

AMSC 664, Final Report, Spring 2013

Locating Faulty Rolling Element Bearing Signal by Simulated Annealing

Jing Tian Course Advisor: Dr. Balan, Dr. Ide Research Advisor: Dr. Morillo,

Background

• Rolling element bearings are used in rotating machines in different industry sections.



Computer cooling fan



Gas turbine engine



http://en.wikipedia.org/wiki/Fil e:Silniki_by_Zureks.jpg

http://en.wikipedia.org/wiki/File: J85_ge_17a_turbojet_engine.jpg



Wind turbine gearbox

http://en.wikipedia.org/wiki/File:Scout_moor_ gearbox,_rotor_shaft_and_brake_assembly.jpg

Health Monitoring of Bearing

- Bearing failure is a concern is a concern for many industrial sections
 - Bearing fault is a main source of system failure, e.g.: Gearbox bearing failure is the top contributor of the wind turbine's downtime [1, 2].
 - The failure of bearing can result in critical lost, e.g.: Polish Airlines Flight 5055 II-62M crashed because of bearing failure [3]. http://en.wikipedia.org/wiki/File

http://en.wikipedia.org/wiki/Fi



Offshore wind turbines



LOT Polish Airlines II-62M

- Vibration signal is widely used in the health monitoring of bearing
 - It is sensitive to the bearing fault. The fault can be detected at an early stage.
 - It can be monitored in-situ.
 - It is inexpensive to acquire.

_OT_Ilyushin_II-62M_Rees.jpg

Project Objective

- To detect fault for a bearing, the vibration signal *x*(*t*) is tested if it contains the faulty bearing signal *s*(*t*)
 - Faulty bearing: x(t) = s(t) + v(t)
 - Normal bearing: x(t) = v(t), where v(t) is the noise
- How to test the existence of faulty bearing signal s(t)? Check if unique frequency component of s(t) can be extracted.
 - Faulty bearing signal is a modulated signal : s(t) = d(t)c(t)
 - d(t) is the modulating signal. Its frequency component is the fault signature. The frequency is provided by the bearing manufacturer.
 - c(t) is the carrier signal, which is unknown.
- Objective of the project: given vibration signal *x*(*t*), test if the frequency component of *d*(*t*) can be extracted.

Fault Detection Using Spectral Kurtosis

- Due to the interference of the noise, modulating signal d(t) may not be extracted directly. Therefore, we want to locate the optimum frequency band which contains the faulty bearing signal s(t) and a minimum amount of noise.
- The optimum frequency band can be detected by spectral kurtosis (SK). The frequency band that contains components of *s*(*t*) has high SK while those contain only noise has low SK [4].
- Simulated annealing (SA) is implemented to optimize the frequency band by maximizing SK.

Approach

- SK can be estimated as the kurtosis of the magnitude of DFT [5]. Its value is related with the frequency band of the signal.
- This approach contains following steps:
 - Use FIR filter-bank to decompose the test signal into sub-signals.
 - Calculate SK of the sub-signals to find an approximation of the optimum band.
 - Apply SA using the result of the last step as the start point.
 - The optimum frequency band is determined by the optimum filter.
 - The filter is optimized by solving the following problem:

Maximize $SK(f_c, \Delta f, M)$

Subject to
$$f_{Fault} \le \Delta f \le \frac{f_s}{2}; \frac{\Delta f}{2} \le f_c \le \frac{f_s - \Delta f}{2}$$

 f_c is the frequency band's central frequency; Δf is the width of the band; M is the order of FIR filter; f_{Faul} is the fault feature frequency; f_s is the sampling rate.

- Band-pass filter the signal with the optimum filter and then perform envelope analysis (EA) to extract the modulating frequency (fault feature).

Algorithm of the Approach



Spectral Kurtosis

• Spectral kurtosis was defined based on the 4th order cumulants in [5], and it is estimated as

$$SK = \frac{E\{|Y(m)|^4\}}{[E\{|Y(m)|^2\}]^2} - 2$$

where Y(m) is the DFT of the time series signal y(n); N is the number of points. SK is a real number.

$$Y(m) = \sum_{n=0}^{N-1} y(n) e^{-i2\pi n \frac{n}{N}}, m = 0, 1, \dots, N-1$$

• This estimation is applied to stationary signal.

Maximize SK by Simulated Annealing

- Simulated annealing [6] is an metaheuristic global optimization tool.
- In each round of searching, there is a chance that worse result is accepted. This chance drops when the iterations increase. By doing so, the searching can avoid being trapped in a local extremum.
- Several rounds of searching are performed to find the global optimum.





Generation of the Simulated Signal

• An accepted bearing vibration signal generation signal was developed in [7].



- To generate the signal, parameters were set as $d_0=1$; $a_0=100$; $q_0=1$; $f_n=1/3000$ (the carrier frequency); $T_0=100$ (the modulating frequency).
- Gaussian white noise v(n) is added to the signal, and the SNR is 8. The signal to be tested is: x(n)=s(t)+v(t)



Verification by Simulated Signal

- The designed optimum frequency band is
 - Central frequency f_c =3000Hz; Bandwidth f_d =100Hz.
 - The modulating frequency to be extracted is 100Hz.
- Start point for the simulated annealing was found to be
 - f_c =3188Hz, f_d =375Hz, filter order M=1024, and spectral kurtosis SK=8314
- The optimized frequency band is
 - f_c =3165Hz; f_d =374Hz, M=975and the maximized SK=10573
- After performing envelope analysis to the optimized frequency band, the modulating frequency component was extracted.



Experimental Data

- The database is open to the public by Case Western Reserve University [8].
- The data was generated by a test rig where an accelerometer collected data from a faulty bearing driven by a motor.



Test rig [8]

- 12 sets of "Fan-End Bearing Fault Data, Inner Race" were used to validate the algorithm.
- The sampling rate is 12,000Hz. 24,000 data points of each set were used in this project.

Experiment Data

• Time series and magnitude of the FFT for the experiment data set (No. 281) is shown below



Analysis Results

Red lines indicate the expected fault feature frequency. This approach does • not work well for the experimental data 1.5 0.5 0.4 0.4 0.3 Magnitude Magnitude Magnitude 1, Magnitude 2 0.3 0.2 0.2 0.5 0.1 0.1 0 0 0 0 300 100 100 100 200 0 200 300 0 200 300 0 100 200 0 300 Frequency(Hz) Frequency(Hz) Frequency(Hz) Frequency(Hz) Dataset 278 Dataset 279 Dataset 280 Dataset 281 5 0.5 0.8 0.5 0.4 4 0.4 0.6 Magnitude Magnitude Magnitude Magnitude 0.3 3 0.3 0.4 0.2 0.2 2 0.2 0.1 0.1 1 0 0 0 0 300 300 0 100 200 300 100 200 Ó0 100 200 0 100 200 300 Frequency(Hz) Dataset 274 Frequency(Hz) Dataset 275 Frequency(Hz) Dataset 276 Frequency(Hz) Dataset 277 0.4 3 2.5 2 2 0.3 1.5 Magnitude Magnitude Magnitude 2 Magnitude 1.5 0.2 1 0.1 0.5 0.5 0 0 0 0 200 0 100 200 300 0 100 300 100 200 300 100 200 300 0 Frequency(Hz) Frequency(Hz) Frequency(Hz) Frequency(Hz) Dataset 270 Dataset 271 Dataset 272 Dataset 273

An Improved Approach

- In another definition [9], SK is defined based on the short-time Fourier transform (STFT) of the signal. Its value is related with the window size and the number of overlaps.
- For each pair of window size and overlaps, we can get SK as a function of frequency. The maximum SK of this function is to be maximized in terms of window size and overlaps.
- This approach contains the following steps:
 - Select a start point for the window size *w* and the number overlaps *p*.
 - maximize SK as a function of *w*, *p*, *f*.

MaximizeSK(w, p, f)N is the number of FFT;
f is the frequency index;Subject to $0 \le w \le N; 0 \le p \le w; 0 < f < f_s / 2$ f_s is the sampling rate.

- Band-pass filter the signal around the optimized *f* with a constant band width.
- Perform envelope analysis (EA) to extract the modulating frequency (fault feature).

Spectral Kurtosis Based on STFT

• For a signal *x*(*n*), spectral kurtosis can be defined as :

$$K(f) = \frac{\left\langle |X(m,f)|^4 \right\rangle}{\left\langle |X(m,f)|^2 \right\rangle^2}$$

where K(f) is the spectral kurtosis around the frequency f; X(m,f) is the STFT.

 $\langle \bullet \rangle$ is the time averaging operator that $\langle f(t) \rangle = \frac{1}{T} \int_0^T f(t) dt$

• For a signal *x*(*n*), STFT is:

$$X(m, f) = \sum_{n=0}^{N-1} x(n) w(n-m) e^{-j2\pi f n}$$

w is the window function. In this project, Hanning window is used, which is:

$$w(n) = 0.5(1 - \cos(\frac{2\pi n}{N - 1}))$$

Algorithm



Results of Serial Computing



Parallel Computing

- To optimize the spectral kurtosis, several cycles of simulated annealing (SA) can be performed in parallel. Therefore parallel computing can be used.
- Multi-core computing is used to implement parallelization. Matlab "parfor" command was used in this project. 4 SA were run in parallel.
- The algorithm was run on a computer with Intel Core Duo CPU E7500 2.93GHz and 2.00GB memory.



Results of Parallel Computing





Observations

- Except for the data set 279 and 271, results for serial computing and parallel computing are the same. Both methods extracted fault feature frequency for some of the data sets.
- Detection of the fault feature frequency: Yes = detected; No = not detected

Data set	278	279	280	281	274	275	276	277	270	271	272	273
Serial	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes	Yes
Parallel	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes

- For 12 experimental data sets, execution time (second) is
 - Serial: Mean time: 78.4

Standard deviation: 42.4

- Parallel: Mean time: 111.5

Standard deviation: 50.7

• For the implementation of the algorithm on the 2-core computer, parallel computing does not improve the efficiency of computation.

Summary

- Spectral kurtosis estimated based on STFT is more suitable for bearing signal analysis than that estimated by calculating the kurtosis of the time series' DFT.
- In this project, it is difficult to fit the experimental data with a model and in this situation simulated annealing is a choice to perform optimization tasks for the data.
- Parallel computation can be applied to the re-annealing stage in simulated annealing. However, depending on the hardware, the efficiency of computation may not necessarily be improved.

Deliverables

- Matlab code
- Test result
- Final report

Milestones

2012

- October
 - Literature review; exact validation methods; code writing
- November
 - Code writing and validation for envelope analysis and spectral kurtosis
- December
 - Semester project report and presentation

2013

•	February	Noticed that the approach is not		
	- Complete validation	suitable for experimental data.		
•	March			
	- Adapt the code for parallel	Code writing and validation for		
	computing	the second approach.		
•	April	A dant the code for parallel		
	- Validate the parallel version	computing.		
•	May	Validata the narallal version with		
-	- Final report and presentation	experimental data.		

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