Structural fatigue prognosis using limited sensor data

Jingjing He[1], Yongming Liu[1]

[1] *Department of Civil & Environmental Engineering, Clarkson University, Potsdam, NY, 13699-5710, USA*
jihe@clarkson.edu
yliu@clarkson.edu

ABSTRACT

In this paper, a general framework for concurrent structural fatigue prognosis using limited sensor data is developed. The Empirical Mode Decomposition method is employed to reconstruct the structural dynamical response for the critical spot susceptible to fatigue damage. The sensor data available at limited locations measured from the usage monitor system are decoupled into several Intrinsic Mode Functions using the Empirical Mode Decomposition method. Those IMFs are applied to extrapolate the dynamic response for the critical spot where the direct response measurements are unavailable. The extrapolated dynamic response time series for the critical spot is then integrated with a physical fatigue crack growth model for fatigue damage prognosis. The proposed procedure is demonstrated using a multi degree-of-freedom (MDOF) cantilever beam example. The proposed method has great potential for the real-time decision making in the vehicle health management framework due to its ability for the concurrent damage prognosis.*

1 INTRODUCTION

Fatigue prognosis is of critical importance for the structural health management and is still a challenging problem despite extensive progresses during the last few decades. Fatigue prognosis attempts to forecast system performance by assessing current damage state of the system (Inman *et al.,* 2005). More specifically, fatigue prognosis is to predict the remaining useful life by using physical models or data-driven models. Data-driven methods are applicable where the physics of the problem does not change much. For example, the loading spectrum of training samples needs to be similar with those of predictions. This paper uses physics-based models for damage prognosis, which is capable of handling different random loading spectrums. One of major sources of uncertainties in fatigue damage prognosis is the unknown loading uncertainties. Classical fatigue damage tolerance analysis and design used specified design spectrums for the entire fleet. The structural health monitoring and usage monitoring systems make it possible for the fatigue damage prognosis using measured loading spectrums for each individual vehicle, which will significantly advance the next generation vehicle health management (Link and Weiland, 2009; Papazian *et al.*, 2007; Gupta *et al.*, 2007). One of the objectives of this study is to propose a general methodology for the fatigue damage prognosis integrating usage monitoring system.

One critical challenge for the overall structural health monitoring is that the number of sensors is limited and it is not possible to put sensor at every critical location. Several methods for fatigue damage prognosis using direct sensor measurements are available (Papazian *et al.*, 2007; Gupta *et al.*, 2007; Li *et al.*, 2001; Adams and Nataraju, 2002; Papazian *et al.*, 2009; Yan and Gao, 2006). If critical locations are not covered by sensors or the critical location is uncertain due to the complex operational conditions, proper extrapolation process using the sensor data obtained from available location is required in order to identify and reconstruct the state on the critical spot. This is especially true when the number of available sensors is limited in structures. The proposed study uses the dynamic system identification technique and finite element extrapolation to estimate the dynamic responses at different critical locations in the structure. Extensive researches have been made on the system identification using sensor data. Wavelet transform (WT), which decomposes the measured signal in the frequency-time domain, is wildly used for system identification (Gurley and Kareem, 1999; Haase and Widjajakusuma, 2003; Pislaru *et al.*, 2003; Tan *et al.*, 2008; Luk and Damper, 2006). Hilbert transform (HT) has also received considerable attention in the system identification field and it has been applied to the single-

* This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

degree-of-freedom (SDOF) case (Feldman, 1985; Feldman, 1997). However, there are several limitations for these two methodologies. The selection of the type of the basic wavelet function is critical for WT method; it will affect the effectiveness in identification (Yan and Gao, 2006). On the other hand, well-behaved HT requires the mono-component frequency for input data which is hardly achieved for practical field (Yang *et al*., 2003; Huang *et al*., 1999; Huang *et al*., 1998). In comparison, Hilbert-Huang transform (HHT) does not suffer from these limitations (Yang *et al*., 2003; Huang *et al*., 1999; Bao *et al*., 2009). In HHT method, the Empirical Mode Decomposition (EMD) method is employed to decompose the signal into several Intrinsic Mode Functions (IMFs) which only contains a single frequency component before the well-behaved HT transform can be performed. In recent years, HHT method has been applied to identify the modal parameters of multi degree-of-freedom (MDOF) for both linear and nonlinear systems (Yang *et al*., 2003; Huang *et al*., 1999; Bao *et al*., 2009; Poon and Chang, 2007). In this paper, the HHT-based system identification method is used.

The current work focuses on fatigue analysis using limited sensor data. EMD is employed to decompose the signal data into a series of IMFs cooperating with intermittency criteria. Those IMFs which represent the dynamic response under mode coordinates are used to extrapolate the dynamic response at the critical spot with respect to mode coordinates. Full Mode information obtained from finite element method is used as the basis of the extrapolation. When all the mode information is extrapolated, mode superposition method is employed to reconstruct the dynamic response in the time domain. After the local dynamic response is determined, fatigue prognosis can be performed by a physical fatigue crack growth model. The flowchart for the proposed method is shown in Figure 1. One major benefit of this method is that only limited number of sensors is required, which greatly facilitate the realistic applications. Another benefit is that the fatigue damage can be obtained concurrently with structural dynamics analysis, which is critical for real-time decision making. A novel small time scale formulation of fatigue crack growth prognosis is employed to predict the crack growth in this paper. This physical fatigue model is fundamentally different with the traditional cycle-based approach. It describes the crack propagation in small time intervals and it is based on the geometry at the crack tip. The fatigue prognosis does not suffer from the cycle-counting requirements and stress ratio effects compares to the cycle-based fatigue prognosis models, which has great potential for real-time structural fatigue prognosis.

This paper is organized as follows. First, the EMD method is briefly introduced. Then, the extrapolation and reconstruction process is proposed and verified with numerical examples. Next, a novel fatigue crack growth model is discussed and integrated with the structural dynamic analysis. Following this, a cantilever beam is taken as an example to demonstrate the structural prognosis procedure using limited sensor data. Finally, some conclusions are drawn based on the current study.

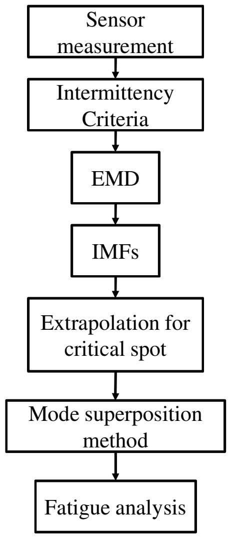


Figure 1: Flowchart of the concurrent fatigue analysis using limited sensor data

2 EMPERICAL MODE DECOMPOSITION

In this section, the EMD methods used in this paper is briefly introduced.

2.1 EMD methodology

EMD method is employed cooperating with intermittency criteria to decompose the measured signal into several IMFs which only have the mono-component of frequency (Yang *et al*., 2003; Huang *et al*., 1999). The basic procedure of EMD (shown in Figure 2) is to construct the upper and lower envelops for the signal using spline fitting methods. The mean values of both envelopes are calculated. Following that, the signal is subtracted from this mean value. The procedure described above is known as the sifting process. By repeating the sifting process until the remaining of the signal is a mono-component, meaning that the number of up-crossings (or down-crossings) of zero is equal to the number of peaks (or troughs). Those mono-component signals are known as Intrinsic Mode Functions (IMFs).

By applying the EMD method, the original signal $\ddot{y}$ can be express as a summation of n IMFs and a residue shown in Eq (1), f_i is the n IMFs, for i from 1 to n. r is the residue which is also the mean trend or constant for this signal (Yang *et al.,* 2003) .

$$\ddot{y} = \sum_{i=1}^{n} f_i + r \tag{1}$$

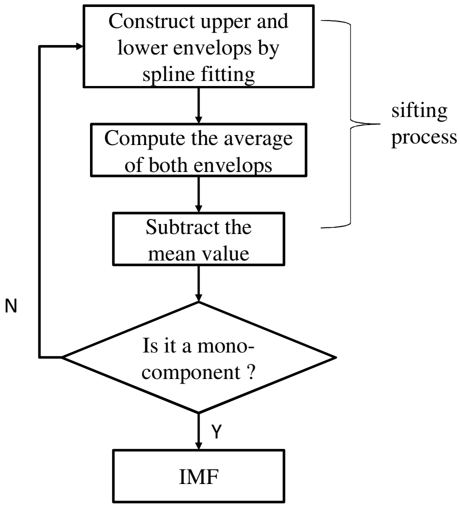


Figure 2: Flowchart for EMD procedure

IMFs obtained from the signal data may contain several frequency components in each IMF, which are not modal responses. Intermittency criteria denoted by w_{int} is used to solve this problem. The IMFs will not contain any frequency component lower than w_{int} by removing the signal which contains frequency lower than w_{int}. The detail procedure for the EMD which is imposed intermittency criteria as follow: First, the measured signal is transformed by Fourier transformation and an approximate frequency range ($f_L < f < f_H$) for each mode can be determined. Then, the EMD with this intermittency frequency range is performed to collect the IMFs which only contain the frequency component within the range. By repeating the above procedures and choosing different frequency range according to each mode, one can get several IMFs. These IMFs have several characteristics: 1) Each IMF contains the intrinsic characteristics of the signal; 2) Once an IMF is obtained, the next IMF will not have the same frequency at the same time instant (Yang *et al*., 2003; Huang *et al*., 1999; Kyong *et al*., 2008). The original signal expression (Eq(1)) can be modified as Eq(2)

$$\ddot{y} \approx \sum_{i=1}^{m} \ddot{x}_i + \sum_{i=1}^{n-m} f_i + r \tag{2}$$

$\ddot{x}$ is the modal response for each mode.

Yang *et al.* reported in 2003 (Yang *et al.,* 2003) that a bandpass filtering can be a good alternative for the above intermittency criteria. From the Fourier spectrum of the original signal, the approximated natural frequencies can be obtained and then the frequency ranges can be determined in advance. A bandpass filter can be applied based on the frequency range. The filtered data will be processed through the EMD method, and the resulting first IMF is the modal response.

By repeating above procedures, all the modal responses at the sensor location can be obtained from the sensor measurements.

2.2 Validation for EMD method

A simple example is used here to verify the accuracy of the modal response obtained from above procedures. The cantilever beam has been divided into two parts to solve the dynamic response. The properties of the beam are listed in Table 2.

Table 2 Dimensions and material properties of the beam

Property name	value
Young's modulus (MPa)	69600
Density (kg/m^3)	2.73×10^3
Width of cross section (m)	0.01
Thickness of beam (m)	0.01
Length of beam (m)	1

An impact force is applied at the free end of the beam. The force and the measured displacement for the last DOF are shown in Figure 3.

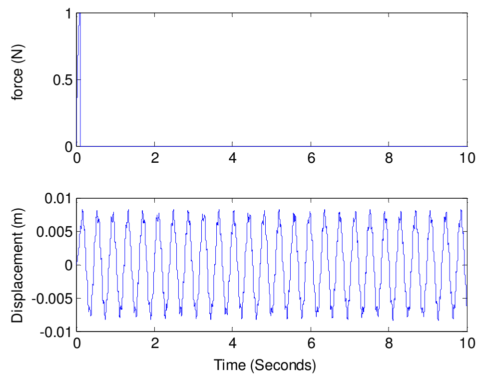


Figure 3: Applied force and displacement at the last DOF

The displacement data obtained from computer simulation are used to represent the direct measurements from sensors. The EMD method is used to extract the mode shape from the sensor data at node point. Natural frequencies obtained from processing the signal through Fourier spectrum are shown in Figure 4. This dynamic system has four natural frequencies. According to the frequency distribution, a bandpass filter is designed to filter the frequency other than the frequency component for the first mode. It is important to notice that the bandpass filter should have as small phase shift as possible (Yang *et al.,* 2003) . The frequency response for the designed filter is shown in Figure 5. After filtering, only the first mode frequency is kept, as shown in Figure 6.

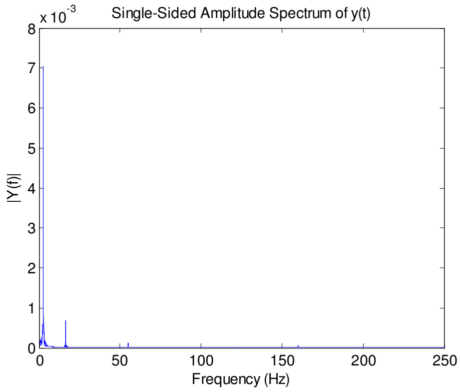


Figure 4: System natural frequencies

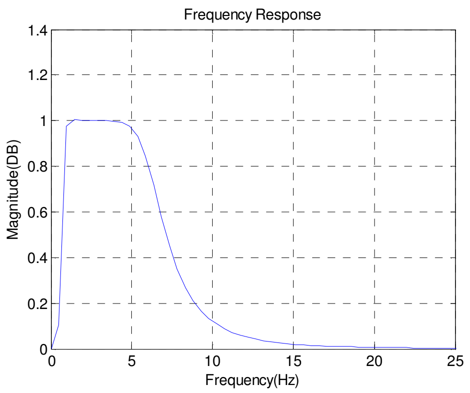


Figure 5: Filter frequency response

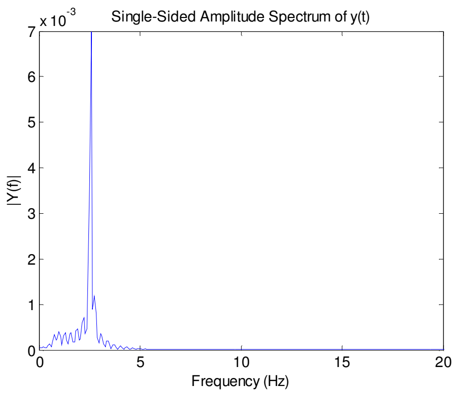
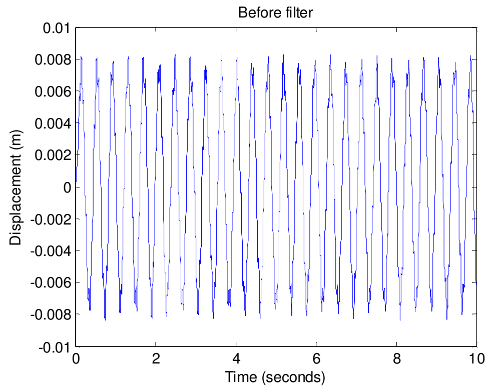
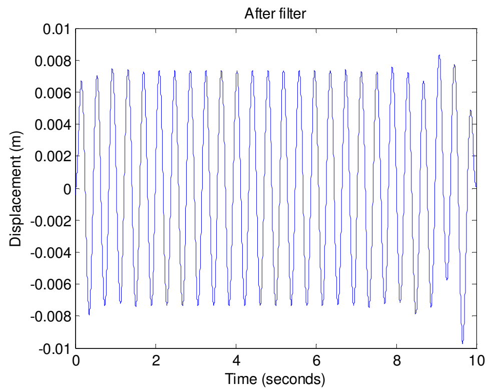


Figure 6: Signal frequency component after filter

The displacement data before and after the filtering process are shown in Figure 7.



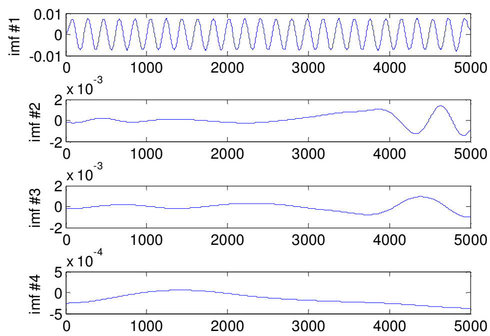
a) before bandpass filter



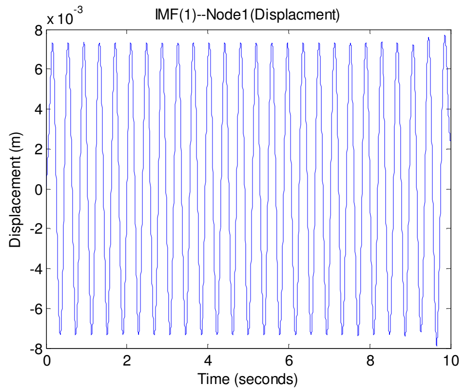
b) after bandpass filter

Figure 7: Displacement signal

Following that, the EMD method is applied to this filtered signal which contains only the frequency for the first mode.



a) Residual and all IMFs after EMD



b) the first IMF

Figure 8: Signal after EMD

Figure 8 a) shows the residual and all IMFs obtained from applying EMD and the first IMF is shown in Figure 8 b). The first IMF represents the displacement under the first mode with respect to mode coordinates. By repeating the above procedure for all DOFs, the displacements under first mode for all DOFs are obtained. The rest of the modes (mode 2, mode 3, and mode 4) can be obtained by using different bandpass filters. This procedure can be described as following steps: 1) Measure displacement signal for all DOFs; 2) Obtain all natural frequencies using the Fourier transform; 3) Choose the proper frequency band ($f_L < f < f_H$) for the specific mode; 4) Use the bandpass filter to collect signal which contains only the frequency component for the required mode; 5) Decompose the signal into several IMFs using the EMD method; 6) Calculate the first IMF under mode coordinates. Signal measurements for all DOFs are required in order to obtain the entire mode shape information. The comparison between the extracted and theoretical mode shape is shown in Table 2.

Table 2 Mode shape comparison between extracted result and theoretical solution

	Mode 1	**Mode 2**	**Mode 3**	**Mode 4**
Theor -etical	{1;3.3487; 2.4639; 3.7685}	{1; - 2.1582; -1.4886;- 7.9749}	{1;89.3601; -10.5884; -111,991}	{1;17.0227; 3.4852; 81.7384}
Extrac -tion	{1;3.3490; 2.4636; 3.7687}	{1; - 2.1582; -1.4886; -7.9761}	{1; 86.8015; -10.2846; - 108.7965}	{1; 16.6546; 3.4850; 81.5701}
Error	≤0.01%	≤0.01%	≤3%	≤2%

Table 2 evinces that good agreement between the identified mode shape and the theoretical solution.

3 IDENTIFICATION FOR CRITICAL SPOT USING LIMITIED SENSOR DATA

From above discussions, the sensor measurements, which are in the time domain, are decomposed into several IMFs using the EMD method with bandpass filters. Following this, the dynamic responses for critical spots without sensors can be extrapolated by combining the available sensor measurements and the finite element model of the entire structure. For fatigue prognosis, several critical spots can be selected based on the structural analysis (i.e., maximum stressed locations, stress concentrations, initial crack locations, etc.). The procedure is discussed below.

For an n DOFs system, it has an $n \times n$ mode shape matrix (Eq. (3)), which can be obtained from the finite element modeling and classical structural dynamics

$$\begin{bmatrix} \phi_{11} & \cdots & \phi_{1n} \\ \vdots & \ddots & \vdots \\ \phi_{1n} & \cdots & \phi_{nn} \end{bmatrix} \tag{3}$$

According to modal analysis, we have the following scaling equation (Eq. (4)),

$$\frac{\phi_{ie}}{\phi_{iu}} = \frac{\delta_{ie}}{\delta_{iu}} \tag{4}$$

where the subscript e denotes DOFs which can be measured by sensors; u denotes the DOFs which are unavailable for sensors; i represents the ith mode; Φ_{ie} represents the mode information for the eth DOF under the ith mode; δ_{ie} represents the dynamic response for the eth DOF under the ith mode with respect to mode coordinates. The dynamic response can be acceleration or displacement. In this paper, displacement is used. Once the sensor data have been decomposed into separated modes, the mode information can be used to extrapolate the dynamic response for the critical spot according to Eq. (4). The mode superposition methodology is applied to obtain the dynamic response in time domain after all the mode information has been extrapolated. The dynamic response reconstruction process is repeated for different critical spots and the obtained local stress/strain will be used for damage prognosis as detailed in the next section.

4 FATIGUE CRACK GROWTH MODEL

The methodology for reconstructing the dynamical response for the critical spot using limited sensor data is introduced above. The reconstructed dynamic response is employed to perform the fatigue analysis. In this part, a brief introduction about the fatigue crack growth model is given.

Traditional fatigue crack growth models are based on the relationship between the crack growth per cycle and the applied stress intensity factor range (Poon and Chang, 2007). The small time scale fatigue crack growth model adopted in this paper is based on the incremental crack growth at any arbitrary time instant during a loading cycle (Lu and Liu, 2010). The key concept is to define the fatigue crack kinetics at any arbitrary time instant (*dt*). The crack will extend a distance *da* during the small time scale *dt*. The geometric relationship between the Crack Tip Opening Displacement (CTOD) and the instantaneous crack growth kinetics is shown in Figure 9.

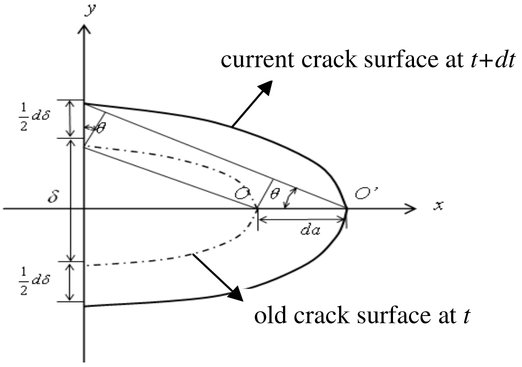


Figure 9: Crack tip geometry

The crack growth rate *da/dt* is derived based on the geometric relationship shown in Eq. (5), where θ is the crack tip opening angle (CTOA).

$$da = ctg\theta \times d\delta / 2 \qquad (5)$$

Following the derivation of (Lu and Liu, 2010), the instantaneous crack growth rate at an arbitrary time is expressed as Eq. (6).

$$\dot{a} = H(\dot{\sigma}) \cdot H(\sigma - \sigma_{ref}) \cdot \frac{2C\lambda}{1 - C\lambda\sigma^2} \cdot \dot{\sigma} \cdot \sigma \cdot a \qquad (6)$$

H is the Heaviside step function. σ_{ref} is the reference stress level above which the crack begins to grow. The crack length at any arbitrary time is calculated by the integration of Eq. (6). Detailed discussion of the model can be found in (Lu and Liu, 2010). One advantage of the proposed small scale model is that it can be used for fatigue analysis at variable time and length scales. The fatigue crack growth analysis under random variable amplitude loading conditions can be performed without cycle-counting. This main advantage makes it possible to couple the fatigue crack model with structural dynamics for concurrent analysis.

5 AN EXAMPLE

In this part, a cantilever beam problem is used as an example to demonstrate the procedure of the dynamic reconstruction and fatigue crack growth prognosis. The beam is divided into ten segments with an impact loading at the end of the beam (shown in Figure 10). A through edge crack is assumed at the fixed end of the beam which is also the critical spot inaccessible for sensors. A displacement sensor is placed at the free end of the beam. The impact force and the dynamic response for the free end are shown as Figure 11. The property of the beam is listed in Table 2.

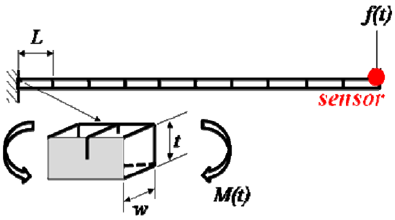


Figure 10: MDOF dynamic system

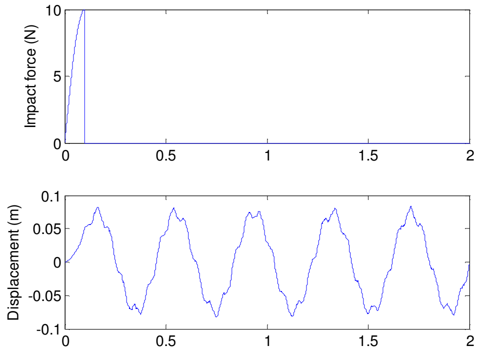


Figure 11 Applied force and displacement for the last DOF

The data representing the sensor measurement are obtained from numerical simulation and 3% Gaussian White Noise (GWN) is added to the deterministic signal (Figure 11) shown in Figure 12. This sensor measurement data are employed to extrapolate the dynamic response for the critical spot.

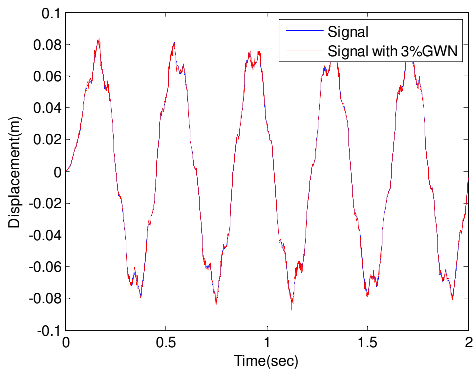


Figure 12: Signal which represents sensor data

The first four modes are chosen to reconstruct the displacement information at the critical spot. The measured displacement signal data need to be decoupled into four modes using the EMD method. Only the procedure for extracting the first mode is demonstrated here. Figure 13 shows the designed bandpass filter with 0.3*dB* pass band attenuation and

10*dB* stop band attenuation. Only the first mode frequency component is kept after the bandpass filtering, as shown in Figure 14. The original data and filtered data are shown in Figure 15 a) and b), respectively.

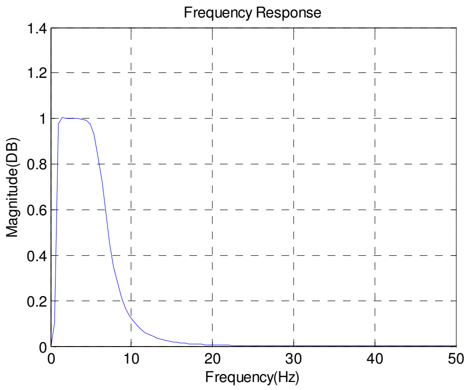


Figure 13: Band-pass filter frequency response

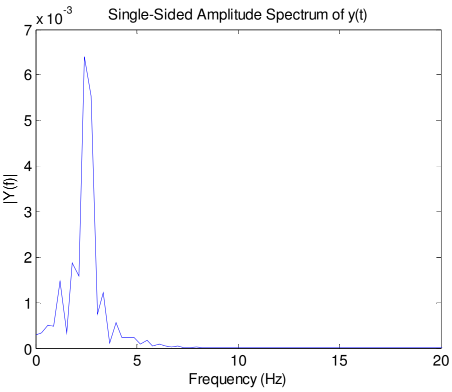
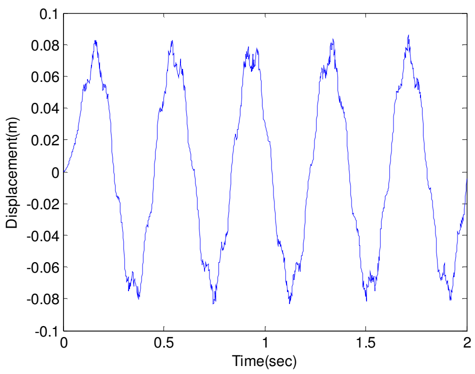
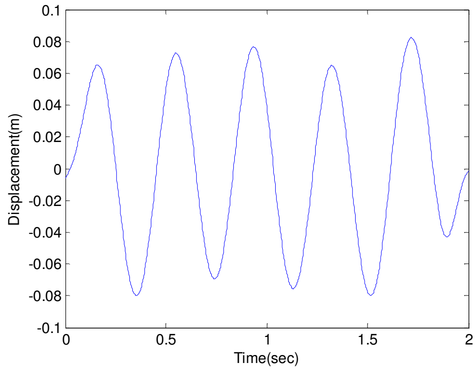


Figure 14: Signal frequency after filter



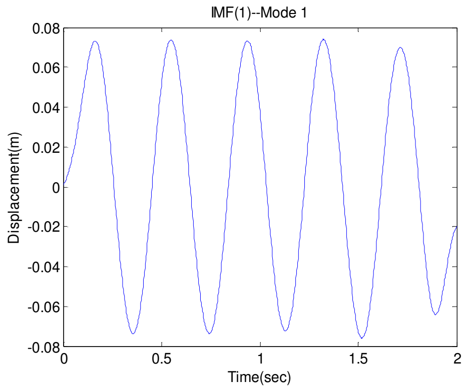
a) before bandpass filter



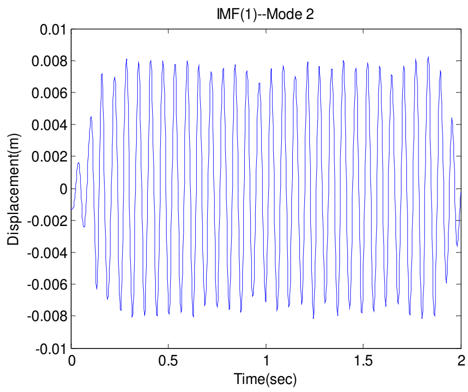
b) after bandpass filter

Figure 15: Displacement signal

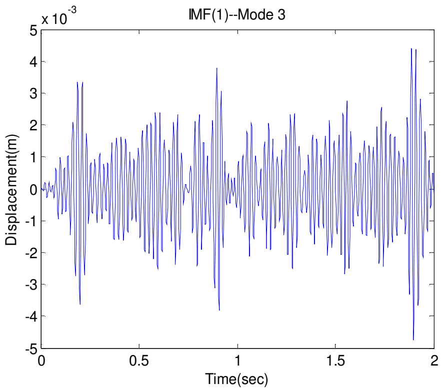
The signal after the filtering (Figure 15 b)) can readily be processed using the EMD method. Figure 16 a) shows the first IMF after the EMD analysis, which also represents the displacement for the first mode. The separated displacement for each of the modes can be obtained using the same procedure. The other IMFs for each of the modes are also shown in Figure 16.



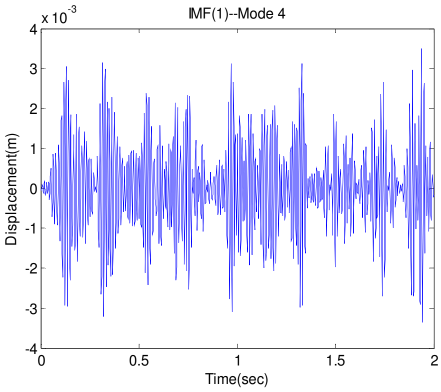
a) Mode 1



b) Mode 2



c) Mode 3



d) Mode 4

Figure 16: Displacement for the first mode

An extrapolation process, according to Eqs.(3-4), is applied to those decoupled data to get the displacement at the critical spot. The mode superposition method is employed to reconstruct the displacement in the time domain using the four extrapolated modal response. A comparison between the theoretical solution and the reconstructed response is shown in Figure. 17. The numerical solution to the beam problem serves as the basis of the comparison. A satisfactory result is observed.

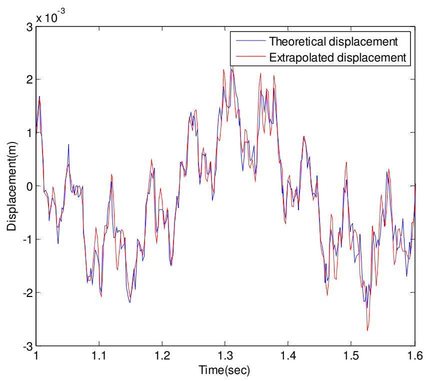


Figure 17: Comparison between extrapolate displacement and theoretical solution

When the extrapolation procedure is completed, the reconstructed dynamic response at the critical spot is employed to perform the fatigue analysis. The local stress calculated using the extrapolated displacement is shown as Figure 18.

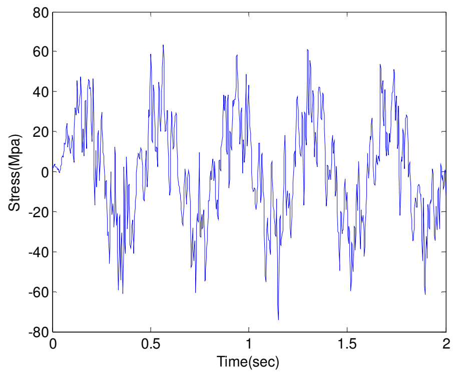


Figure 18: Local stress at the critical spot

The fatigue crack growth prognosis under the identified loading spectrum (Figure 18) is performed using Eqs.(5-6). The predicted crack growth curve and the exact numerical solution of the crack growth curve are shown in Figure 19, where a consistent result is observed.

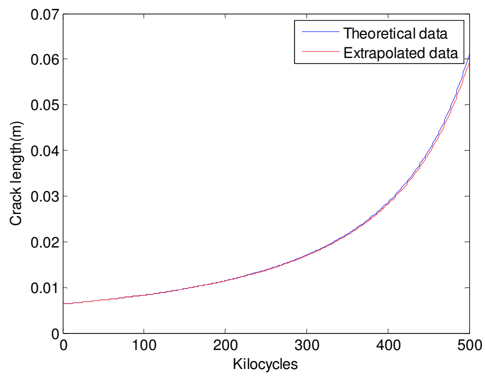


Figure 19: Fatigue crack growth

6 CONCLUSION

In this study, a new methodology for the structural fatigue prognosis is proposed. EMD method is employed to decompose the signal into a series of IMFs with a specific filtering process. Those IMFs, which represent the displacement for each mode, are used to extrapolate the dynamic response under mode coordinates for a critical spot. It should be noticed that the mode shape information is required and can be obtained from the classical finite element analysis. The fatigue crack growth prognosis is performed after the extrapolation process. Based on the current study, several conclusions are drawn:

1. The proposed procedure for fatigue crack prognosis provides a fast method for structure fatigue analysis with limited sensor data.
2. The proposed extrapolation process can effectively identify the dynamic response for the critical spot where direct sensor measures are not available

The research results evince that the proposed reconstruction process can effectively identify the dynamic response using the existed sensor data. However, some discussion and clarification in this aspect are needed. Firstly, the participation factor of modes should not be too small. Only the first several modes are detectable for more complicated structures. Secondly, signal-to-noise ratio may have influence on the accuracy of the extrapolation for realistic applications. Thirdly, the extrapolation results will have inconsistency with the theoretical solution for the region near $t = 0$, this phenomenon also is known as the end boundary effect for the EMD method and has been widely discussed in the literature (Huang *et al.,* 1998). This difference will not affect the fatigue prognosis since the time history for fatigue loading is very long. Small difference at the beginning and ending of the signal will not change the RUL prediction much (e.g., 2~3 cycles vs. one million cycles).

ACKNOWLEDGMENT

The research reported in this paper was supported in part by the NASA ARMD/AvSP IVHM project under NRA NNX09AY54A and in part by NSF (Award No. CMMI-0900111, Project Manager: Dr. Mahendra Singh). The support is gratefully acknowledged.

REFERENCES

(Adams and Nataraju, 2002) D. E. Adams and M. Nataraju. A Nonlinear Dynamical Systems Framework for Structural Diagnosis and Prognsis, *International Journal of Engineering Science*, vol. 40, pp. 1919-1941. 2002.

(Bao *et al.,* 2009) C. Bao, H. Hao, Z. Li and X. Zhu, Time-varying System Identification Using a Newly Improved HHT Algorithm, *Computers and Structures*, vol. 87, pp. 1611-1623. 2009.

(Feldman, 1985) M. Feldman. Investigation of the Natural Vibrations of Machine Elements Using the Hilbert Transform. *Soviet Machine Science*, vol. 2, pp. 44-47. 1985.

(Feldman, 1997) M. Feldman. Nonlinear Free-Vibration Identification via the Hilbert Transform. *Journal of Sound and Vibration*, vol. 208, pp. 475 – 489. 1997.

(Gupta *et al.,* 2007) S. Gupta, A. Ray and E. Keller. Online Fatigue Damage Monitoring by Ultrasonic Measurements: A Symbolic Dynamics Approach, *International Journal of Fatigue*, vol. 29, pp. 1100-1114. 2007.

(Gurley and Kareem, 1999) K. Gurley and A. Kareem. Application of Wavelet Transform in Earthquake, Wind, and Ocean Engineering, *Journal of Engineering Structures*, vol. 21, pp. 149-167. 1999.

(Haase and Widjajakusuma, 2003) M. Haase and J. Widjajakusuma. Damage Identication Based on Ridges and Maxima Lines of the Wavelet Transform, *International Jounral Engineering Science*, vol. 41, pp. 1423-1443. 2003.

(He *et al.,* 2009) J. He and Y. Liu. A New Method for Concurrent Multi-scale Fatigue Damage Prognosis, *The 7th International Workshop Structural Health Monitoring, Stanford University,* CA, 2009.

(Huang *et al.,* 1999) N. E. Huang, Z. Shen and S. R. Long, A New View of Nonlinear Water Waves: The Hilbert Spectrum, *Annual Review of Fluid Mechanics*, vol. 31, pp. 417-457. 1999.

(Huang *et al.,* 1998) N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.C. Yen, C.C. Tung and H.H. Liu The Empirical Mode Decomposition and Hilbert Spectrum for Nonlinear and Nonstationary Time Series Analysis. *Proceedings of the Royal Society of London-Series A 454*, pp. 903-995. 1998.

(Inman *et al.,* 2005) D. J. Inman, C. R. Farrar, V. Lopes Jr and V. Steffen Jr. *Damage Prognosis: For Aerospace, Civil and Mechanical System*, John Wiley, pp.1-11, 2005.

(Janssen, 2004) M. Janssen. *Fracture Mechanics*, Taylor and Francis. 2004.

(Kyong *et al*., 2008) Y. Kyong, D. Kim, J. Dayou, K. Park, S. Wang, Mode Shape Reconstruction of an Impulse Excited Structure Using Continuous Scanning Laser Doppler Vibrometer and Empirical Mode Decomposition, *Review of Scientific Instruments*, vol. 79.

(Li et al., 2001) Z. X. Li, T. H. T. Chan and J. M. Ko. Fatigue Analysis and Life Prediction of Bridges with Structural Health Monitoring Data - Part I: Methodology and Strategy, *International Journal of Fatigue*, vol. 23, pp. 45-53. 2001.

(Link and Weiland, 2009) M. Link and M. Weiland. Damage Identification by Multi-model Updating in the Modal and in the Time Domain, *Mechanical System and Signal Processing*, vol. 23, pp.1734-1746. 2009.

(Lu and Liu, 2010) Z. Lu and Y. Liu. Small Time Scale Fatigue Crack Growth Analysis, I*nternational Journal of Fatigue*. vol. 32, pp. 1306-1321.

(Luk and Damper, 2006) R. W. P. Luk and R. I. Damper. Non-parametric Linear Time-invariant

System Identification by Discrete Wavelet Transforms, *Digital Signal Processing*, vol. 16, pp. 303-319. 2006.

(Papazian *et al.,* 2007) J. M. Papazian, J. Nardiello, R. P. Silberstein, G. Welsh, D. Grundy, C. Craven, L. Evans, N. Goldfine, J. E. Michaels, T. E. Michaels, Y. Li and C. Laird. Sensor for Monitoring Early Stage Fatigue Cracking, *International Journal of Fatigue*, vol. 29, pp. 1668-1680. 2007

(Papazian *et al.,* 2009) J. M. Papazian, E. L. Anagnostou, S. J. Engel, D. Hoitsma, J. Madsen, R. P. Silberstein, G. Welsh and J. B. Whiteside. A Structural Integrity Prognosis System, *Engineering Fracture Mechanics*, vol. 79, pp. 620-632. 2009

(Paris and Erdogan, 1963) P. C. Paris, F. Erdogan. A Critical Analysis of Crack Propagation Laws. *Journal of Basic Engineering*, vol. 85, pp. 528-534. 1963.

(Patankar *et al.,* 1998) R. Patankar, A. Ray and A. Lakhtakia. A State-space Model of Fatigue Crack Growth, *International Journal of Fracture*, vol. 90, pp. 235-249. 1998.

(Poon and Chang, 2007) C. W. Poon and C. C. Chang, Identification of Nonlinear Elastic Structures Using Empirical Mode Decomposition and Nonlinear Normal Modes, *Smart structures and Systems*, vol. 3, pp. 1-15. 2007.

(Porter, 1972) T. R. Porter. Method of Analysis and Prediction for Variable Amplitude Fatigue Crack Growth, *Engineering Fracture Mechanics*, vol. 4, pp. 717-736. 1972.

(Pislaru *et al.,* 2003) C. Pislaru, J. M. Freeman and D. G. Ford. Modal Parameter Identification for CNC Machine Tools Using Wavelet Transform, *International Journal of Machine Tools & Manufacture*, vol. 43, pp. 987-993. 2003.

(Riera *et al.,* 2004) J. J. Riera, J. Watanabe, I. Kazuki, M. Naoki, E. Aubert, T. Ozaki and R. Kawashima. A State-space Model of the Hemodynamic Approach: Nonlinear Filtering of BOLD Signals, *NeuroImage*, Vol. 21, pp. 547-567. 2004.

(Tan *et al.,* 2008) J. Tan, Y. Liu, L. Wang and W. Yang. Identification of Modal Parameters of a System with High Damping and Closely Spaced Modes by Combining Continuous Wavelet Transform with Pattern Search, *Mechanical System and Signal Processing*, vol. 22, pp. 1055-1060. 2008.

(Yan and Gao, 2006) R. Yan and R. X. Gao. Hilbert-Huang Transform-Based Vibration Signal Analysis for Machine Health Monitoring, *IEEE Transactions on Instrumentation and Measurement*, vol. 55, pp. 2320-2329. 2006.

(Yang *et al.,* 2003) J. N. Yang, Y. Lei, S. Pan and N. E. Huang, System Identification of Linear Structures Based on Hilbert-Huang Spectral Analysis. Part 1: Normal Modes, *Earthquake engineering and structural dynamics*, vol. 32, pp. 1443-1467. 2003.

Jingjing He is a graduate research assistant in the department of civil and environmental engineering at Clarkson University. Her research interests are fatigue analysis, structural dynamics, diagnosis and prognosis. She received her B.S. degree in reliability engineering and M.S. degree in aerospace system engineering from Beihang University in China in 2005 and 2008, respectively.

Yongming Liu is an assistant Professor in the department of civil and environmental engineering. His research interests include fatigue and fracture analysis of metals and composite materials, probabilistic methods, computational mechanics, and risk management. He completed his PhD at Vanderbilt University, and obtained his Bachelors' and Masters' degrees from Tongji University in China. Dr. Liu is a member of ASCE and AIAA and serves on several technical committees on probabilistic methods and advanced materials.