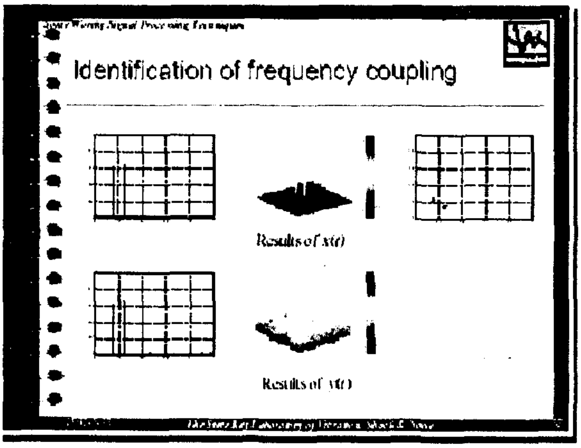
$f_2=0.25f_{\max}$

$f_3=f_1+f_2=0.40f_{\max}$

θ_1 and θ_2 are the uniformly distributed random number in region $[0,2\pi]$, and they are mutually independent.

$\theta_3=\theta_1+\theta_2$, θ_4 is uniformly distributed random number in region $[0,2\pi]$

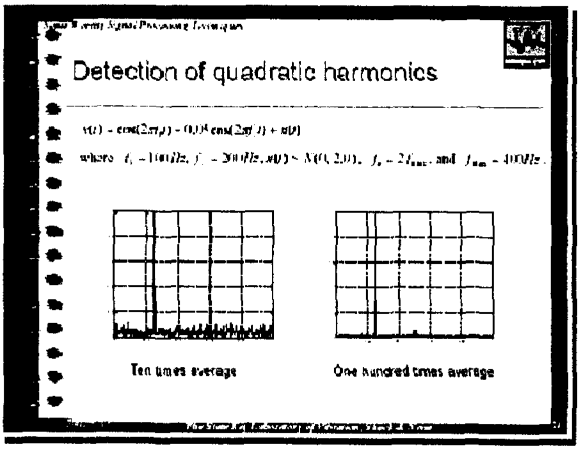
$n(t)\sim N(0,0.1)$



Identification of frequency coupling

Results of $x(t)$

Results of $y(t)$



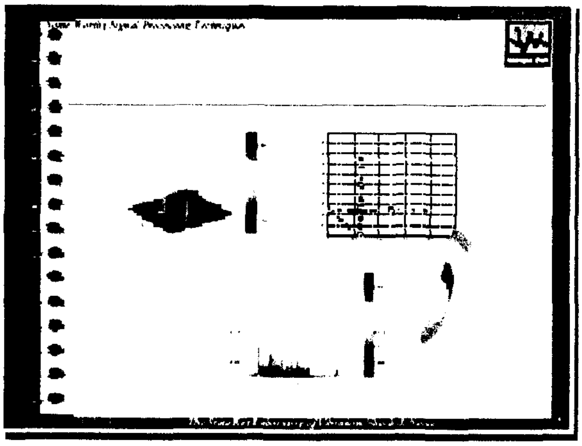
Detection of quadratic harmonics

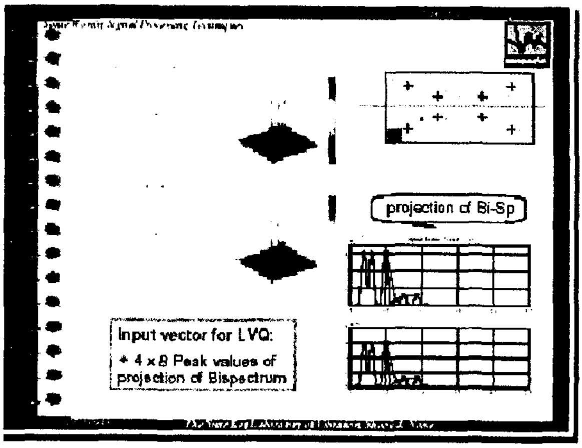
$x(t)=\cos(2\pi f_1 t)+0.05\cos(2\pi f_2 t)+n(t)$

where $f_1=100Hz$, $f_2=200Hz$, $n(t)\sim N(0,2.0)$, $f_s=2f_{\max}$, and $f_{\max}=400Hz$.

Ten times average

One hundred times average

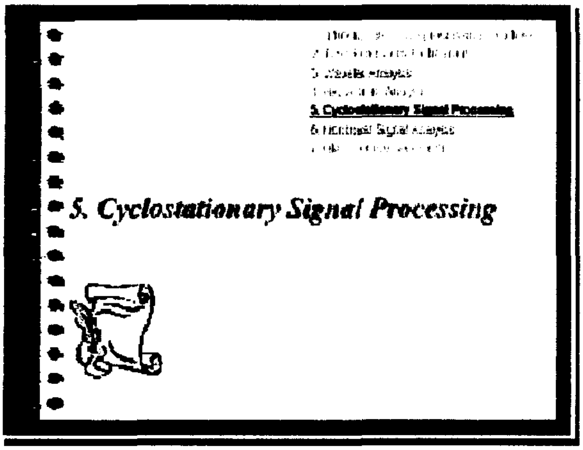




projection of Bi-Sp

Input vector for LVQ:

+ 4 x 8 Peak values of projection of Bispectrum

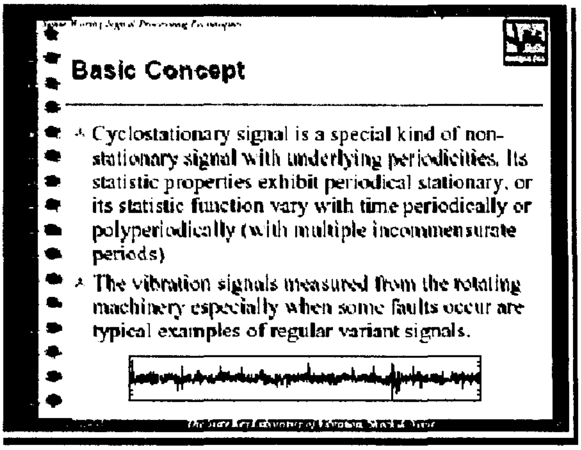


3. Wavelets Analysis

5. Cyclostationary Signal Processing

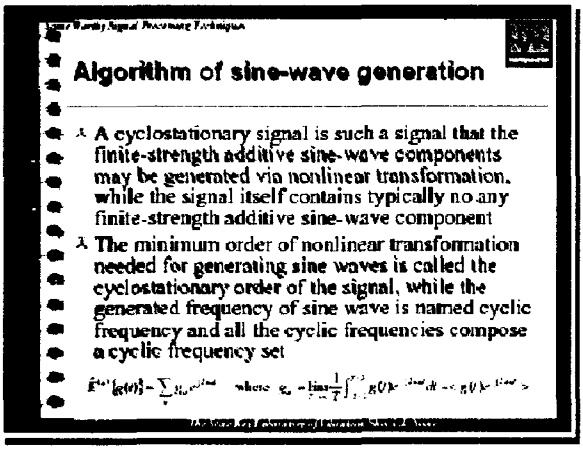
6. [illegible] Signal Analysis

5. Cyclostationary Signal Processing



Basic Concept

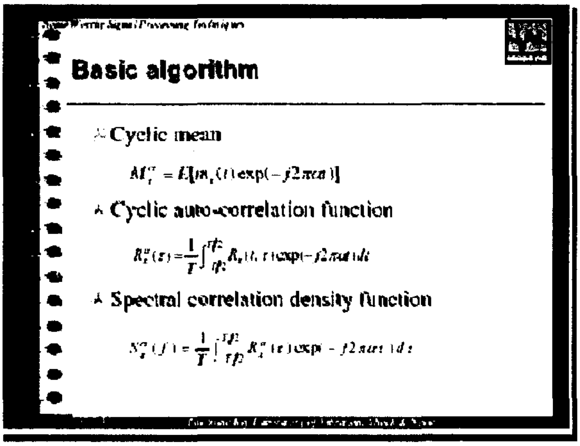
- Cyclostationary signal is a special kind of non-stationary signal with underlying periodicities. Its statistic properties exhibit periodical stationary, or its statistic function vary with time periodically or polyperiodically (with multiple incommensurate periods)
- The vibration signals measured from the rotating machinery especially when some faults occur are typical examples of regular variant signals.



Algorithm of sine-wave generation

- A cyclostationary signal is such a signal that the finite-strength additive sine-wave components may be generated via nonlinear transformation, while the signal itself contains typically no any finite-strength additive sine-wave component
- The minimum order of nonlinear transformation needed for generating sine waves is called the cyclostationary order of the signal, while the generated frequency of sine wave is named cyclic frequency and all the cyclic frequencies compose a cyclic frequency set

$$\hat{E}^{\{\alpha\}}\{g(t)\} = \sum_{\alpha} g_{\alpha} e^{j2\pi\alpha t} \quad \text{where} \quad g_{\alpha} = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} g(t)e^{-j2\pi\alpha t}dt = \langle g(t)e^{-j2\pi\alpha t}\rangle$$



Basic algorithm

- Cyclic mean

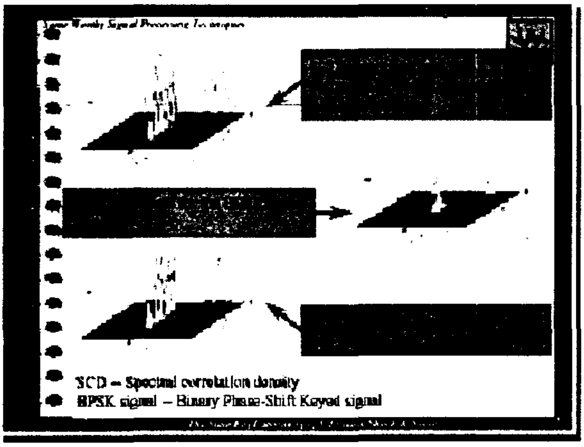
$$M_x^{\alpha} = E[m_x(t)\exp(-j2\pi\alpha t)]$$

- Cyclic auto-correlation function

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} R_x(t,\tau)\exp(-j2\pi\alpha t)dt$$

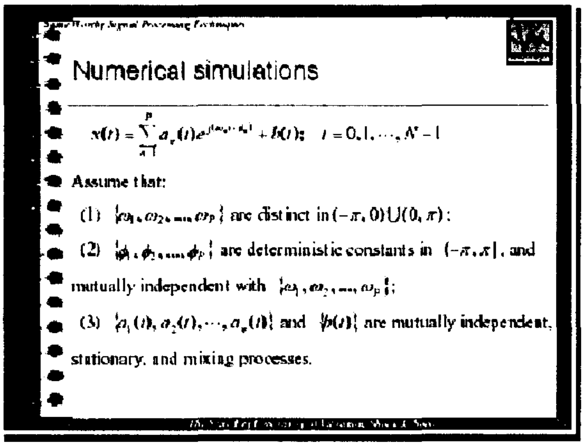
- Spectral correlation density function

$$S_x^{\alpha}(f) = \frac{1}{T}\int_{-T/2}^{T/2} R_x^{\alpha}(\tau)\exp(-j2\pi f\tau)d\tau$$



SCD – Spectral correlation density

BPSK signal – Binary Phase-Shift Keyed signal



Numerical simulations

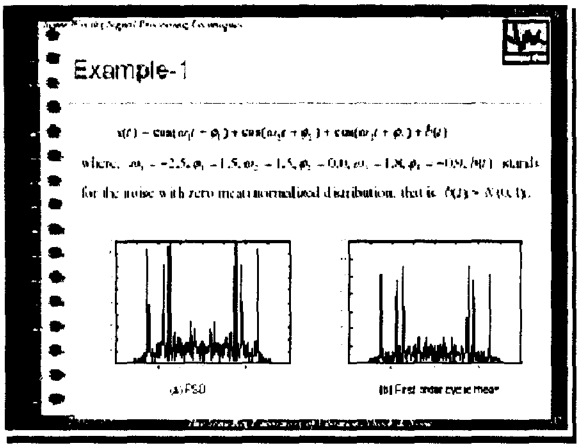
$$x(t) = \sum_{k=1}^{p} a_k(t)e^{j(\omega_k t+\phi_k)} + b(t); \quad t = 0,1,\cdots,N-1$$

Assume that:

(1) $\{\omega_1,\omega_2,\ldots,\omega_p\}$ are distinct in $(-\pi,0)\cup(0,\pi)$;

(2) $\{\phi_1,\phi_2,\ldots,\phi_p\}$ are deterministic constants in $(-\pi,\pi]$, and mutually independent with $\{\omega_1,\omega_2,\ldots,\omega_p\}$;

(3) $\{a_1(t),a_2(t),\cdots,a_p(t)\}$ and $\{b(t)\}$ are mutually independent, stationary, and mixing processes.



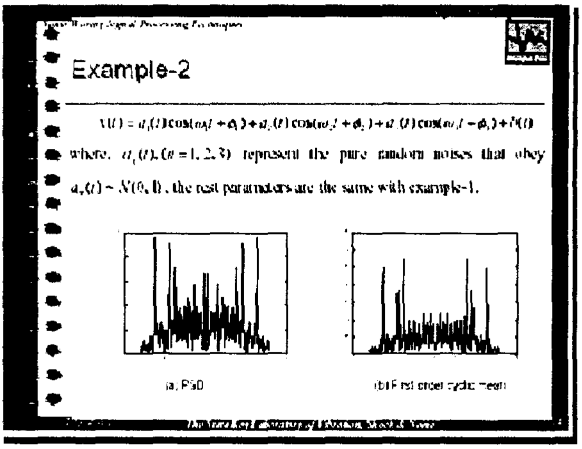
Example-1

$$x(t) = \cos(\omega_1 t + \phi_1) + \cos(\omega_2 t + \phi_2) + \cos(\omega_3 t + \phi_3) + n(t)$$

where, $\omega_1 = -2.5, \phi_1 = 1.5, \omega_2 = 1.5, \phi_2 = 0.0, \omega_3 = 1.8, \phi_3 = -0.9$, $n(t)$ stands for the noise with zero mean normalized distribution, that is $n(t) \sim N(0,1)$.

(a) PSD

(b) First order cyclic mean



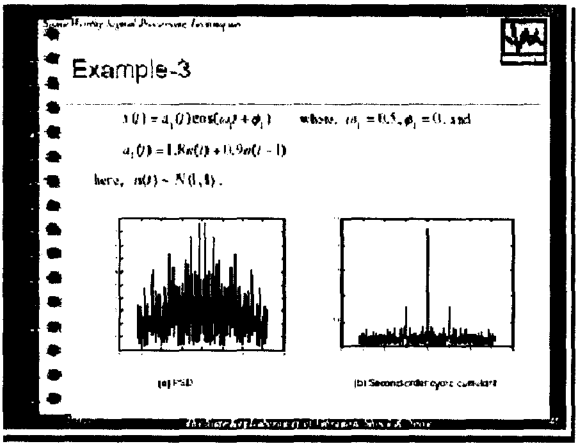
Example-2

$$x(t) = a_1(t)\cos(\omega_1 t + \phi_1) + a_2(t)\cos(\omega_2 t + \phi_2) + a_3(t)\cos(\omega_3 t - \phi_3) + n(t)$$

where, $a_i(t), (i = 1, 2, 3)$ represent the pure random noises that obey $a_i(t) \sim N(0,1)$, the rest parameters are the same with example-1.

(a) PSD

(b) First order cyclic mean



Example-3

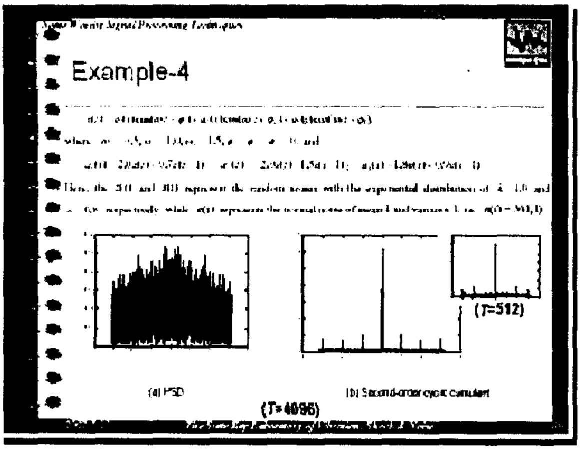
$x(t) = a_1(t)\cos(\omega_1 t + \phi_1)$ where, $\omega_1 = 0.5, \phi_1 = 0$, and

$a_1(t) = 1.8n(t) + 0.9n(t-1)$

here, $n(t) \sim N(1,1)$.

(a) PSD

(b) Second-order cyclic cumulant



Example-4

$x(t) =$ [illegible]

where [illegible] 0.5, [illegible] 1.0, [illegible] 1.5, [illegible] 0, and

$a_1(t) = 2.0a(t) + 0.7a(t-1)$, [illegible] $= 2.0b(t) + 1.5b(t-1)$; $a_3(t) = 1.8n(t) + 0.9n(t-1)$

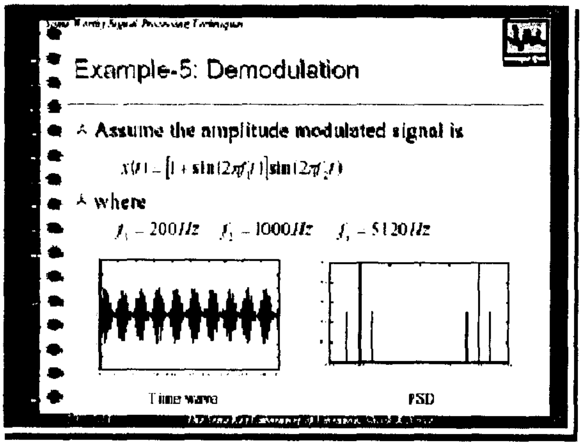
Here, the $a(t)$ and $b(t)$ represent the random noises with the exponential distribution of $\lambda = 1.0$ and $\lambda = 0.5$ respectively, while $n(t)$ represents the normal noise of mean 1 and variance 1, i.e. $n(t) \sim N(1,1)$

(T=512)

(a) PSD

(b) Second-order cyclic cumulant

(T=4096)



Example-5: Demodulation

- **Assume the amplitude modulated signal is**

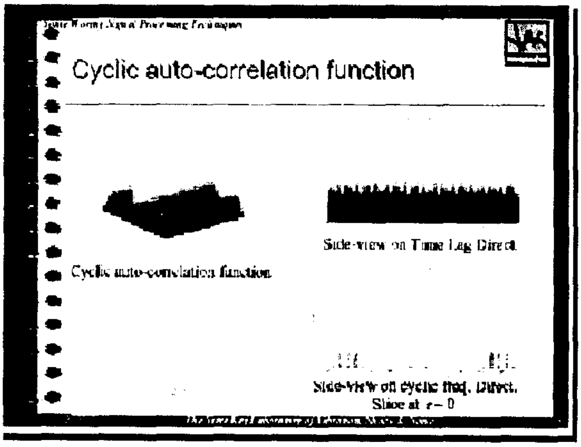
  $x(t) = [1 + \sin(2\pi f_1 t)]\sin(2\pi f_2 t)$

- **where**

  $f_1 = 200Hz \quad f_2 = 1000Hz \quad f_s = 5120Hz$

Time wave

PSD

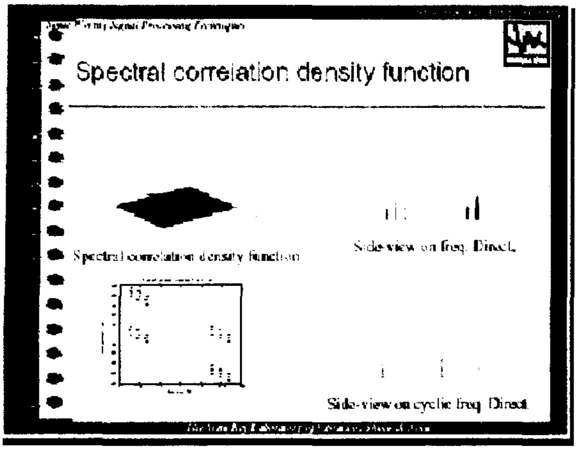


Cyclic auto-correlation function

Side-view on Time Lag Direct.

Cyclic auto-correlation function

Side-view on cyclic freq. Direct.
Slice at $\tau = 0$

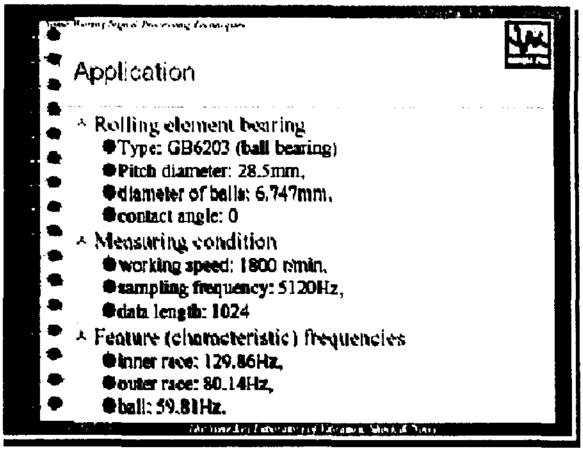


Spectral correlation density function

Spectral correlation density function

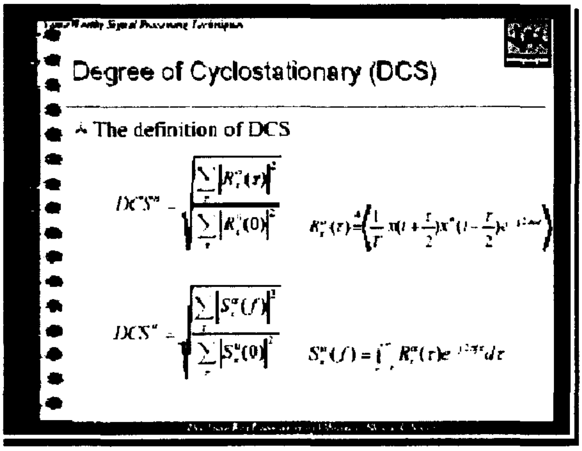
Side-view on freq. Direct.

Side-view on cyclic freq. Direct.



Application

- Rolling element bearing
  - Type: GB6203 (ball bearing)
  - Pitch diameter: 28.5mm,
  - diameter of balls: 6.747mm,
  - contact angle: 0
- Measuring condition
  - working speed: 1800 r/min,
  - sampling frequency: 5120Hz,
  - data length: 1024
- Feature (characteristic) frequencies
  - inner race: 129.86Hz,
  - outer race: 80.14Hz,
  - ball: 59.81Hz.

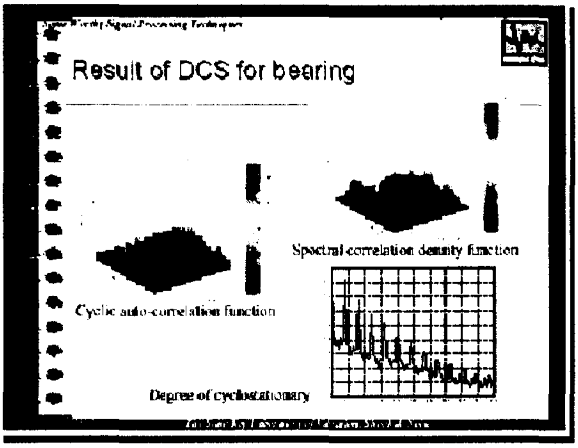


Degree of Cyclostationary (DCS)

- The definition of DCS

$$DCS^{\alpha} = \sqrt{\frac{\sum_{\tau}\left|R_x^{\alpha}(\tau)\right|^2}{\sum_{\tau}\left|R_x^{0}(0)\right|^2}} \qquad R_x^{\alpha}(\tau) \triangleq \left(\frac{1}{T} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j2\pi\alpha t} \right)$$

$$DCS^{\alpha} = \sqrt{\frac{\sum_{f}\left|S_x^{\alpha}(f)\right|^2}{\sum_{f}\left|S_x^{0}(0)\right|^2}} \qquad S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau$$

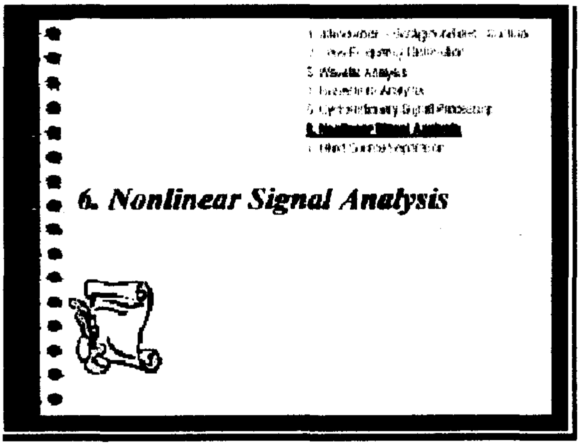


Result of DCS for bearing

Spectral correlation density function

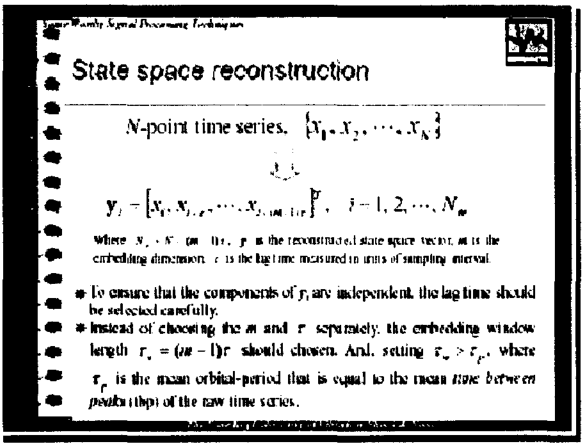
Cyclic auto-correlation function

Degree of cyclostationary



[illegible]
[illegible]
3. Wavelet Analysis
[illegible]
5. Cyclostationary Signal Processing
6. Nonlinear Signal Analysis
[illegible]

6. Nonlinear Signal Analysis



State space reconstruction

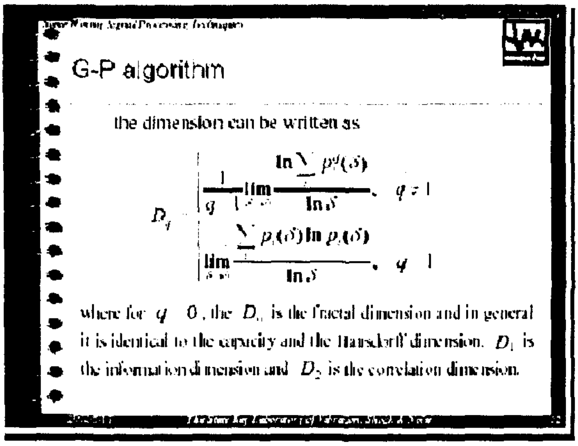
N-point time series. $\{x_1, x_2, \cdots, x_N\}$

$$\Downarrow$$

$$\mathbf{y}_i = \left[x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau}\right]^T, \quad i = 1, 2, \cdots, N_m$$

Where $N_m = N-(m-1)\tau$, $\mathbf{y}_i$ is the reconstructed state space vector, m is the embedding dimension, τ is the lag time measured in units of sampling interval.

- To ensure that the components of $\mathbf{y}_i$ are independent, the lag time should be selected carefully.
- Instead of choosing the m and τ separately, the embedding window length $\tau_w = (m-1)\tau$ should chosen. And, setting $\tau_w > \tau_p$, where τ_p is the mean orbital-period that is equal to the mean *time between peaks* (tbp) of the raw time series.


Some Modern Signal Processing Techniques

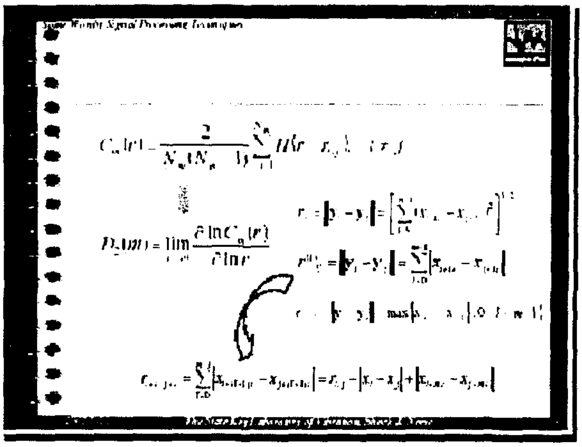
G-P algorithm

the dimension can be written as

$$D_q = \begin{cases} \frac{1}{q-1}\lim_{\delta\to 0}\frac{\ln\sum_i p_i^q(\delta)}{\ln\delta}, & q \neq 1 \\ \lim_{\delta\to 0}\frac{\sum_i p_i(\delta)\ln p_i(\delta)}{\ln\delta}, & q = 1 \end{cases}$$

where for $q = 0$, the D_0 is the fractal dimension and in general it is identical to the capacity and the Hausdorff dimension. D_1 is the information dimension and D_2 is the correlation dimension.

The State Key Laboratory of Vibration, Shock & Noise


Some Modern Signal Processing Techniques

$$C_m(r) = \frac{2}{N_m(N_m-1)}\sum_{i,j=1}^{N_m} H(r - r_{ij}), \quad i \neq j$$

$$D_2(m) = \lim_{r\to 0}\frac{\partial \ln C_m(r)}{\partial \ln r}$$

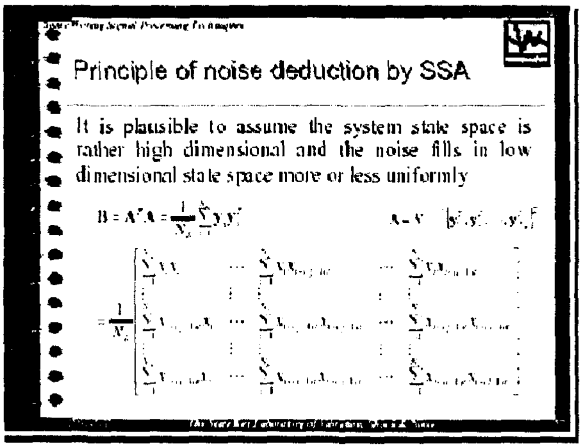
$$r_{ij} = \|y_i - y_j\| = \left[\sum_{l=0}^{m-1}(x_{i+l\tau} - x_{j+l\tau})^2\right]^{1/2}$$

$$r^{(1)}_{ij} = \|y_i - y_j\| = \sum_{l=0}^{m-1}\left|x_{i+l\tau} - x_{j+l\tau}\right|$$

$$r_{ij} = \|y_i - y_j\| = \max\left|x_{i+l\tau} - x_{j+l\tau}\right|, 0 \le l \le m-1$$

$$r_{i+1,j+1} = \sum_{l=0}^{m-1}\left|x_{i+(l+1)\tau} - x_{j+(l+1)\tau}\right| = r_{ij} - \left|x_i - x_j\right| + \left|x_{i+m\tau} - x_{j+m\tau}\right|$$

The State Key Laboratory of Vibration, Shock & Noise


Some Modern Signal Processing Techniques

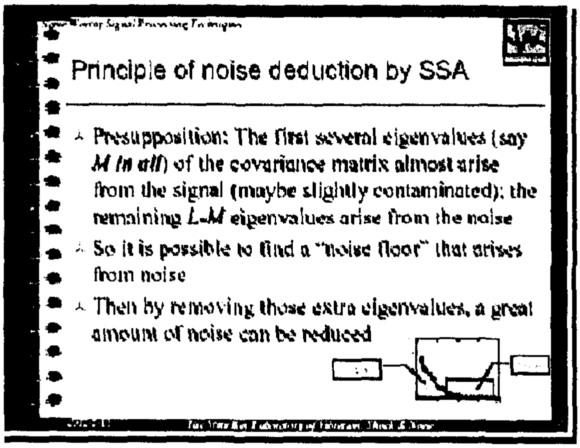
Principle of noise deduction by SSA

It is plausible to assume the system state space is rather high dimensional and the noise fills in low dimensional state space more or less uniformly

$$B = A^T A = \frac{1}{N_x}\sum_{i=1}^{N_x} y_i y_i^T \qquad A = N_x^{-1/2}\left[y_1^T, y_2^T, \ldots, y_{N_x}^T\right]^T$$

$$= \frac{1}{N_x}\begin{bmatrix} \sum_{i=1}^{N_x} x_i x_i & \cdots & \sum_{i=1}^{N_x} x_i x_{i+(j-1)\tau} & \cdots & \sum_{i=1}^{N_x} x_i x_{i+(m-1)\tau} \\ \vdots & & \vdots & & \vdots \\ \sum_{i=1}^{N_x} x_{i+(j-1)\tau} x_i & \cdots & \sum_{i=1}^{N_x} x_{i+(j-1)\tau} x_{i+(j-1)\tau} & \cdots & \sum_{i=1}^{N_x} x_{i+(j-1)\tau} x_{i+(m-1)\tau} \\ \vdots & & \vdots & & \vdots \\ \sum_{i=1}^{N_x} x_{i+(m-1)\tau} x_i & \cdots & \sum_{i=1}^{N_x} x_{i+(m-1)\tau} x_{i+(j-1)\tau} & \cdots & \sum_{i=1}^{N_x} x_{i+(m-1)\tau} x_{i+(m-1)\tau} \end{bmatrix}$$

The State Key Laboratory of Vibration, Shock & Noise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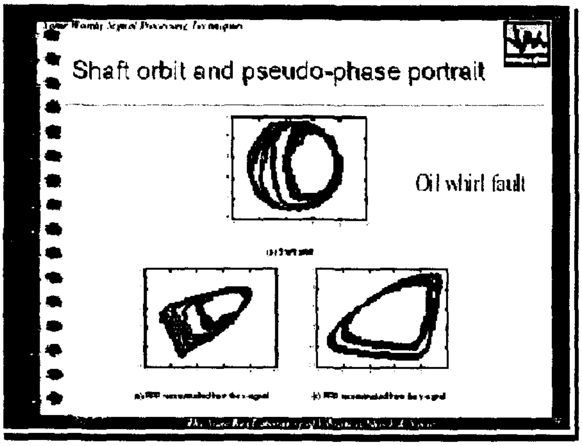
Principle of noise deduction by SSA

- **Presupposition: The first several eigenvalues (say *M in all*) of the covariance matrix almost arise from the signal (maybe slightly contaminated); the remaining *L-M* eigenvalues arise from the noise**
- So it is possible to find a "noise floor" that arises from noise
- Then by removing those extra eigenvalues, a great amount of noise can be reduced

The State Key Laboratory of Vibration, Shock & Noise


Some Modern Signal Processing Techniques

Shaft orbit and pseudo-phase portrait

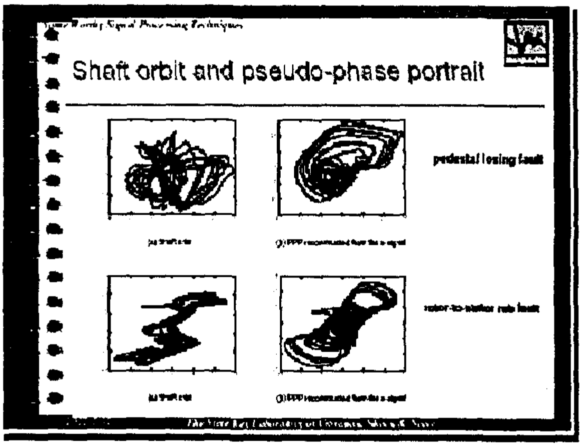
Oil whirl fault

(a) Shaft orbit

(b) PPP reconstructed from the x signal

(c) PPP reconstructed from the y signal

The State Key Laboratory of Vibration, Shock & Noise


Some Modern Signal Processing Techniques

Shaft orbit and pseudo-phase portrait

pedestal losing fault

(a) Shaft orbit

(b) PPP reconstructed from the x signal

rotor-to-stator rub fault

(a) Shaft orbit

(b) PPP reconstructed from the x signal

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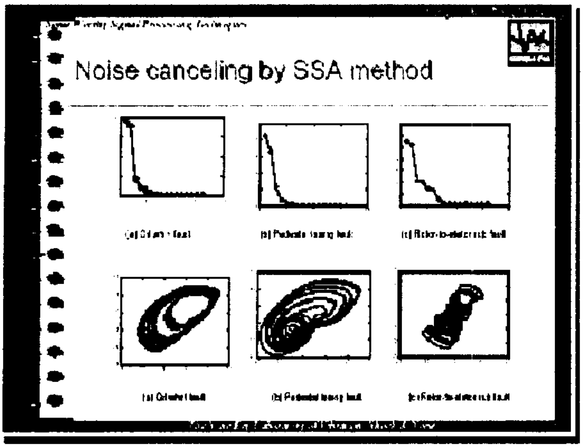
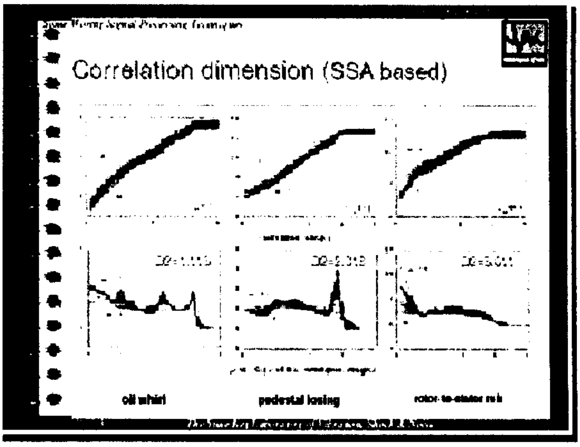


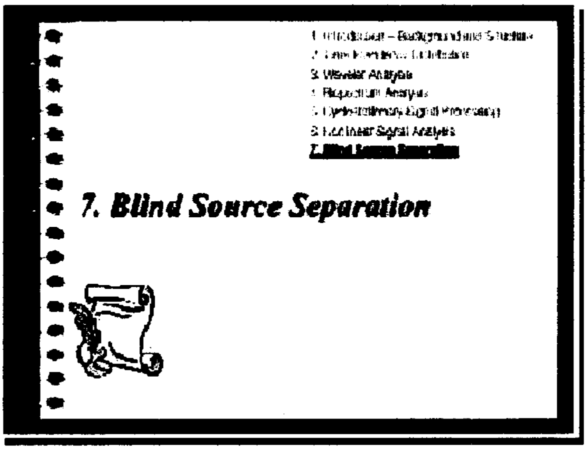
Some Worthy Signal Processing Techniques

Noise canceling by SSA method

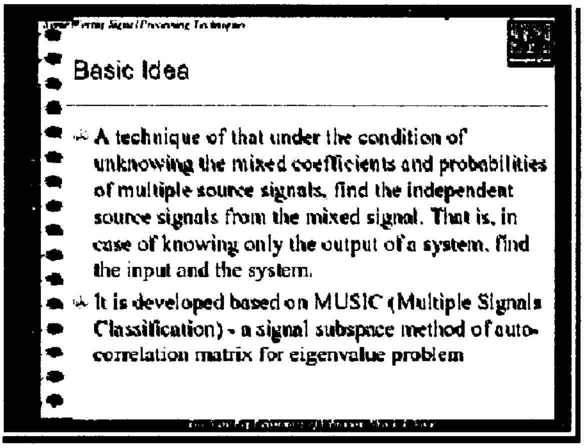


Some Worthy Signal Processing Techniques

Correlation dimension (SSA based)



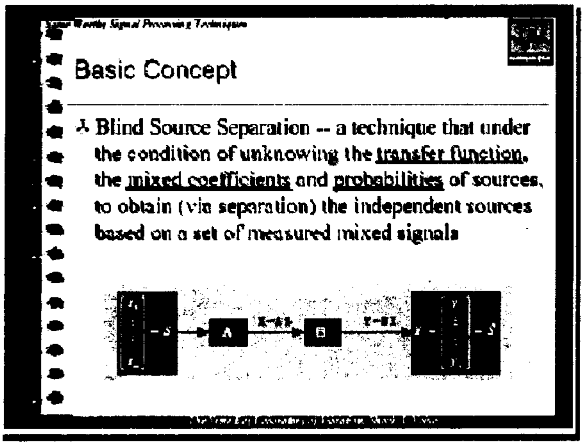
7. Blind Source Separation



Some Worthy Signal Processing Techniques

Basic Idea

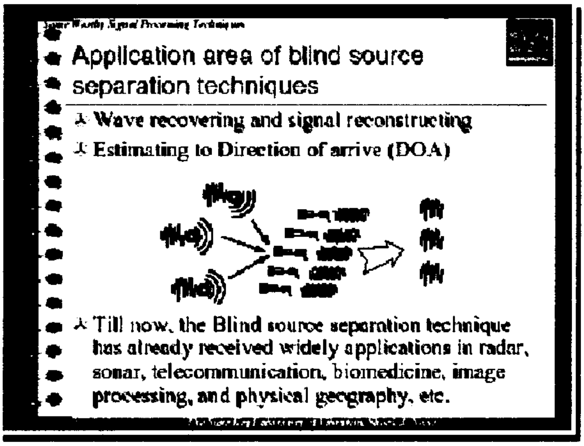
- A technique of that under the condition of unknowing the mixed coefficients and probabilities of multiple source signals, find the independent source signals from the mixed signal. That is, in case of knowing only the output of a system, find the input and the system.
- It is developed based on MUSIC (Multiple Signals Classification) - a signal subspace method of auto-correlation matrix for eigenvalue problem



Some Worthy Signal Processing Techniques

Basic Concept

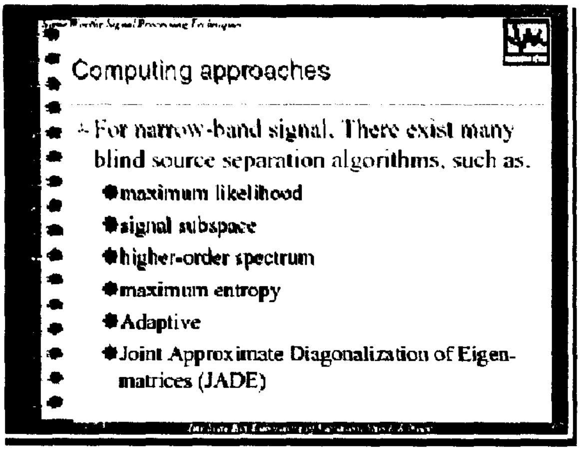
- Blind Source Separation -- a technique that under the condition of unknowing the <u>transfer function</u>, the <u>mixed coefficients</u> and <u>probabilities</u> of sources, to obtain (via separation) the independent sources based on a set of measured mixed signals



Some Worthy Signal Processing Techniques

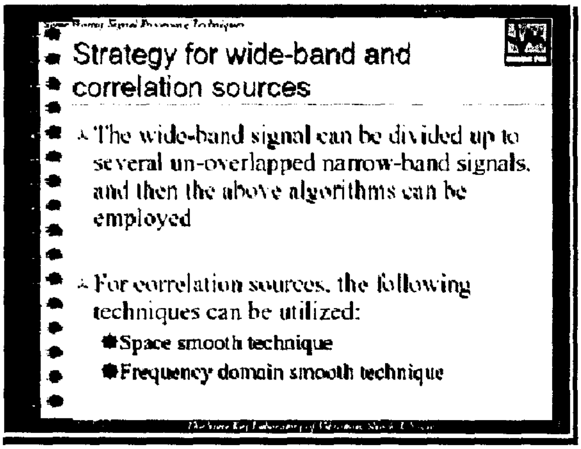
Application area of blind source separation techniques

- Wave recovering and signal reconstructing
- Estimating to Direction of arrive (DOA)
- Till now, the Blind source separation technique has already received widely applications in radar, sonar, telecommunication, biomedicine, image processing, and physical geography, etc.



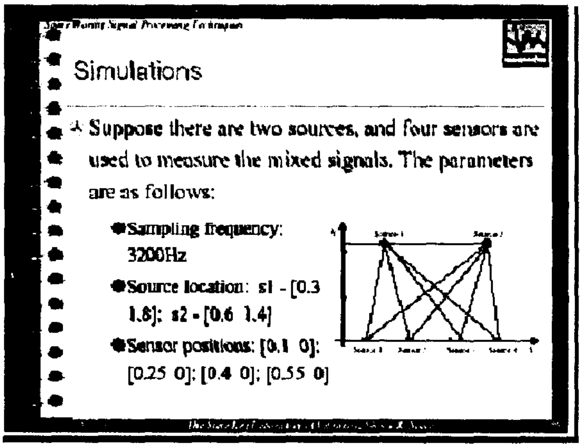
Computing approaches

- For narrow-band signal. There exist many blind source separation algorithms, such as.
  - maximum likelihood
  - signal subspace
  - higher-order spectrum
  - maximum entropy
  - Adaptive
  - Joint Approximate Diagonalization of Eigen-matrices (JADE)



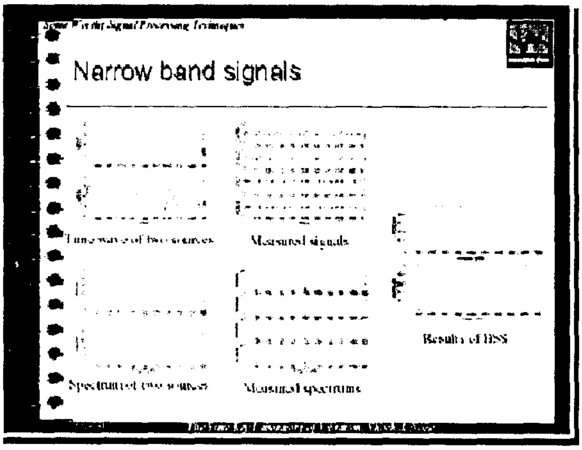
Strategy for wide-band and correlation sources

- The wide-band signal can be divided up to several un-overlapped narrow-band signals, and then the above algorithms can be employed
- For correlation sources, the following techniques can be utilized:
  - Space smooth technique
  - Frequency domain smooth technique



Simulations

- Suppose there are two sources, and four sensors are used to measure the mixed signals. The parameters are as follows:
  - Sampling frequency: 3200Hz
  - Source location: s1 - [0.3 1.8]; s2 - [0.6 1.4]
  - Sensor positions: [0.1 0]; [0.25 0]; [0.4 0]; [0.55 0]



Narrow band signals

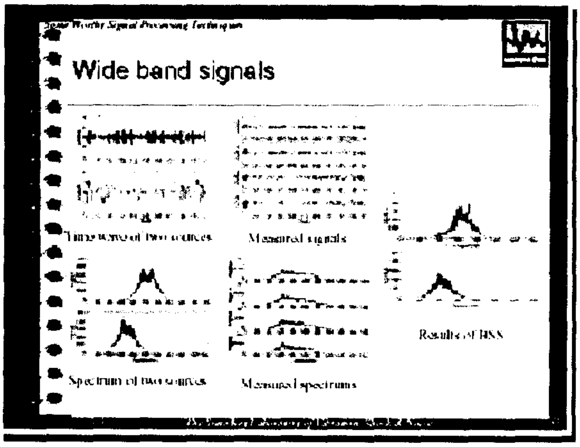
Time waves of two sources

Measured signals

Results of BSS

Spectrum of two sources

Measured spectrums



Wide band signals

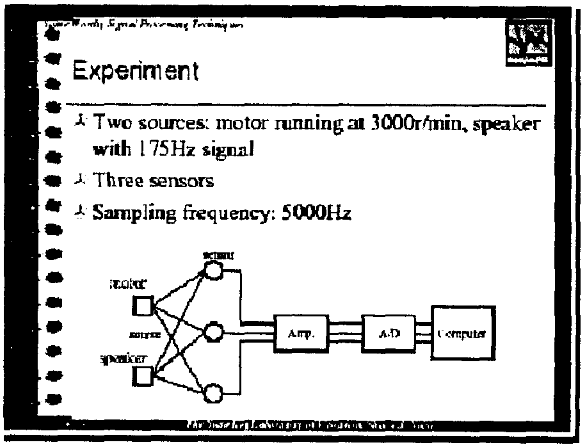
Time waves of two sources

Measured signals

Results of BSS

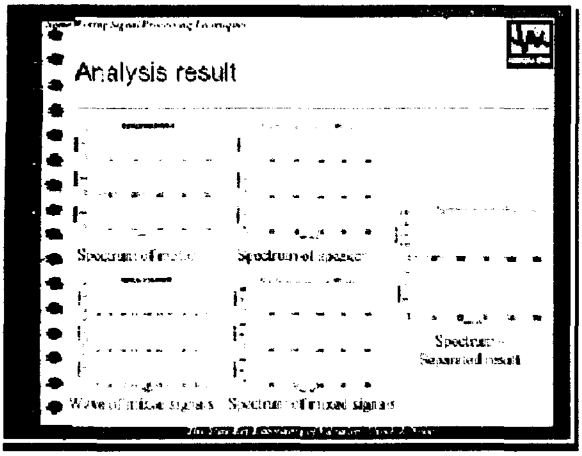
Spectrum of two sources

Measured spectrums



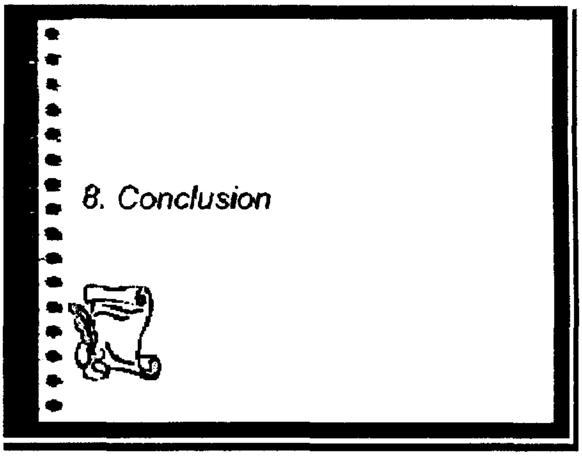
Experiment

- Two sources: motor running at 3000r/min, speaker with 175Hz signal
- Three sensors
- Sampling frequency: 5000Hz

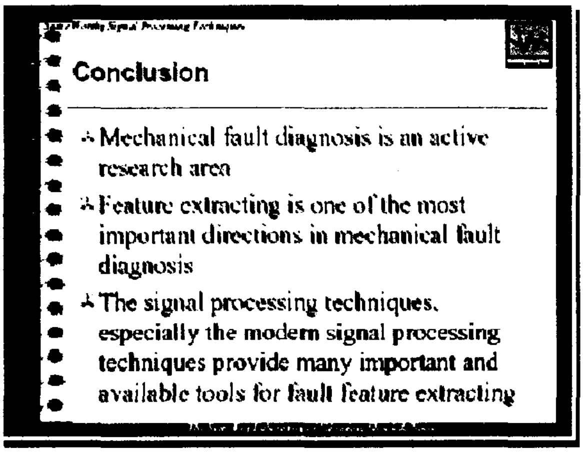


Some Modern Signal Processing Techniques

Analysis result



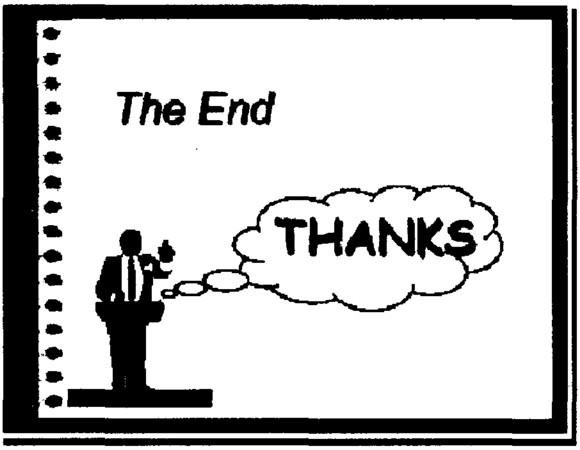
8. Conclusion



Some Modern Signal Processing Techniques

Conclusion

- Mechanical fault diagnosis is an active research area
- Feature extracting is one of the most important directions in mechanical fault diagnosis
- The signal processing techniques, especially the modern signal processing techniques provide many important and available tools for fault feature extracting



The End