Regression-Based Algorithms for Structural Damage Identification and Localization

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ABSTRACT

Early damage detection and localization is very important for maintenance and retrofit of civil structures. In the past decades, a lot of research has been conducted on structural condition prognosis using vibration measurements, which can be very conveniently procured in large quantities at a moderate cost. Many of these approaches, however, concern only the identification of structural damage existence, and do not attempt higher level damage detection. In this paper, three regression-based damage detection algorithms are be presented and applied for damage identification in a two-span steel girder in the lab. All of them can perform local damage detection and evaluation to a certain extent. They have different modeling complexities, and thus have different performance levels. Damage identification/localization/severity evaluation results obtained from these algorithms are compared and contrasted.

INTRODUCTION

Structural Health Monitoring (Farrar and Worden 2007; Ratcliffe 1997; Sohn *et al* 2004) is a technique used to detect the early warning signs of deterioration and fatigue of a structure to help prevent catastrophic failures. With the variability of loading, material properties, and accuracy in construction it is important to verify the response and behavior of a structure during everyday loading conditions. It is also important to measure the response of a structure during extreme situation such as, earthquakes, overloaded vehicles, hurricane, and other phenomenon. Due to the improvements over the past decade, structural health monitoring provides an economical solution to assessing the long term performance of a structure.

With today's technology and current system identification algorithms, it is still sometimes difficult to detect local damage. To address this problem, statistical pattern recognition (SPR) (Farrar *et al* 1999) techniques have been introduced into the field of structural health monitoring to provide a way to account for environmental uncertainty while using vibrational data for structural damage identification. The essence of this family of algorithms is to use well-established concepts in statistics for boundary/threshold construction between different structural states.

Many recent research literatures (Gul and Catbas 2009; Sohn *et al* 2004; Yao and Pakzad 2011; Yao and Pakzad 2011) can be found on damage identification in civil structures by using small scale time series analysis (e.g. univariate AR modeling; ARX modeling on responses from a sensor cluster) for damage feature extraction and SPR techniques for damage threshold evaluation. The algorithms thus devised are reported to be successful and relatively sensitive to minor damage. However, most of them are concerned only with the damage existence identification, and do not address higher level damage detection problems such as damage localization and severity assessment. Hence in this paper, damage detection techniques with local damage evaluation capabilities will be described and validated.

Section 3 presents three types of damage indices from regression analysis; the first one is influence coefficients (IC) (Labuz *et al* 2010; Labuz 2011, Yao and Pakzad 2011), which are the regression coefficients of one node's acceleration response on another; the second one is the improved influence coefficients (IIC), which are obtained by regressing a node's acceleration responses on those from all its adjacent nodes; the third one is influence coefficients using hybrid vibration responses(ICHVR), they are from regression models that incorporate in the repressor matrix not only acceleration responses at neighbor nodes, but also strain data from close-by nodes. It can be seen that these three algorithms have an increasing modeling complexity. As such, their performance levels for damage identification will also be different. Change point analysis is used here to set the damage threshold for all damage indices.

The organization of this paper is as follows: Section 2 gives a detailed description of the damage feature extraction algorithms. Section 3 presents the cumulative sum based change point analysis. Section 4 contains the experimental validation results of all three algorithms, with their damage identification/localization/severity assessment performance compared and contrasted.

FORMULATION OF THE DAMAGE FEATURE EXTRACTION ALGORITHMS

In this paper time-domain regression based algorithms for damage identification are adopted. These methods are computationally efficient and easy to implement, and thus effective for fast damage prognosis and on-line decision making regarding the current structural state. Three approaches will be described in the remainder of this section; they follow the same principles, only with different modeling complexities.

2.1 The Influence Coefficients (IC)

If a linear structure is subjected to a static/quasi-static load, then the ratio between responses at any two arbitrary locations should be a constant as long as the structural condition and load pattern stay the same. Therefore, the linear regression coefficient $\alpha_{j,i}$ between responses collected at two nodes i and j can be used as a viable damage index (Labuz *et al* 2010; Labuz *et al* 2011, Yao and Pakzad 2011). The coefficient can be estimated by regression from the equation below:

$$u_j(t_k) = \alpha_{j,i} \cdot u_i(t_k) + \varepsilon(t_k)$$

Where u_i and u_j are structural responses from node i and j, t_k is the time label, and ε is the regression residual.

When the load is actually dynamic, this method can still be applied to a local area of the structure, where the stiffness is large and the mass is comparatively small. In the subsequent section, this method will be applied to acceleration signals from a steel girder subjected to a white noise excitation.

2.2 The Improved Influence Coefficients (IIC)

It can be seen that influence coefficients are estimated from a very simple model. If the goal is just to detect the existence of major damage, they may suit the purpose. But if higher level damage detection (e.g. damage localization; damage severity assessment) is needed, then the regression model needs to be refined to capture the local vibration behavior.

An improved influence coefficient approach is proposed here by incorporating, for responses from a given sensor node, all its neighboring nodes' responses. The mathematical expression for this algorithm can be expressed as follows:

$$u_j(t_k) = \sum_{i=1}^{n} \alpha_{j,i}\, u_i(t_k) + \varepsilon(t_k)$$

Here u_i stands for the vibration responses collected from a certain adjacent node of sensor j, and n is the total number of adjacent nodes of j. This algorithm is more complicated than the IC approach not only in the sense of an increased number of parameters, but also in that it actually takes into account the structural geometry and sensor network topology.

2.3 Influence Coefficients from Hybrid Vibration Responses (ICHVR)

If the end displacements and rotations of a Finite Element Model for a beam element are known, then the deformation at any point along the element can be computed using a set of interpolation functions. In practice, it is difficult to measure dynamic joint rotations; however, strains, which reflect end moments, can be measured through strain gages. With the end displacements and moments known, the complete behavior of a beam is known.

The regression model can be further modified to include the strain data from neighboring nodes:

$$u_j(t_k) = \sum_{i=1}^{n} \alpha_{j,i} u_i(t_k) + \sum_{l=1}^{m} \beta_{j,l} \phi_l(t_k) + \varepsilon(t_k)$$

where ϕ_ls are the strain measurements from adjacent nodes of node j, and $\beta_{j,l}$ is the corresponding regression coefficients. This technique is the most complex of the three, and is expected to yield the most accurate performance on damage identification and prognosis.

DAMAGE THRESHOLD CONSTRUCTION METHOD

A damage threshold needs to be created to determine if the variation in the estimated influence factors from an unknown structural state is significant enough to categorize it as damaged. It is also important to note at what confidence this level of damage has been identified, and also if multiple damage location have been detected. In order to make conclusions about these inquiries, a change point analysis can be performed.

A change point analysis (Taylor 2000) used in this paper utilizes a combination of the cumulative sum method and bootstrapping (Good 1999). The procedure is as follows:

1) Calculate the overall mean, $\bar{x}$
2) Subtract the mean from every value in the data set
3) Sum the difference at time step i and the differences prior to time step i, $S_i = S_{i-1} + \overline{(x_i - x)}$
4) Resample the data and repeat the procedure for the new data set

Once the process has been completed for a sufficient number of data sets, *N*, then, S_{max} and S_{min}, can be determined for each set and then, $S_{max} - S_{min} = S_{dif}$, can be calculated. The threshold can be denoted as, S_{dif}^0, and the subsequent difference values are smaller than the original, $S_{dif}^0 > S_{diff}$, is denoted as X. Then the confidence interval can be computed by

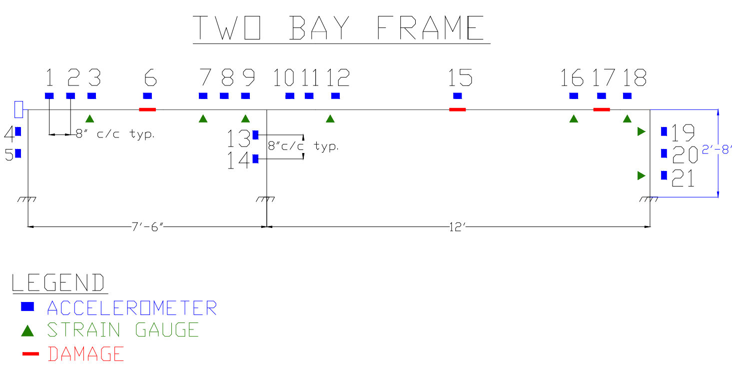
$$Confidence\ Interval = \frac{X}{N} * 100$$

Only influence factor sequences with S_{dif} outside a 95% confidence level (Koch 1999) were considered as from the damaged state.

EXPERIMENTAL VALIDATION OF THE DAMAGE DETECTION ALGORITHMS

To test the accuracy of the three algorithms, three different damage scenarios were set up on a two-bay steel frame constructed from steel tubes (Figure 1a). The frame is instrumented with 21 accelerometers and 9 strain gages. The first damage state is simulated by replacing the right beam end portion with a section of reduced stiffness, and 14 datasets were collected. The second damage mode consists of replacing the right bay, middle portion with a reduced stiffness member, with 30 datasets collected, and finally the third damage scenario consists of replacing the left bay, middle link with a reduced stiffness member, with an additional 30 datasets collected (Figure 1b). For each case, half of the datasets are from the damaged case, and half are from the undamaged case.

(a)



(b)

Fig. 1(a) Two Bay Steel Frame, (b) Two Bay Steel Frame Drawing with Strain Gauge and Accelerometer Locations

Figure 2 shows the histograms of the change point locations. The most notable observation is that as the model complexity increases, the change point location indication becomes more exact. It can be seen that, for the first damage scenario, the IC method failed to identify the damage existence while the rest two succeeded. Also, for other damage cases, the histograms obtained from the IIC and ICHVR methods all have a sharper peak at the correct change point location than the established IC method.

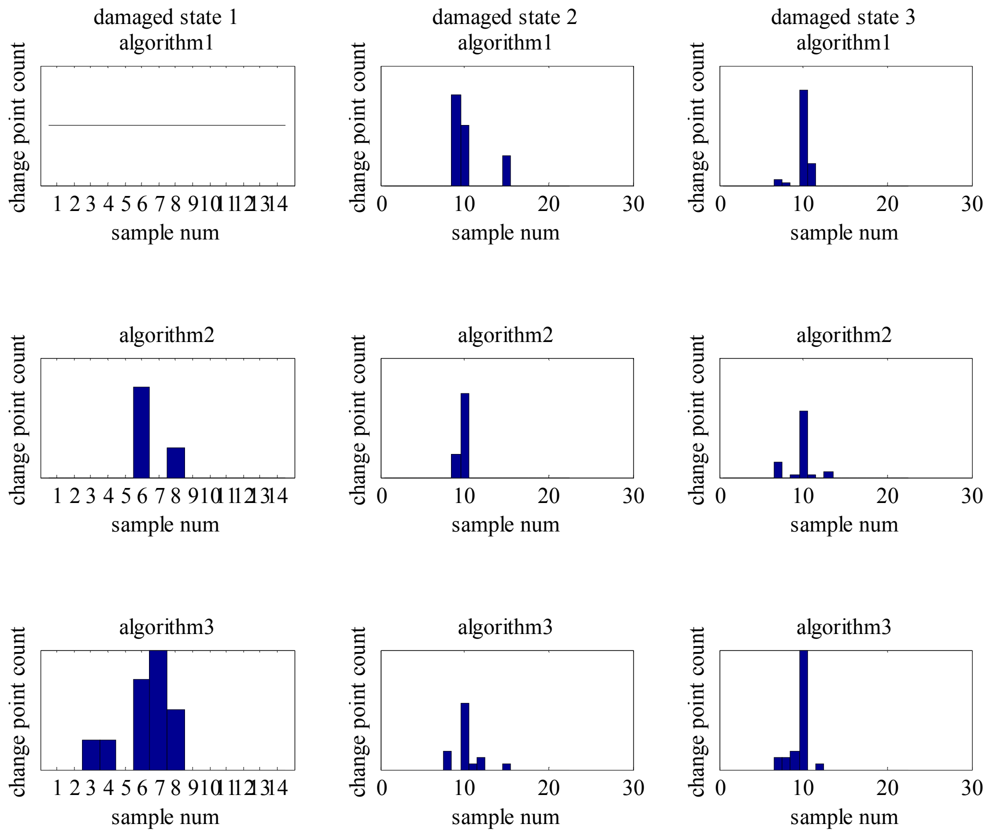


Fig. 2 histograms for the change point locations. Each sample corresponds to a particular dataset. For each algorithm implementation, there are a number of regression coefficients sequences that report damage. Each histogram basically pooled all these change point locations together.

Figure 3 are the damage localization results from different algorithms/scenarios. It can be observed that as the model complexity increases, the damage localization becomes more accurate. For all three damage scenarios, the IC method does not report change for the locations at/next to the damage, IIC method yield a more satisfactory performance, and the ICHVR identifies structural change at most places that are in the vicinity of actual damage. This further solidifies the point that the more complex the algorithm, the more accurately damage location is indicated. In addition, the sensors which reported only one regression parameter, has a higher likely hood of a false alarm. For more accurate results it is recommended to use regression models that report damage for multiple parameters.

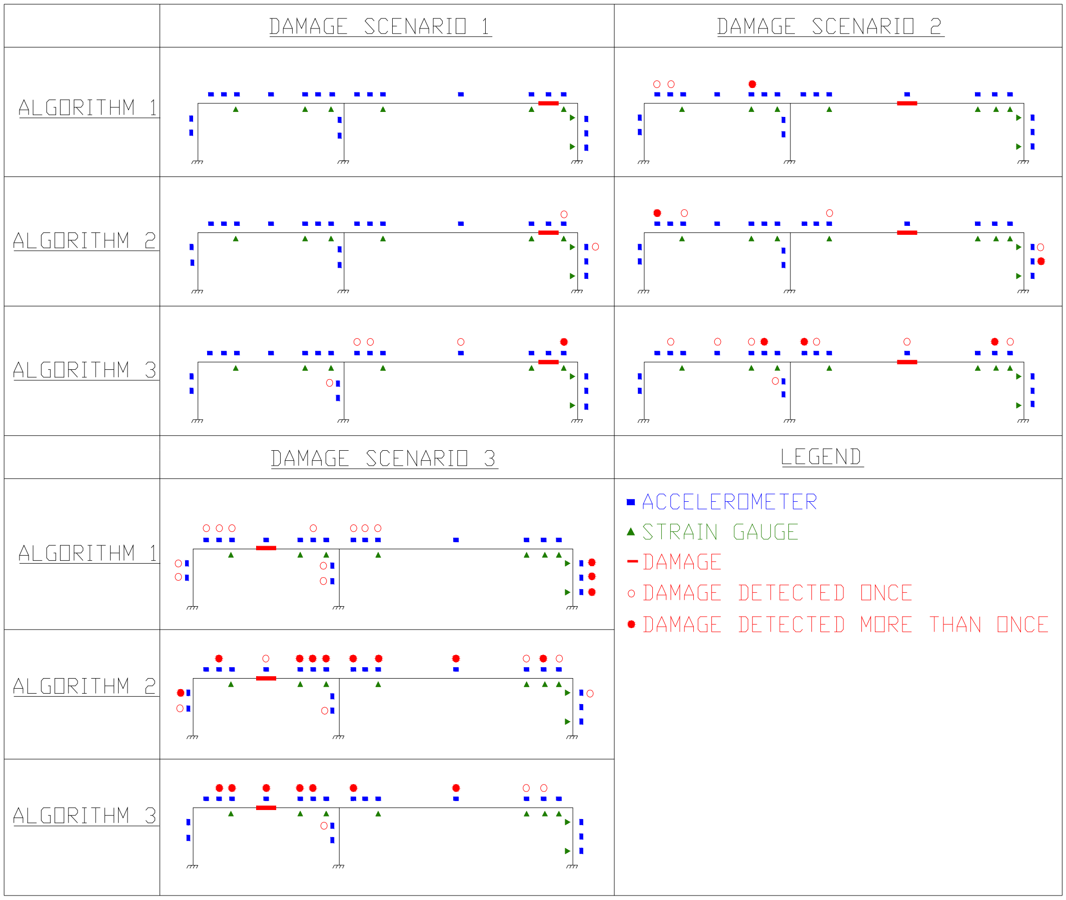


Fig. 3 examination of the damage localization capability of different algorithms

Figure 4 contains plots of influence coefficients obtained from the node combinations at the damage location for the different damage scenarios. It is clear that as the model complexity increases, from algorithm 1 to algorithm 3, the difference between the undamaged data sets' average influence coefficients and damaged data sets' average influence coefficients becomes greater. Thus in this case study, adopting more complex and comprehensive models did help to better characterize the difference between the damaged and undamaged state, which is important for local/minor damage detection.

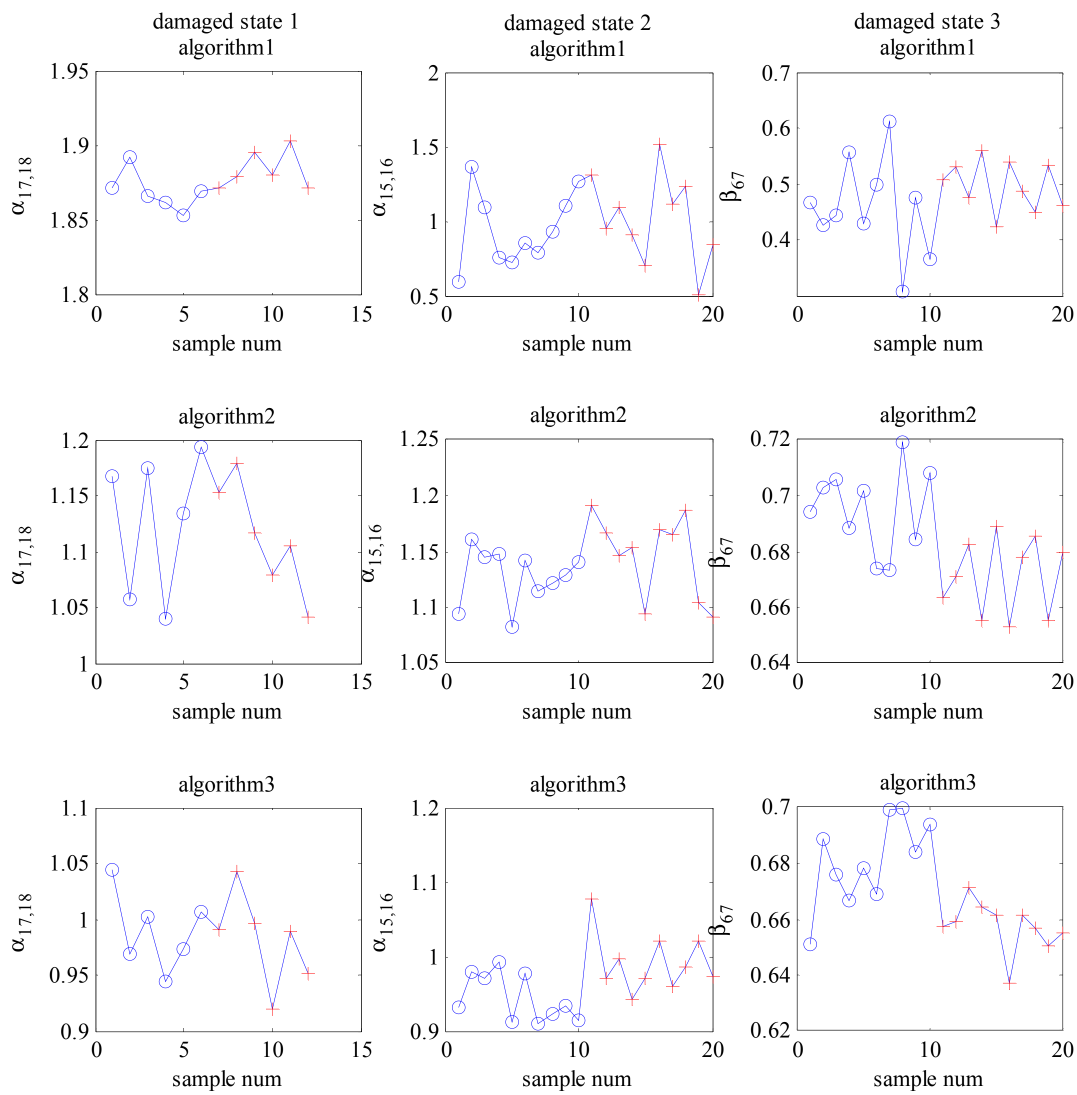


Fig. 4 plots of the influence coefficient values at the damage location for different algorithms/damage scenarios. Each sample corresponds to a particular dataset. The circles are influence coefficient values from undamaged state, the crosses are from the damaged state.

CONCLUSION

In this paper, three regression-based damage detection algorithms are presented and applied for damage diagnosis in a scaled two-bay steel frame specimen. The first algorithm, the influence coefficients method, is an established node-pair-wise regression technique that has been shown to be effective in several previous researches. The improved influence coefficients method regresses responses from one node on those from all its adjacent nodes. The influence coefficients using hybrid vibration responses further refines the model by including strain data from neighboring nodes as regressors. It is demonstrate in their application results that as the algorithm modeling complexity increases, so does their performance on damage identification and localization.

The research presented here addresses partly to the problem of optimal data collection and information compression and extraction in structural health monitoring applications. The quality of results on structural state diagnosis is directly related to the quantity of useful data and the truthfulness of the analysis model adopted. And when it comes to local damage identification, generally substructural analysis methods will be needed.

In finite element modeling, if there is a truss element in a structure, then to see if the element properties have changed, all that is needed is the displacements at the bar ends and the axial force. If further damage localization is desired, displacements at the midpoint of the member can be measured and used for analysis. The result will be exact as long as the data is accurate and the modeling assumption is correct, regardless of what the behavior of the rest of the structure is. If the data is contaminated by noise or if the real member is actually a beam element, then the result will become less reliable.

This simple example illustrates the general difficulties encountered when vibration-based damage identification is attempted: incomplete/ambiguous information and modeling error. For example, if the response at every location and the input at every location, and the basic constitutive relationship is known for a given structure, then damage identification is a simple task. But when only vibration responses from a limited number of sensors are available, damage identification, especially high level damage identification, becomes difficult. The performance of damage detection algorithms is largely dependent on the extent of the environmental and operational conditions, and the validity of the assumptions. Still, the quest for automatic structural diagnosis system continues, and with the improvements of sensor technology and computing facilities, this goal is becoming more obtainable.

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