TIME-DOMAIN STRUCTURAL DAMAGE IDENTIFICATION: FROM A DICTIONARY LEARNING PERSPECTIVE

Ying Wang [1*], Tong Zhang [2] and Hong Hao [3]

[1] *School of Engineering, Deakin University, Geelong, Australia.*

[2] *School of IT, the University of Sydney, Sydney, Australia.*

[3] *School of Civil and Mechanical Engineering, Curtin University, Perth, Australia.*

ABSTRACT

Structures inevitably deteriorate during their service lives. To accurately evaluate their structural condition, the methods capable of identifying and assessing damage in a structure timely and accurately have drawn increasing attention. Compared to widely-used frequency-domain methods, the processing of time-domain data is more efficient, but remains difficult since it is usually hard to discern signals from different conditions. In fact, the signal processing fields have observed the evolution of techniques, from such traditional fixed transforms as Fourier, to dictionary learning (DL). DL leads to better representation and hence can provide improved results in many practical applications. In this paper, an innovative time-domain damage identification algorithm is proposed from a DL perspective, using D-KSVD algorithm. The numerical simulated soil-pipe system is used for verifying the performance of the proposed method. The results demonstrate that this damage identification scheme is a promising tool for structural health monitoring.

KEYWORDS

Damage identification, civil infrastructure, pattern recognition, dictionary learning, time-domain

INTRODUCTION

The safety, integrity and stability of civil infrastructure are critical to every nation, due to their enormous investment, long service period, and negative impacts after failure. Therefore, structural health monitoring (SHM) has received increasingly more research attentions in the last two decades, and become a viable technique for protection of civil, mechanical and aerospace structures. As its core component, damage identification strategies have been extensively studied. For vibration based SHM system, the majority of studies focus on two groups of approaches. For the first group, damage identification can be achieved through finding the variation of predefined damage indicators. Most of the damage indicators are based on modal parameters (Alvandi and Cremona, 2006), e.g., change of natural frequency (Salawu, 1997), mode shape curvature change (Pandey *et al.*, 1991), and modal strain energy change (Shi *et al.*, 2000). The advantage of this kind of approaches is that they are solely based on experimental results without the requirement of numerical models, and hence computationally efficient. However, these methods suffer from the difficulty of discerning the variations caused by noise and environmental factors, from those caused by structural damage. Thus, the computational accuracy of damage indicators becomes increasingly unreliable for complex structures. Therefore, more research efforts have been placed on the second group of

* Corresponding author: Tel: (+61)3-52272106, Email: ying.wang@deakin.edu.au

damage identification approaches since 2000, i.e., inverse / model updating method (Friswell, 2007). This kind of approaches requires the integration of both numerical models and experimental results. The computed damage features based on numerical models are compared to those obtained from tests. The discrepancies between them are minimised through iteratively updating the parameters of the numerical model, which is a typical optimisation process (Jaishi and Ren, 2006). Although such methods are theoretically sound and have the potential to analyse complex structures (Brownjohn *et al.*, 2001; Domaneschi *et al.*, 2013), the high computational costs of the numerical simulation (e.g. finite element analysis) limited them from being used for on-line SHM systems.

To realise such on-line SHM framework, a damage identification strategy must be efficient and effective. Time-domain data are more suitable for on-line SHM systems, as the data conversion from time-domain to frequency-domain is not necessary (Wang *et al.*, 2013; Ay and Wang, 2014). However, it remains difficult since it is usually hard to discern signals from different conditions. Further, it may lack the physical meaning. Under this condition, a new modelling theory that is capable of discerning different structural conditions from time-domain data is in demand. In essence, damage identification can be regarded as a process of data interpretation and understanding, which is a typical pattern recognition problem. Among the state-of-the-art pattern recognition technologies, sparse coding has proven to be an extremely powerful tool for acquiring, representing, and compressing high-dimensional signals (Wright *et al.*, 2010) and can be used as a structural pattern classification scheme.

Recently, Wang and Hao (2013a, 2013b, 2014) proposed and developed an innovative damage identification scheme based on sparse representation and l_1 optimization. Generally, data acquired from a structure under one specific condition will be different from those under other conditions. Therefore, data under each condition can be regarded as a representation of a unique structural condition. If the different conditions are defined as various damage types, locations and severities, and all the signals representing those structural conditions are collected, a "data dictionary" can be constructed. Then, when there is a new signal associated with an unknown structural condition, we just need to find the closest pattern from the "dictionary" to match this new signal. This pattern can be used to represent the pattern for the new signal. The classification of the monitoring data will lead to damage classification, localisation, and quantification.

In fact, the signal processing fields have observed the evolution of techniques, from traditional Fourier or wavelet transforms, to dictionary learning (DL), especially sparse DL (Rubinstein *et al.*, 2010). The linear decomposition of a signal using a few atoms of a learned dictionary, instead of predefined ones, such as Fourier or wavelet, usually leads to better representation and hence can provide improved results in many practical applications such as reconstruction and classification (Mairal *et al.*, 2008). This has been demonstrated in areas, including face recognition (Zhang and Li, 2010), image denoising (Elad and Aharon, 2006), and classification (Mairal *et al.*, 2012).

In this paper, we propose an innovative time-domain damage identification method from a DL perspective. The theory and application of DL and its implementation will be presented in Methodology section. Then, a complex pipe-soil interaction system (Wang and Hao, 2013a) will be used to demonstrate the performances of the proposed method. The data in time-domain are directly used to learn a discriminative dictionary for classification. The numerical simulation results demonstrate that the performance of the proposed method is promising for time-domain damage identification.

METHODOLOGY

Dictionary Learning

The signal representation is a pivotal step in signal processing and pattern recognition. The idea of representing a signal in a dictionary is actually not new. Traditionally, this is achieved via signal transforms. In 1960s, the Fourier transform emerged as a basis that describes a signal in terms of its frequency contents (Rubinstein *et al.*, 2010). In theory, every signal can be uniquely represented as a linear combination of basis, or dictionary atoms. In SHM, it is still a dominant technique in vibration-based damage identification. In 1980s and 1990s, more flexible non-linear transforms were pursued, as sparser representations and more efficient transforms were required (Rubinstein *et al.*, 2010). Wavelet-based methods are the most important contributions at that time. Together with Fourier transform and many others, they are regarded as analytic dictionaries, with predefined basis. Generally, a signal can be linearly represented by projecting it onto a fixed subset of $K < N$ basis elements:

$$\boldsymbol{x} = \sum_{n \in I_k} (\boldsymbol{\varphi}_n^{\mathrm{T}} \boldsymbol{x}) \boldsymbol{\varphi}_n = \sum_{n \in I_k} \alpha_n \boldsymbol{\varphi}_n \tag{1}$$

where $\{\boldsymbol{\varphi}_n\}_{n=0}^{N-1}$ is a given basis of $\boldsymbol{R}^N$, such as Fourier, which can be regarded as a fixed dictionary. α_n is the coefficient of each element in the dictionary. When $\boldsymbol{\alpha} = \{\alpha_n\}_{n=0}^{N-1}$ becomes sparser (more zeroes), the representation will become more efficient.

In the second half of 1990s, the idea of DL has been proposed to represent a given signal. Through learning process which optimise the dictionary efficiency, the learned dictionary can achieve better results than its predefined counterparts (Mairal *et al.*, 2008). The signal reconstruction can be represented as:

$$x = D\boldsymbol{\alpha} \tag{2}$$

where $\boldsymbol{D}$ is the dictionary. The difference between Eqs (1) and (2) is that $\boldsymbol{D}$ is not confined itself as a collection of fixed basis. The flexibility makes a sparser dictionary possible, which can increase the representation efficiency and performance.

One typical DL method for image processing is the K-SVD algorithm, which learns an over-complete dictionary from a training dataset of natural image patches (Aharon *et al.*, 2006). However, K-SVD is not suitable for classification tasks because it only requires that the learned dictionary could faithfully represent the training samples. Based on this method, Zhang and Li (2010) proposed an algorithm called discriminative K-SVD (D-KSVD) for face recognition. The results show that the learned dictionary and the corresponding classifier are better modelled for sparse-representation-based recognition. This paper will implement D-KSVD method into damage identification algorithm and investigate its performances.

Implementation of DL in Damage Identification

In Wang and Hao (2013a, 2013b, 2014), it is assumed that a new signal $\boldsymbol{x}$ associated with a condition *j* can be represented as a linear superposition of the training data associated with the same condition:

$$x = \alpha_{j,1} \boldsymbol{x}_{j,1} + \alpha_{j,2} \boldsymbol{x}_{j,2} + \cdots + \alpha_{j,n_j} \boldsymbol{x}_{j,n_j} \tag{3}$$

where $\alpha_{j,n_i}, n_i = 1,\ldots,n_j$ are the representation scalars for the new signal. $\boldsymbol{x}_{j,n_i}$ is the number n_i signal vector ($n_i = 1,\ldots,n_j$) associated with structural pattern *j*. Further, $\mathbf{x}$ can be represented in terms of dictionary as Eq. (2), where $\boldsymbol{\alpha} = [0,\ldots,0,\ldots,\alpha_{j,1},\alpha_{j,2},\ldots,\alpha_{j,n_j},0,\ldots,0]^{\mathrm{T}}$ is a coefficient vector whose entries are mostly zeroes except those associated with pattern *j*, and

$\boldsymbol{D} = [\boldsymbol{x}_{1,1}, \boldsymbol{x}_{1,2}, ..., \boldsymbol{x}_{1,n_1}, \boldsymbol{x}_{2,1}, ..., \boldsymbol{x}_{m,n_m}]$ is the data dictionary. $\boldsymbol{\alpha}$ is mathematically sparse, and thus the damage identification problem becomes to find sparsest $\boldsymbol{\alpha}$ through an optimisation process:

$$\boldsymbol{\alpha} = \arg\min \|\boldsymbol{\alpha}\|_p \quad \text{s.t.} \quad x = D\boldsymbol{\alpha} \tag{4}$$

where $\|\cdot\|_p$ is l_p norm.

In Wang and Hao (2013a and 2013b), $\boldsymbol{D}$ was constructed using frequency-domain data, after performing FFT on time-domain test data, i.e., structural acceleration responses under impact hammer tests. However, this kind of operation will highly increase the computational efforts. Based on D-KSVD method, the dictionary can be trained efficient and discriminative, without the data conversion process from time-domain to frequency-domain. This is achieved by introducing a linear classifier $\boldsymbol{H} = \boldsymbol{W} * \boldsymbol{\alpha} + \boldsymbol{b}$ and using K-SVD to find the globally optimal solution for all the parameters $\langle \boldsymbol{D}, \boldsymbol{W}, \boldsymbol{\alpha} \rangle$ simultaneously. The formulated optimisation problem is:

$$\langle \boldsymbol{D}, \boldsymbol{W}, \boldsymbol{\alpha} \rangle = \arg\min \left\| \begin{pmatrix} \boldsymbol{Y} \\ \sqrt{\gamma} * \boldsymbol{H} \end{pmatrix} - \begin{pmatrix} \boldsymbol{D} \\ \sqrt{\gamma} * \boldsymbol{W} \end{pmatrix} * \boldsymbol{\alpha} \right\|_2 + \beta * \|\boldsymbol{W}\|_2 \quad \text{s.t.} \quad \|\boldsymbol{\alpha}\|_0 \leqslant T \tag{5}$$

where $\boldsymbol{Y}$ is the set of input signals, $\boldsymbol{H}$ the label of the training images, $\boldsymbol{W}$ the parameter of the classifier, and γ and β are scalars controlling the relative contribution of the corresponding terms. The detailed process of D-KSVD method can be found in Zhang and Li (2010).

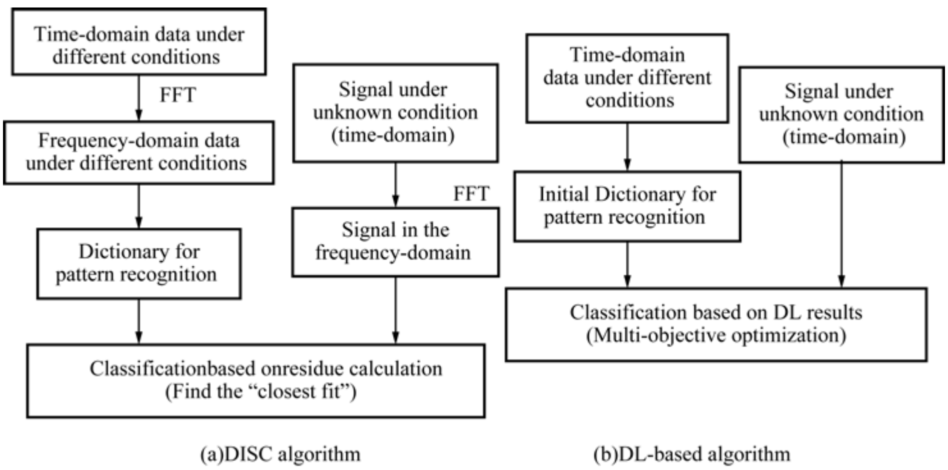

Figure 1. Flowcharts for two algorithms

The flowcharts for DISC algorithm and DL-based algorithm are shown above. As can be seen, the DL-based algorithm is more concise, which does not include time-frequency conversion step. The classification method is also different. For original DISC algorithm, the classification is based on the calculation of residue describing comparison between signal under unknown condition and those in dictionary. In contrast, the DL-based algorithm achieves classification based on the learning/optimisation results.

RESULTS AND DISCUSSIONS

Numerical Simulation

In this study, vibration responses of a pipe-soil model in the impact hammer test is simulated with commercial software ANSYS. A simplified FE model for this system is shown in Figure 2.

In this model, the 5.936m steel pipe is modelled as a beam and the soil under the pipe is simplified as distributed springs. The pipe is divided into 16 parts and a total of 16 springs under each part are considered. The concrete blocks at two ends of the pipe are simulated as two rotational springs. The detailed geometrical and material properties of this structure can be found in Wang *et al.* (2010). According to experimental conditions, the vibration time history induced by impact hammer is simulated. The hitting point is selected as 0.19*L* (*L*=5.936m) to the left end of the pipe. The impact force is simulated as a unit load acting on the pipe vertically downwards, for 1ms duration. The accelerations at these two points are recorded for 1s, and then normalised, as it is a common step in tests. The sensing points are selected as 1/8*L* to the left end of the pipe and 7/16*L* to the right end of the pipe, respectively.

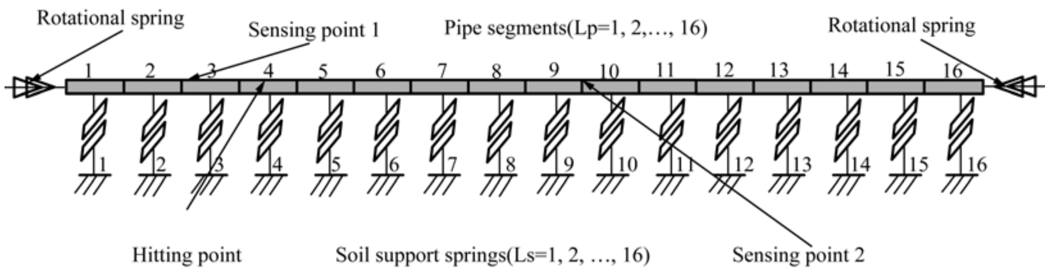

Figure 2. Simplified pipe-soil interaction finite element model

Extensive numerical simulation works on the above model were conducted to construct the initial dictionary. For pipe damage, damage severity θ is defined as the stiffness ratio between the pipe elements with and without damage, and damage location L_p is the number of pipe segment. Overall, the pipe includes 16 segments. The damage severities are considered to vary from 0.1 (90% damage) to 1.0 (intact) with 0.1 increments. Since two sensing points are recorded in this study, the number of atoms in the initial dictionary is 320.

Damage identification results

In this study, D-KSVD method is incorporated to the damage identification algorithm. The successful implementation of this method needs definition of the following parameters: dictionary size, iteration number, and classes. Based on extensive simulation results, optimal parameters are selected as a trade-off between accuracy and efficiency, i.e., 160 for dictionary size and 150 for iteration number. As for classes, they are defined by two ways in order, and represented by a matrix. Firstly, 16 classes are divided based on damage locations, and secondly, 10 classes are allocated based on damage severities.

To assess the performance of the proposed method, 4 cases were randomly selected, i.e., L_p=13, θ=0.9; L_p=13, θ=0.2; L_p=4, θ=0.1; L_p=3, θ=0.8. At first, only data from sensing point 1 were used for damage identification. The numerical simulation results were added with white noise at 0%, 1%, 5% and 10% levels. The identification results can be found in Table 1. As can be seen, by using the proposed method, damage localisation results are reliable with noise level $\leqslant$5%, irrespective of damage locations and severities. At 10% noise level, the identified damage locations become unstable and even random. The results shown in Table 1 are just one example. This further demonstrates that noise has obviously negative effects on the performance of time-domain damage identification methods. As for damage quantification, the algorithm can achieve the correct damage severity in all cases.

Table 1. Damage localisation and quantification results using information from sensing point 1

Cases	Damage localisation				Damage quantification			
	No noise	1% noise	5% noise	10% noise	No noise	1% noise	5% noise	10% noise
L_p=13, θ=0.9	L_p=13	L_p=13	L_p=13	L_p=7	θ=0.9	θ=0.9	θ=0.9	θ=0.9
L_p=13, θ=0.2	L_p=13	L_p=13	L_p=13	L_p=16	θ=0.2	θ=0.2	θ=0.2	θ=0.2
L_p=4, θ=0.1	L_p=4	L_p=4	L_p=4	L_p=13	θ=0.1	θ=0.1	θ=0.1	θ=0.1
L_p=3, θ=0.8	L_p=3	L_p=3	L_p=3	L_p=14	θ=0.8	θ=0.8	θ=0.8	θ=0.8

* Wrong identification results were underlined.

To examine the identification accuracy using information from sensing point 2, the parametric studies on the same cases were conducted. The results were summarised in Table 2, which can be found much worse than those from point 1. When the damage location is far away from the impact hitting point and damage severity is small (case: L_p=13, θ=0.9), even under no noise, the damage cannot be localised. The reason is that when sensing point is far away from the hitting point, the structural vibration responses become smaller and insensitive to damage. Similarly, damage quantification results are better than localisation. However, the worst case (L_p=13, θ=0.9) overestimated the damage, even under 5% noise.

Table 2. Damage localisation and quantification results using information from sensing point 2

Cases	Damage localisation				Damage quantification			
	No noise	1% noise	5% noise	10% noise	No noise	1% noise	5% noise	10% noise
L_p=13, θ=0.9	L_p=16	L_p=16	L_p=12	L_p=8	θ=0.9	θ=0.9	θ=0.8	θ=0.7
L_p=13, θ=0.2	L_p=13	L_p=13	L_p=12	L_p=14	θ=0.2	θ=0.2	θ=0.2	θ=0.2
L_p=4, θ=0.1	L_p=4	L_p=4	L_p=4	L_p=12	θ=0.1	θ=0.1	θ=0.1	θ=0.8
L_p=3, θ=0.8	L_p=3	L_p=3	L_p=1	L_p=7	θ=0.8	θ=0.8	θ=0.8	θ=0.7

* Wrong identification results were underlined.

The time-domain damage identification methods are more susceptible to noise than the frequency-domain methods. In this study, if the sensing point is close to impact hitting point, the damage can be localised and quantified accurately under a normal noise level (5%). In contrast, the results from sensing point 2 are unacceptable, especially for damage localisation. This clearly suggests that the sensing and hitting points for this method should be carefully selected.

Except for the selection of hitting point and sensing points, the construction of initial dictionary is crucial for this method. The more signals can be incorporated, the more refined results can be obtained. Fortunately, for on-line SHM system, enormous data can be collected every day. If they are incorporated in the initial dictionary in this method, the performance of this method will be more reliable.

CONCLUSIONS

This paper applied up-to-date pattern recognition techniques, i.e., DL, to developing an innovative time-domain damage identification method. The time-domain data extracted from sensors can be directly employed to learn a discriminative dictionary for damage identification. A complex pipe-soil interaction system was used to demonstrate the performances of the proposed method. Accelerations at two sensing points under impact hammer force were simulated and employed to construct the initial dictionary. The results demonstrate that the performance of the proposed method is affected by two main factors, i.e., noise level and the location of impact hitting and sensing points. If the sensing point is close to impact force and the noise level is normal (5%), damage can be efficiently and correctly localised and quantified, irrespective of damage locations. The proposed method is promising as an effective time-domain damage identification algorithm for on-line SHM system. Future efforts can be placed on the selection of hitting and sensing points, and the construction of initial dictionary.

ACKNOWLEDGMENTS

This study is partially supported by Collaborative Research Center for Integrated Engineering Asset Management (CIEAM II project).

REFERENCES

Aharon, M., Elad, M. and Bruckstein A. (2006). K-SVD: an algorithm for designing overcomplete dictionaries for sparse representation. *IEEE Transactions on Signal Processing*, 54(11), 4311-4322.

Alvandi, A. and Cremona, C. (2006).Assessment of vibration-based damage identification techniques. *Journal of Sound and Vibration*, 292(1-2), 179-202.

Ay, A.M. and Wang, Y. (2014). Structural damage identification based on self-fitting ARMAX model and multi-sensor data fusion. *Structural Health Monitoring*. 13(4), 445-460.

Brownjohn, J.M.W., Xia, P.Q., Hao, H. and Xia, Y. (2001). Civil structure condition assessment by FE model updating: methodology and case studies. *Finite Elements in Analysis and Design*, 37(10), 761-775.

Domaneschi, M., Limongelli, M.P. and Martinelli, L. (2013). Vibration Based Damage Localization Using MEMS on a Suspension Bridge Model. *Smart Structures and Systems*, 12(6), 679-694.

Elad, M. and Aharon, M. (2006). Image denoising via sparse and redundant representations over learned dictionaries. *IEEE Transactions on Image Processing*, 15(12), 3736-3745.

Friswell, M.I. (2007). Damage identification using inverse methods. *Philosophical Transactions of The Royal Society A*, 365, 393-410.

Jaishi, B. and Ren, W.X. (2006). Damage detection by finite element model updating using modal flexibility residual. *Journal of Sound and Vibration*, 290(1-2), 369-387.

Mairal, J., Ponce, J., Sapiro, G., Zisserman, A. and Bach, F.R. (2008). Supervised dictionary learning. *Advances in Neural Information Processing System*, *NIPS* 2008.

Mairal, J., Bach, F. and Ponce, J. (2012). Task-driven dictionary learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(4), 791-804.

Pandey, A.K., Biswas, M. and Samman, M.M. (1991). Damage detection from changes in curvature mode shapes. *Journal of Sound and Vibration*, 145(2), 321-332.

Rubinstein, R., Bruckstein, A.M. and Elad, M. (2010). Dictionaries for sparse representation modelling. *IEEE Proceedings*, 98(6), 1045-1057.

Salawu, O.S. (1997). Detection of structural damage through changes in frequency: a review. *Engineering Structures*, 19(9), 718-723.

Shi, Z.Y., Law, S.S. and Zhang, L.M. (2000). Structural damage detection from modal strain energy change. *Journal of Engineering Mechanics, ASCE*, 126(12), 1216-1223.

Wang, Y. and Hao, H. (2013a). Damage identification scheme based on compressive sensing. *Journal of Computing in Civil Engineering, ASCE*. (DOI: 10.1061/(ASCE) CP.1943-5487. 0000324).

Wang, Y. and Hao, H. (2013b). Damage identification scheme via sparse representation. *6th International Conference on Structural Health Monitoring of Intelligent Infrastructure*, Hong Kong, 9-11 December 2013.

Wang, Y. and Hao, H. (2014). Guided-wave-based method for concrete de-bonding damage

identification using DISC. *6th World Conference on Structural Control and Monitoring*, Barcelona 15-17 July 2014.
Wang, Y., Hao, H. and Peng, X.L. (2010). Simplified pipeline-soil interaction model for vibration- based damage detection of onshore pipelines. *ISSE11: The 11th International Symposium on Structural Engineering*, Guangzhou, China.
Wang, Y., Khoo, S.Y., Li, A.J. and Hao, H. (2013). FEM calibrated ARMAX Model Updating Method for Time Domain Damage Identification. *Advances in Structural Engineering*, 16(1), 51-60.
Wright, J., Ma, Y., Mairal, J., Sapiro, G., Huang, T.S. and Yan, S. (2010). Sparse representation for computer vision and pattern recognition. *IEEE Proceedings*, 98(6), 1031-1044.
Zhang, Q. and Li, B. (2010). Discriminative K-SVD for dictionary learning in face recognition. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2691-2698.