Deterioration Sensitive Feature using Enhanced AR Model Residuals

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ABSTRACT: An extensive number of already built buildings are deteriorating due to environmental effects, varying service loads, and aging. Hence, it is extremely crucial to accurately and continuously track the deterioration condition of these structures by employing some structural health monitoring (SHM) based assessment procedures. In this regard, vibration-based methods are amongst the most effective ones as they can be used in ambient vibration and operational loading conditions. Each building has unique vibration characteristics that will change due to accumulated deterioration and damage. However, the changes due to deterioration are generally subtler than changes due to damage, and consequently more difficult to detect. Therefore, deterioration detection procedures need to be more accurate and sensitive to these changes. This paper presents an autoregressive (AR) time-series residual-based deterioration assessment method which uses SHM data to capture changes in dynamic characteristics of building structures. A novel AR model order estimation procedure was proposed in order to enhance the sensitivity of the method. The result shows that the proposed methodology can clearly detect deterioration.

1 INTRODUCTION

All infrastructures deteriorate at a slow-pace and progressive process due to the variety of challenges in their lifespan such as aging, environmental effects, and varying service loads. Due to the changing characteristics of buildings, SHM data is crucial to evaluate deterioration condition, to maintain their safety, to increase their life expectancy, and to reduce their costs of maintenance and repairs. Many existing building structures are in great need of repair and maintenance, but detecting deterioration condition prior to damage is not easy.

Due to accumulated deterioration and damage in a structure, its unique vibration characteristics change. Some researchers defined deterioration as a continuous loss of cross-sectional area in time (Okasha and Frangopol, 2010). It is worth to note that the changes owing to damage are generally far higher than changes due to deterioration. Du et al. (2013) concluded that undamaged surface of concrete on a structure does not confirm the healthy condition of the structure. As a result, deterioration is much more difficult to detect, and needs more accurate and sensitive methods. Farrar et al. (1999) asserted that dynamic properties of a structure alter due to changes in the structure's mass, stiffness or energy dissipative characteristics.

One of the key roles of using SHM data is to identify damage in structures. In fact, most studies so far in SHM area are on damage detection, not deterioration identification. Doebling et al. (1998), Carden and Fanning (2004), and Chan and Thambiratnam (2011) reviewed damage identification methods employing SHM data. The past literature shows that not much research has been done on deterioration assessment, especially using vibration response data. However, deterioration has been evaluated in some other approaches, for instance using reliability algorithm (Huang and Chen, 2015). To identify deterioration, the existing vibration based assessment methods need to be enhanced in regard to their sensitivity. Within the scope of this paper, only the assessment methods which have the potential to be developed for deterioration detection will be reviewed below.

Vibration-based damage detection (VBDD) methods have been investigated in the past three decades (Shih et al., 2009, Alvandi and Cremona, 2006). Some researchers such as Mosavi et al. (2012) asserted that time-series analysis modelling for ambient vibration has some advantages over the usual frequency domain methods. Based on these reviews, time-series analysis which estimates mathematical models using statistical tools to describe and analyze data such as signals seems to be more capable of developing deterioration features. These vibration feature data formats such as autoregressive time-series (Gul and Catbas, 2009, Omenzetter and Brownjohn, 2006, Carden and Brownjohn, 2008, Gul and Catbas, 2011, Nguyen et al., 2014) have been used extensively among VBDD ones to detect and locate damage in structures. Statistical time-series methods compare two main different conditions of a considered structure called baseline and assessment phases. The former is defined as the reference or healthy state of the structure and the latter is defined as the assessment state. In each phase, statistical time-series methods use response signals from the structure to describe and model the data. The concept of these methods is that a newly estimated time-series of a damaged and/or deteriorated structure differ from the time-series of the baseline state of that structure (Ling et al., 2009, Lei et al., 2003). In real-world structures, environmental and operational (E&O) variations such as external loading and temperature may produce dire effects on structural health assessment and mask subtler structural changes. Damage- and especially deterioration-sensitive features are often sensitive to these E&O changes. Therefore, in order to achieve successful deterioration assessment, it is vital to develop data normalization techniques distinguishing the effects of deterioration from those caused by E&O variations. Recently, damage detection has been addressed from a statistical perspective. For instance, Wang and Ong (2015) defined damage indicators by using three types of statistical hypothesis of two-sample Kolmogorov-Smirnov test, Mann-Whitney test, and Mood test. They defined a function of *P*-values for each of the mentioned hypotheses.

In this study, in order to remove the effect of E&O variations on the extracted features, a data normalization procedure including the following two steps are employed. First, data standardization is applied to remove E&O effects on measured acceleration response data. Second, a low-pass Chebyshev filter is employed to mitigate high-frequency content requiring complex time-series models with high model orders to well estimate the data. After vibration data is normalized, to detect deterioration, an autoregressive (AR) model is utilized to develop a time-series residual-based deterioration assessment method which uses acceleration data recorded by SHM systems to capture changes in dynamic characteristics of structures. Many researchers, such as Silva et al. (2007), have used this approach to detect damage. The feature in this approach is defined as a function of model residuals generated by using the data corresponding to the current health state when fitted in the AR model created in the reference state. In order to ensure sufficient sensitivity of the method, a novel framework called the best model order (BMO) algorithm is developed to estimate the ideal model order satisfying both minimal residual and simplicity of the model. The time-series model orders are unknown values which are required to be estimated with care to be generalized to a wide range of data sets and to be high enough to capture the dynamic characteristics of the structures. These are the two key factors of optimal model orders to be addressed in the present study.

In the following sections, first, the health evaluation framework based on time-series models is discussed. Then, the novel algorithms for structural deterioration detection are presented. Details of the experiment are next summarized, and deterioration detection method is verified using the experimental data. Finally, deterioration detection results are presented before the conclusion is made.

2 DETERIORATION DETECTION ALGORITHM

The AR model was chosen to detect deterioration assuming that the structural response is stationary. In order to remove the E&O effects of variations, data normalization procedure is designed as follows. First, data is collected from the structure using each sensor and standardized as follows:

$$\hat{x}_i = \frac{x_i - \overline{x}}{\sigma} \tag{1}$$

where, x_i denotes amplitude of measured acceleration response data; $\overline{x}$, σ and $\hat{x}_i$ are the mean, standard deviation (STD) and standardized signal of x_i, respectively. Second, the data are filtered with a twelve-order Chebyshev type II low-pass filter with a cutoff frequency of 50. This filter removes high-frequency content. The primary attribute of this filter is its speed. More information can be obtained from Smith (1997). Third, assuming the structural response as stationary, an AR model is fitted to the data:

$$x_k = \sum_{i=1}^{p} \Phi_i^x x_{k-i} + e_k^x \tag{2}$$

where, p is the model order, x_{k-i} represents the $(k-i)^{th}$ previous response, Φ_i^x is the i^{th} AR coefficient of the corresponding previous response, and e_k^x is the residual error of the model.

To increase the sensitivity of time-series analyses, a new framework named the BMO algorithm was developed to estimate an ideal model order satisfying both minimum residual and simplicity of the model. This method estimates the best-fit model to the data considering its complexity. When time-series models are well fitted to the data, the residuals against baseline become very small and so close to zero. The best-fit model order is the one with the least residual and suitable complexity. This technique enables deterioration sensitive features to be detected even with slight changes of vibration characteristics of the deteriorated buildings. It is worth noting that the current procedures are mostly suitable for detecting damage. As the changes in the response of structures due to deterioration are much smaller than the one caused by damage, the current techniques for estimating model orders which are widely used in damage detection, cannot be directly used. This is one of the basic concepts for obtaining sensitive features to identify anomalies and deterioration in buildings. If a number of time-series models from the structure in the reference (healthy) are available, the BMO algorithm runs according to the following steps. As this algorithm tries to estimate the most sensitive model order to the changes in the data, a number of data sets in the reference state are required to obtain a good estimation.

Step 1: Obtain AR models using different model orders for the first data ($i = 1, 2, ..., \mathrm{n}$; and n is a high enough model order).

Step 2: Feed another data and predict the data using the obtained AR models in step 1.

Step 3: Calculate residuals of time-series models in step 2.

Step 4: Calculate STD of residuals in step 3.

$$FR_{(i,j)} = \sigma(e_{(i,j)}) \tag{3}$$

where, $j = 1, 2, ..., m$; and m is the number of data sets in reference state.

Step 5: Calculate C parameter using the following equation to obtain the changes ratio in residuals of different models and data sets.

$$C_{(i,j)} = \frac{FR_{(i,j)} - FR_{(i,1)}}{FR_{(i,1)}} \tag{4}$$

Step 6: Repeat steps 2-5 for the number of data sets in reference state (m). C is the $n \times m$ matrix.

Step 7: Use the following equations and calculate $\boldsymbol{\beta}$ criterion. The minimum value of this parameter corresponds to the model order with a higher sensitivity to changes in data, including changes in data due to deterioration in structures.

$$\boldsymbol{\beta} = \boldsymbol{M} + 2 \times \boldsymbol{S} \tag{5}$$

where, $\boldsymbol{S}$ and $\boldsymbol{M}$ are STD and mean of $\boldsymbol{C}_i$, respectively. $\boldsymbol{C}_i$ is a vector of C parameter for different data sets obtained by using the same model order.

Step 8: The best model order is equal to the model order corresponding to the minimum value of $\boldsymbol{\beta}$ criterion having fit greater than 95% in order to ensure AR models capture the dynamic characteristics of structures.

In this study, a novel residual-based deterioration detection method was developed. In this method, statistical hypothesis of two-sample F-test for equal variances was conducted on residual of time-series analyses, which were estimated in the reference/healthy and assessment states of structures, as a deterioration detector. The *P*-values of the hypothesis test are used to define the deterioration feature. The relevant details can be found in statistics literature such as Gibbons and Chakraborti (2003).

3 DESCRIPTION OF TEST STRUCTURE AND DATA

In this study, an experimental three-story bookshelf structure was used to verify the proposed deterioration detection method. The experimental data was downloaded from the website of the Los Alamos National Laboratory (LANL), USA (Figueiredo et al., 2009). The three-story building structure (Figures 1 and 2) was used as accumulated-deterioration detection test bed.

Force and acceleration time histories (time-series or sample records) for various structural states were collected as shown in Table 1 along with information that describes the different states. The structural state conditions were categorized into nine states. The first state (State#1) is the baseline condition. The other states (States #2-#9) are related to the structure when the mass or stiffness of the structure is slightly changed. Real-world structures have E&O variations, which create difficulties in detecting and identifying structural deterioration. Such variations often manifest themselves in changes of the mass or stiffness of a structure. In order to simulate these variations, tests were conducted with different stiffness and mass conditions (States #2-#9). For example, the state condition labelled “State #4” means there was an 87.5% stiffness reduction in the column located between the base and 1st floor at the intersection of plane B and D (abbreviated as 1BD, other abbreviations can be identified in a similar way) (Figure 1). The stiffness reduction consists of replacing the corresponding column by another one with lower stiffness in the direction of shaking. It is assumed that the structure is deteriorated in each of the considered states. In other words, each state shows the condition of the deteriorated structure after a specific time. For instance, it is supposed that in State #4, column 1BD in the first story is deteriorated (87.5% stiffness reduction). It should be noted that each state must be studied individually.

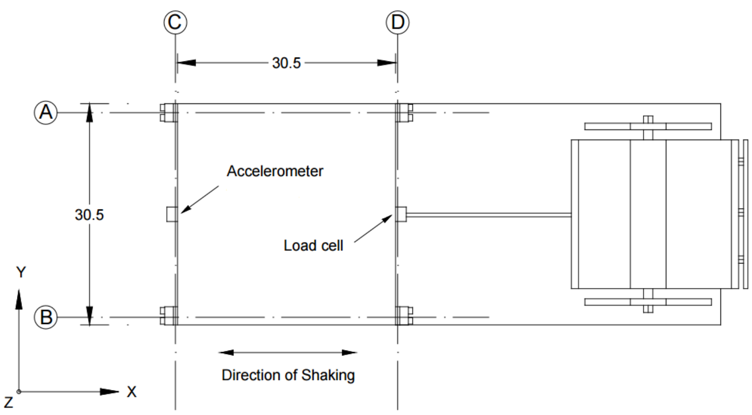


Figure 1. Basic dimensions of the building model (dimensions are in cm) (Figueiredo et al., 2009)

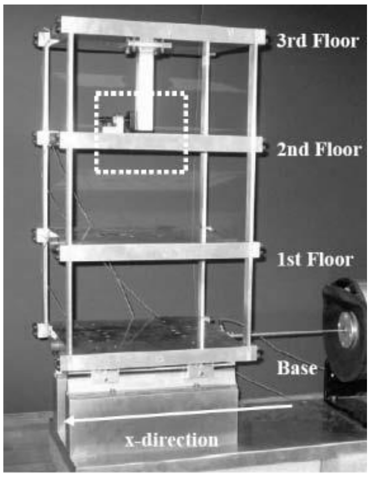


Figure 2. Three-story building model (Figueiredo et al., 2009)

Table 1. Data labels of structural state conditions

State No.	Record No.	Description
State #1	1~50	Baseline condition
State #2	51~100	Mass = 1.2 kg at the base
State #3	101~150	Mass = 1.2 kg on the 1st floor
State #4	151~200	87.5% stiffness reduction in column 1BD
State #5	201~250	87.5% stiffness reduction in column 1AD and 1BD
State #6	251~300	87.5% stiffness reduction in column 2BD
State #7	301~350	87.5% stiffness reduction in column 2AD and 2BD
State #8	351~400	87.5% stiffness reduction in column 3BD
State #9	401~450	87.5% stiffness reduction in column 3AD and 3BD

On the one hand, no research has been conducted on deterioration assessment of structures. On the other hand, simulating deterioration on structures is not easy and in some cases impractical. As a result, these data sets related to minor damage of the experimental data, which can be considered as accumulated deterioration, were used to validate the proposed deterioration detection method. A total of 450 records (nine states each of which have 50 records) of 8192 data points with a sampling frequency of 320 Hz is used in each level.

4 ANALYSIS AND RESULTS

The mentioned experimental data sets were utilized as input data. In this method, a data normalization procedure including the following two steps were employed. First, data standardization was applied. Second, a low-pass Chebyshev filter was employed. Then, the BMO algorithm was utilized to estimate the best model order. Finally, statistical hypothesis of two-sample F-test was conducted on residual of time-series models and the *P*-values of the hypothesis test were used to define a deterioration indicator. This deterioration detection procedure was carried out using MATLAB.

4.1 Model Order Selection

The first step to assess the deterioration using the proposed methods was estimating time-series model orders. To obtain the best model order, 12 datasets in the reference state were used utilizing the novel BMO algorithm. In this case study, AR time-series model was used and the maximum value for model orders (p) is considered to be 20 as the higher model orders result larger $\boldsymbol{\beta}$ criterion. Figure 3 shows $\boldsymbol{\beta}$ criterion in the BMO algorithm in which the horizontal axis indicates the model orders. The best model order is equal to the model order corresponding to the minimum value of $\boldsymbol{\beta}$ criterion having fit greater than 95%. For instance, in this case study, the best model order was 7; as for the first 6 model orders, the fit ratio was less than 95%.

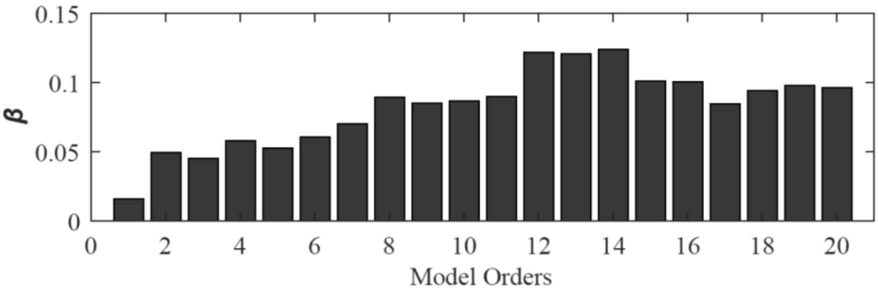
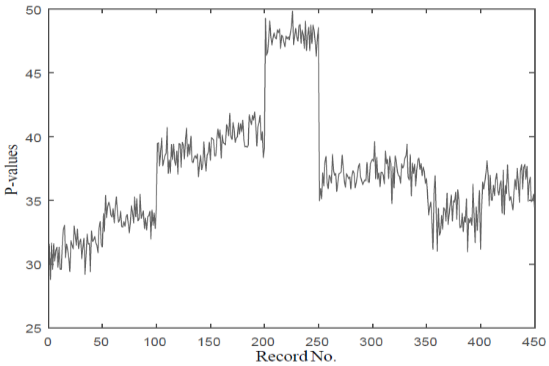


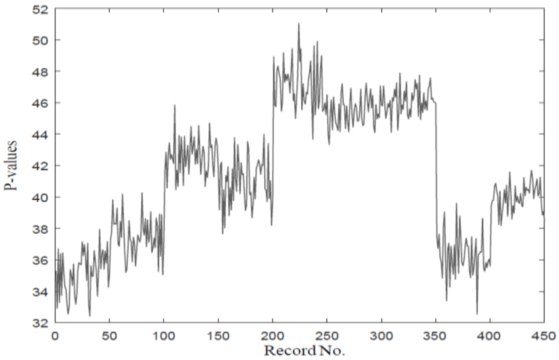
Figure 3. $\boldsymbol{\beta}$ criterion of model orders

4.2 Deterioration detection

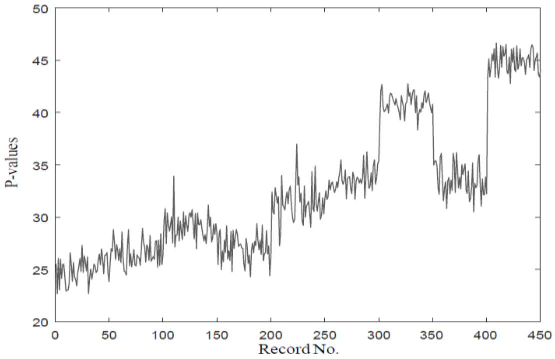
In this paper, residual-based deterioration detection is carried out with the experimental data sets. Each state is related to a specific health state of the structure. For instance, record number 400 to 450 is related to deterioration of two columns at the third story. In each state, the response of the structure is recorded at the same time in all the three stories. Figure 4 shows the results of the proposed method. It can be seen that deterioration was detected and there were no false alarms. Record number 201 to 250 is related to the State #5 which is corresponding to deterioration of two columns in the first story. Deterioration was detected from the recorded response in the all three stories. However, the higher *P*-values at the first story (Figure 4(a)) indicate that the first story is deteriorated. In other words, it should be noted that deterioration in each story can also be detected from other stories. Furthermore, the results showed that the more deterioration, the higher *P*-values. For instance, record 351 to 400 is related to the State #6 and record 401 to 450 is related to State #7. State #6 indicates that one column of the second story is deteriorated, and State #7 points out that two columns of the second story are deteriorated. Figure 4(c) also shows larger *P*-values in State #7 than State #6.



(a) Story 1



(b) Story 2



(c) Story 3

Figure 4. Deterioration detection results

5 CONCLUSIONS

All structures, including newly built ones start to deteriorate at a progressive slow-pace process due to environmental effects, varying service loads, and ageing. Dynamic characteristics of buildings change due to deterioration. There is no doubt that it is highly crucial to assess the deterioration status of structures to maintain cost-effective maintenance and to extend their life expectancy. This paper presented a deterioration sensitive feature using enhanced AR model residuals. In this method, statistical hypothesis of two-sample F-test for equal variances was conducted on residual of time-series analyses and the *P*-values of the hypothesis test were used to define a deterioration indicator. In order to increase the sensitivity of the developed method, the BMO algorithm was developed. This novel algorithm estimates the best model order. The effectiveness of the proposed method was shown using an experimental case study. The results showed that the proposed method can clearly detect deterioration. In this procedure, the highest *P*-values in each story corresponds to the deterioration of that story. Moreover, deterioration in a story can be detected in adjacent stories. For instance, the deterioration of the first story can be detected with the second story data. It can be concluded that this procedure may be capable of being developed for locating deterioration in structures, but more work needs to be done to address the cross-level detection problem. This issue will be addressed in the future publications of the authors.

6 REFERENCES

Alvandi, A. and C. Cremona, 2006. Assessment of vibration-based damage identification techniques, Journal of Sound and Vibration, 292(1): 179-202.

Carden, E. P. and J. M. W. Brownjohn, 2008. ARMA modelled time-series classification for structural health monitoring of civil infrastructure, Mechanical Systems and Signal Processing, 22(2): 295-314.

Carden, E. P. and P. Fanning, 2004, Vibration based condition monitoring: a review, Structural health monitoring, 3(4): 355-377.

Chan, T. H. T. and D. P. Thambiratnam, 2011, Structural health monitoring in Australia, Nova Science Publishers.

Doebling, S. W., C. R. Farrar and M. B. Prime, 1998, A summary review of vibration-based damage identification methods, Shock and vibration digest, 30(2): 91-105.

Du, Y. G., A. H. C. Chan, L. A. Clark, X. T. Wang, F. Gurkalo and S. Bartos, 2013, Finite element analysis of cracking and delamination of concrete beam due to steel corrosion, Engineering Structures, 56: 8-21.

Farrar, C. R., T. A. Duffey, P. J. Cornwell and S. W. Doebling, 1999, Excitation methods for bridge structures, Society for Experimental Mechanics, Inc, 17th International Modal Analysis Conference, vol. 1: 1063-1068.

Figueiredo, E., G. Park, J. Figueiras, C. Farrar and K. Worden, 2009, Structural health monitoring algorithm comparisons using standard data sets, Los Alamos National Laboratory (LANL), LA-14393, 6.

Gibbons J. D. and S. Chakraborti, 2003, *Nonparametric statistical inference, 4th Edition*. New York: Marcel Dekker.

Gul, M. and F. N. Catbas, 2009, Statistical pattern recognition for Structural Health Monitoring using time series modeling: Theory and experimental verifications, Mechanical Systems and Signal Processing, 23(7): 2192-2204.

Gul, M. and F. N. Catbas, 2011, Structural health monitoring and damage assessment using a novel time series analysis methodology with sensor clustering, Journal of Sound and Vibration, 330(6): 1196-1210.

Huang, X. and J. Chen, 2015, Time-Dependent Reliability Model of Deteriorating Structures Based on Stochastic Processes and Bayesian Inference Methods, Journal of Engineering Mechanics, 141(3): 04014123.

Lei, Y., A. S. Kiremidjian, K. K. Nair, J. P. Lynch, K. H. Law, T. W. Kenny, E. D. Carryer and A. Kottapalli, 2003, Statistical damage detection using time series analysis on a structural health monitoring benchmark problem, Proceedings of the 9th international conference on applications of statistics and probability in civil engineering.

Ling, Q., Z. Tian, Y. Yin and Y. Li, 2009, Localized structural health monitoring using energy-efficient wireless sensor networks, Sensors Journal, IEEE, 9(11): 1596-1604.

Mosavi, A. A., D. Dickey, R. Seracino and S. Rizkalla, 2012, Identifying damage locations under ambient vibrations utilizing vector autoregressive models and Mahalanobis distances, Mechanical Systems and Signal Processing, 26: 254-267.

Nguyen, T., T. H. T. Chan and D. P. Thambiratnam, 2014, Controlled Monte Carlo data generation for statistical damage identification employing Mahalanobis squared distance, *Structural Health Monitoring*, 13(4): 461-472.

Okasha, N. M. and D. M. Frangopol, 2010, Time-variant redundancy of structural systems, Structure and Infrastructure Engineering, 6(1-2): 279-301.

Omenzetter, P. and J. M. W. Brownjohn, 2006, Application of time series analysis for bridge monitoring, Smart Materials & Structures, 15(1): 129-138.

Shih, H. W., D. P. Thambiratnam and T. H. T. Chan, 2009, Vibration based structural damage detection in flexural members using multi-criteria approach, Journal of Sound and Vibration, 323(3-5): 645-661.

Silva, S. D., M. Dias Júnior and V. Lopes Junior, 2007, Damage detection in a benchmark structure using AR-ARX models and statistical pattern recognition, Journal of the Brazilian Society of Mechanical Sciences and Engineering, 29(2): 174-184.

Smith, S. W. 1997, The scientist and engineer's guide to digital signal processing.

Wang, V.Z. and K.C.G. Ong, 2015, Nonparametric statistical formulations for structural health monitoring, *Computers & Structures*, 148: 63-74.