Structural Health Monitoring from Discrete Binary Data through Pattern Recognition

Conference Paper · August 2016

DOI: 10.1201/9781315641645-304

Hadi Salehi
University of Michigan

Shantanu Chakrabartty
Washington University in St. Louis

Structural Health Monitoring from Discrete Binary Data through Pattern Recognition

H. Salehi & R. Burgueño
Dept. of Civil and Environmental Engineering, Michigan State University, East Lansing, Michigan, USA

S. Das & S. Biswas
Dept. of Electrical and Computer Engineering, Michigan State University, East Lansing, Michigan, USA

S. Chakrabartty
Dept. of Computer Science and Engineering, Washington University, St. Louis, Missouri, USA

ABSTRACT: A continuing challenge in structural health monitoring is power availability for sensors to collect and communicate data. While self-powered sensors are helping address this concern, the harvested power with current technology is limited and improving the network efficiency requires reducing the power budget. A way to minimize the communication power demand is to transmit the minimum amount of information, namely one bit. The binary signal can be generated at a sensor node according to a local rule based on physical measurements, but interpretation at the global level requires dealing with discrete binary (1 or 0) data. This study presents an investigation on pattern recognition (PR) methods adapted from image data analysis techniques for the interpretation of binary data for use in structural health monitoring. The ability of the PR methods to identify service demands and localized material degradation was evaluated through finite element simulations and experiments on simple plates. Results indicates that PR techniques are able to use binary data to discern structural response and detect the presence and location of damage.

1 INTRODUCTION

Structural health monitoring (SHM) and damage detection have become an important technical field in many disciplines such as civil, mechanical and aerospace engineering. In turn, SHM methods that can detect and localize of damage have been the subject of much study (Chang and Chen 2004). Among the most studied SHM methods are wavelet transform or vibration control techniques, which deal with continuous data that from a physical response and are based on the availability of continuous time-history data (Li et al. 2002). The energy required for measuring and sensing data is a crucial challenge in SHM. The required energy budget becomes even more important when it is used for communication between different sensor nodes. Several researchers have studied the use of smart materials and wirelessly networked sensors for embedded monitoring in SHM (Lynch et al. 2006). A limitation is that the operating battery life -powered sensors is limited and replacing the batteries of structure-embedded sensors is a major issue. Self-powered sensors have recently become a reality by overcoming the gap between the achievable scavenged energy and the energy required for sensing, computing and communication (Huang et al. 2006). Self-powered sensors are able to harvest the required power for computational, storage and transmission from the signal being sensed. However, communication, processing, and buffering overheads of the large number of bits within data packets may lead to energy-inefficiency for event sensing with conventional communication protocols. Biswas et al (2013) introduced the concept of pulse switching for static event sensing in sensor networks to address this issue. This technology consists of an energy-efficient pulse switching protocol for ultra-weight wireless network applications. For this purpose, event localization can be combined with the pulse switching protocol. Events are localized by a receiver by observing the temporal position of a received pulse with respect to a reference frame. However, pulse-based communication decreases the available information to a binary format and this turns the received information into a spatially discrete, time-based binary set at the SHM processor.

The interpretation of discrete binary data over a domain resembles a pattern recognition (PR) problem. Therefore, the hypothesis driving the research herein is that binary data generated through a pulse communication protocol can be evaluated through PR methods. In other words, it is postulated that binary data can be interpreted by PR methods for SHM purposes based on image data analysis concepts.

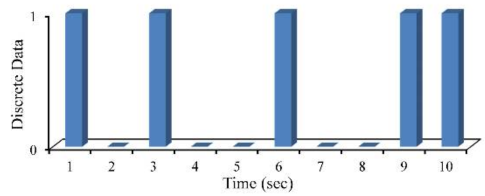

Figure 1. Discrete binary data vs time.

PR methods have achieved extensive attention for SHM applications in order to detect changes in a structure and they have been identified as a promising avenue for system identification in structural damage evaluation (Jain et al. 2000 & Kiremidjian et al. 2008).

The aim of this study is to develop global interpretation algorithms based on discrete (i.e., not continuously available in time) binary data (Fig. 1). The binary events are generated following rules based on measurements at a local level. Accordingly, the generated binary events are used to interpret and investigate structural behavior at a global level. Different PR methods are then assessed for use in structural response and condition assessment using simulated data from finite element (FE) analyses as well as experimental data. The input to the assessment algorithms was the structural response from physical tests and FE simulations on cantilevered and simply supported plates. The presented concepts were developed as part of a novel SHM strategy using self-powered sensors. Such system requires dealing with power budgets for sensing and communicating. However, in this work it was initially assumed that the system is able to operate with full data availability, and the constraints of the communication power budget for the embedded sensors and the communication time delay were disregarded. In this way, the presented methods were examined only from the aspect of dealing with binary data.

2 PATTERN RECOGNITION METHODS

The binary data generated from self-powered sensors resembles an image and it was thus hypothesized that it can be interpreted through PR methods based on image data-analysis techniques. Different PR methods were used for data classification.

2.1 *Proposed method based on deviation of patterns*

Anomaly detection is an effort to identify unusual patterns that depart from the expected behavior. In recent years, there has been a growth in research activity aimed at utilizing anomaly detection along with PR techniques for SHM applications (Lankewicz & Benard 1991). The proposed PR method is based on the anomaly detection which uses deviation of patterns (i.e., an image) with respect to each other. In this way, the method is able to recognize a change in a structure's response through different shapes (patterns). The deformed shape of the structure in normal conditions is first memorized. From this baseline knowledge the method can classify the deviation from the memorized patterns and identify new common patterns resulting from load variations or changes in material properties (e.g., damage).

2.2 *Two-principal component analysis*

Two-dimensional principal component analysis (2DPCA) is an image feature extraction and data representation technique used in the fields of pattern recognition and computer vision (Wang et al. 2006). According to image processing methods, each image can be represented as a matrix. Letting X denote an n-dimensional unitary column vector, the main idea is to project matrix (image) A, onto X by a linear transformation as expressed by Equation 1:

$$Y = AX \tag{1}$$

where Y is the projected feature vector of matrix A. The 2DPCA method introduces the image covariance (scatter) matrix (S_t), which can be directly determined from the training datasets according to Equation 2:

$$S_t = \frac{1}{N}\sum_{i=1}^{N}\left[A(i) - \overline{A}\right]^T\left[A(i) - \overline{A}\right] \tag{2}$$

where $A(i)(i=1,2,\ldots,N)$ is an $m\times n$ matrix and denotes the ith training image, and $\overline{A}$ denotes the average image from all training data and shall be determined using Equation 3:

$$\overline{A} = \frac{1}{N}\sum_{i=1}^{N}A(i) \tag{3}$$

The optimal projection axes $X_1,\ldots, X_d$ are the orthonormal eigenvectors of the image covariance matrix (S_t) corresponding to the first d largest eigenvalues. Accordingly, these optimal projection vectors $X_1,\ldots, X_d$ were used for feature extraction. For a given image sample A, the principal components vectors $Y_1,\ldots, Y_d$ are be defined by Equation 4:

$$Y_k = AX_k, k = 1,\ldots,d \tag{4}$$

2.3 *Two-dimensional linear discriminant analysis*

Two-dimensional linear discriminant analysis (2DLDA) aims to extract features that well discriminate a set of data that belongs to a number of classes (Li and Yuan 2005). The main idea is to project image A, onto X by the transformation presented in Equation 3. Considering that there are L known pattern classes in the training set, and M denotes the size of the training set, the 2DLDA method introduces an image within-class matrix $S_W{}^{IM}$ and an image between-class scatter matrix $S_B{}^{IM}$ that can be expressed by Equation 5 and Equation 6:

$$S_W{}^{IM} = \sum_{i=1}^{L} \sum_{A_k \in T_i} (A_k - \bar{A}_i)^T (A_k - \bar{A}_i) \tag{5}$$

$$S_B{}^{IM} = \sum_{i=1}^{L} N_i (\bar{A}_i - \bar{A})^T (\bar{A}_i - \bar{A}) \tag{6}$$

where $\bar{A}_i$ and $\bar{A}$ denotes mean of the data matrices and global mean matrix, respectively:

$$\bar{A}_i = \frac{1}{N_i} \sum_{A_k \in T_i} A_k \tag{7}$$

$$\bar{A} = \frac{1}{N} \sum_{i=1}^{L} \sum_{A_k \in T_i} A_k \tag{8}$$

The Fisher optimal projection axes $X_1, \ldots, X_d$ are the orthonormal eigenvectors of $S_W{}^{-1} S_B$ corresponding to the first d largest eigenvalues.

3 APPROACH TO DATA INTERPRETATION

The pattern recognition algorithms were evaluated through finite element simulations as well as testing. Finite element (FE) analyses provided a platform to evaluate the algorithms using the simulation output as virtual sensor nodes while the tests used conventional strain gages. The evaluation was made on two structural models, namely, a plate simply supported along all edges and a plate cantilevered from one side. A schematic view of the simply supported and cantilever plates, along with distribution of output locations (i.e., simulated sensors and strain gages) are shown in Figure 2a, b The plates (both numerically and experimentally) were subjected to a harmonic loading pattern with a frequency of 2.3 Hz. The FE simulations were conducted using the program ABAQUS. A schematic of the proposed methodology used for data interpretation and event prediction algorithm based on pattern recognition methods is illustrated in Figure 3.

3.1 *Multiple binary events concept*

Simple pilot-type local rules for binary event generation were defined in terms of transverse displacements and maximum principal strains at the sensor nodes and introduced to the PR system. However, a benchmark, or normal

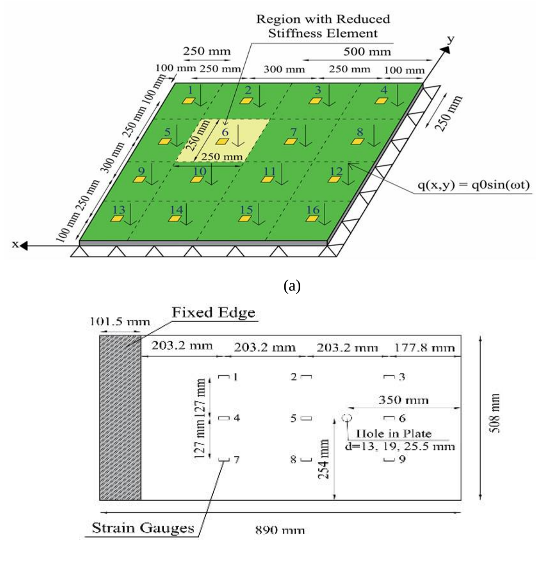

Figure 2. (a) Schematic of a simply supported plate used for FE simulations along with an arrangement of virtual sensors (b) Layout of the cantilever plate used for experiments

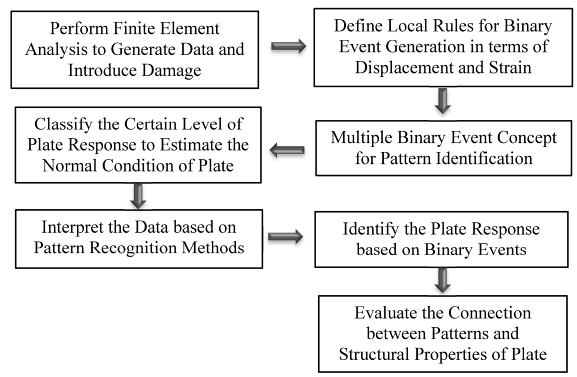

Figure 3. Framework of proposed methodology for data interpretation.

condition, performance level needs to be defined to be able to determine changes in loading of structural condition. For this purpose, the concept of multiple binary events was proposed and used for this study. The concept can be implemented in substrate communication techniques through variance in frequency or time spacing of the communication pulse; while at the sensor nodes is implemented by defining different local event generation rules. Three event thresholds (R1, R2, and R3) were thus defined. A schematic of the multiple binary concept and the definition of local event generation rules based on this concept are presented in Figure 4. It should be noted that, as a pilot test, the considered thresholds were simply based varying levels of displacement or strain responses.

3.2 *Local damage identification*

The method's ability to identify local damage was evaluated through the finite element simulations in two forms. First, localized damage on the simply supported plate model was done by gradual reduction in stiffness (elastic modulus) in a region of the plate (see Fig. 2a). For the experiments on the cantilever plate, damage consisted of a hole in the plate and damage severity was controlled by varying the hole diameter. The plates' response with uniform stiffness (undamaged plate) was first memorized. The PR algorithms were used to identify new patterns (damaged plates) once the stiffness was locally decreased or by changing the hole diameter. Figure 5 schematically illustrates experiment setup for the cantilever plate on a universal test machine.

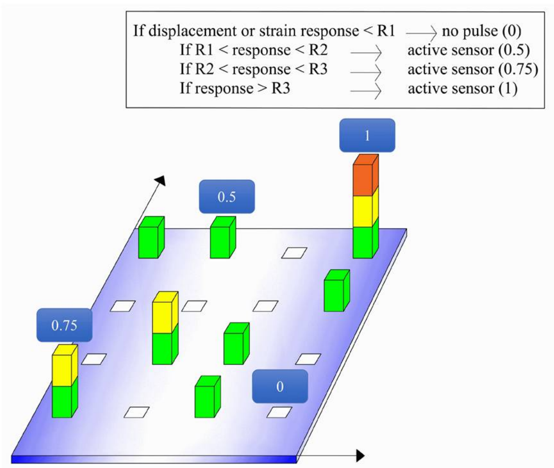

Figure 4. Multiple binary event generation and distribution of sensors on a simply supported plate.

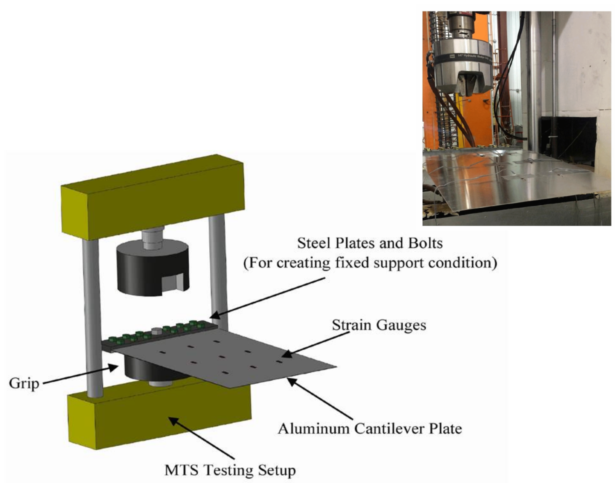

Figure 5. Schematic of experimental setup for cantilever plate.

4 SIMULATION RESULTS AND DISCUSSION

The effect of change in material properties on a plate for structural assessment and event prediction was investigated. A custom program in the Matlab platform was used for implementing the different PR techniques. Harmonic amplitudes with different noise levels were considered for several FE analyses and the results were used to evaluate the algorithms. In this way, the proposed algorithms were assessed for the effects of signal noise. It was determined that the system has acceptable performance with respect to the variation of noise level. However, performance of the system can be affected by higher levels of noise.

4.1 *Case I: FE simulation of simply supported plate*

This section provides results based on the FE simulation of a simply supported plate.

4.1.1 *Results based on Deviation of Patterns method*

Performance of the proposed PR algorithm in terms of material degradation was evaluated. FE analyses were carried out for 5 seconds with a time step of 0.01 s; therefore, the dataset size was 500. Three strain values corresponding to the structural response of the plate were assumed as a threshold to recognize the normal plate's response. The distributed load with a specified harmonic amplitude was applied and common patterns were identified as the stiffness of the critical region was gradually reduced. Accordingly, four patterns were identified by the system for a constant stiffness. Once the stiffness was locally decreased, the SHM algorithm could successfully recognize new patterns. The distribution of identified patterns with time for the case of localized 40% stiffness reduction is shown in Figure 6.

Spatial-temporal integration of the binary events based on the multiple threshold was also computed. Results are provided in Figure 7. As it can be seen, the effect of material degradation on the output of the sensor nodes is noticeable. Accordingly, stiffness reduction leads to a change in the binary patterns, and this variation permits locating the element with reduced stiffness in the FE model. Several attempts were also performed to establish a relationship between recognized patterns and the plate's structural properties. In this context, displacement values were considered as feature vectors and introduced to the proposed classifier to investigate the behavior of the sensor nodes with respect to their neighbors. The multiple binary events concept was also used for pattern identification.

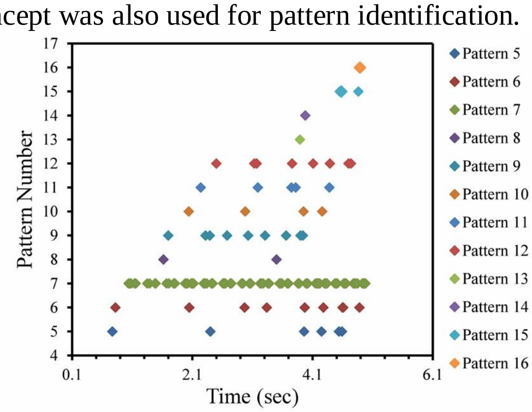

Figure 6. Distribution of new identified patterns with time based on a localized 40% stiffness decrease.

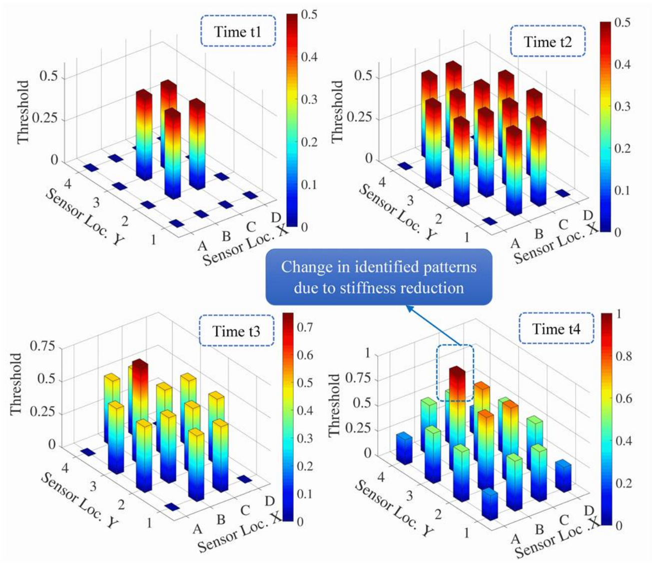

Figure 7. Response of sensor nodes based on multiple thresholds according to a localized 40% stiffness decrease.

Common patterns based on responses at the virtual sensor nodes with a constant stiffness were determined. Consequently, the elastic modulus in a region of the plate was reduced from 20% up to 90% in the FE simulations. The frequency of recognized patterns with respect to modulus reductions of 30% and 80% were obtained and they are illustrated in Figures 8-9, respectively. The frequency of new recognized patterns representing damage due to 80% localized stiffness decrease is also presented in Figure 10 .As can be observed, the frequency of patterns 1 and 3 tend to zero with increased stiffness reduction, while the frequency of abnormal patterns representing damage, that is patterns 4 and 5, increases as the flexural rigidity reduces. Different square colors (shown in Figs. 8 and 10) represent the plate's response based on the measurement/output at the sensor nodes. In this way, inactive sensors (white regions) denote that the displacement response of that region of the plate does not exceed the predefined threshold R1; while a yellow region means that the displacement or strain response of the plate exceeds threshold R2 but it is less than threshold R3.

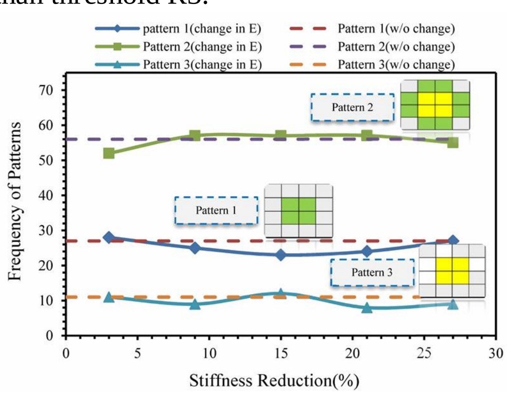

Figure 8. Frequency of normal patterns with respect to a localized stiffness reduction (up to 30% decrease).

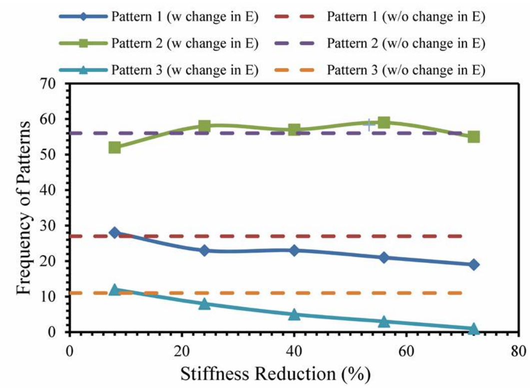

Figure 9. Frequency of normal patterns with respect to a localized stiffness reduction (up to 80% decrease)

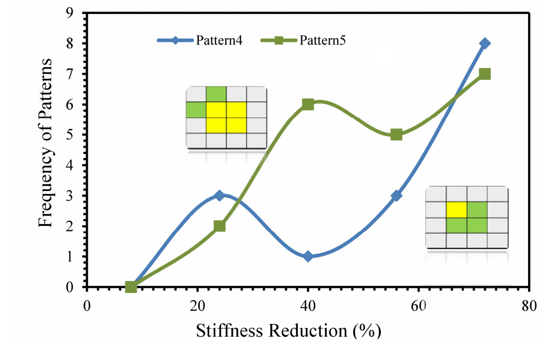

Figure 10. Frequency of damaged patterns with respect to a localized stiffness reduction (up to 80% decrease).

4.2 *Case II: Experiments on cantilever plate*

This section provides results based on experiments on a cantilever plate.

4.2.1 *Results based on 2DPCA method*

K-means clustering along with the nearest neighbor classifier were utilized for calibrating the classifier based on 2DPCA and 2DLDA methods. For this purpose, strain values were extracted according to these methods and used for the classification process. Thereafter, patterns were classified from the training dataset (intact plate) to 5 classes using k-means clustering. After extracting strain values generated from testing of the damaged plate, a nearest neighbor classifier was used to classify patterns. For this purpose, a nearest neighbor classifier was found based on a Euclidean distance. It should be noted that classes 1 and 2 represent patterns identified due to normal condition, while classes 3 and 4 denote patterns due to noise of the system. Finally, class 5 represents patterns recognized owing to damage. Figure 11 illustrates the frequency of recognized patterns with respect to time for the damaged cantilever plate with a hole diamater of 25.5 mm. Similarly, frequency of normal patterns during time analysis considerably reduces as hole diameter increases; and correspondingly the frequency of patterns from class 5 noticeably increases.

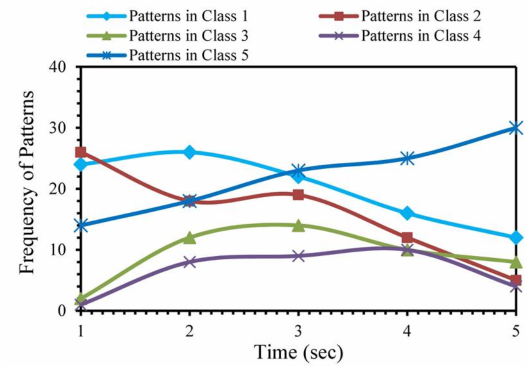

Figure 11. Frequency of patterns based on 2DPCA method for a cantilever plate with a hole diameter equal to 25.5 mm.

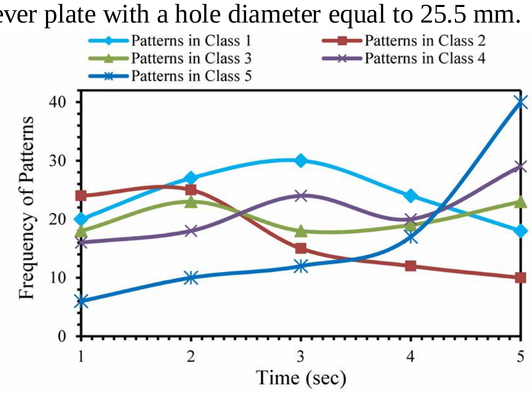

Figure 12. Frequency of patterns based on the 2DLDA method for a cantilever plate with a hole diameter equal to 25.5 mm.

4.2.2 *Results based on 2DLDA method*

Patterns were initially classified into 5 classes through k-means clustering. Accordingly, strain values were extracted from the damaged plate and new patterns were recognized using a nearest neighbor classifier. The frequency of identified patterns with time analysis for the damaged cantilever plate with a hole diamater equal to 25.5 mm is presented in Figure 12. Results show that the frequency of normal patterns reduces with respect to both time and hole size variation, while patterns recognized due to noise show more variation in comparison with similar patterns according to the 2DPCA method. Moreover, not only does the frequency of patterns from damaged class extremely increase with time, but the number of pattern occurrences also significantly grows as the hole diameter in plate increases.

5 CONCLUSIONS

This study investigated damage identification algorithms using discrete binary data. The proposed damage identification methodology was based on pattern recognition (PR) methods. PR methods based on image data analysis techniques were adapted for the study and used for data interpretation and pattern identification. Finite element (FE) simulations were used to generate virtual experimental data in order to evaluate the proposed methods. Furthermore, an experiment of a cantilever plate was conducted to examine the applicability of the PR algorithms in real applications. Simple pilot-type local rules for binary event generation were defined in terms of displacements and strains at the virtual sensor nodes and corresponding responses were provided as input to the PR algorithms. Results indicate that the deviation of patterns method can effectively recognize patterns due to material stiffness degradation. Also, 2DPCA and 2DLDA methods were found as an effective techniques for dealing with binary data. According to the obtained results, the 2DLDA method has superior performance in terms of recognizing potential damage since this method deals directly with the discrimination between classes, whereas the 2DPCA deals with the data in its entirety for the principal components analysis. The results demonstrate that PR methods can be efficiently used as damage identification algorithms based for binary data sets.

6 REFERENCES

Chang, Ch., Chen, L. 2004. Damage Detection of a Rectangular Plate by Spatial Wavelet based Approach. *Applied Acoustics*, 65: 819-832.

Cheung, A., Cabrera, C., Sarabandi, P., Nair, K. K., and Kiremidjian, 2008. The Application of Statistical Pattern Recognition Methods for Damage Detection to Field Data. *Smart Materials and Structures*, 17: 1-12.

Huang, Ch., Lajnef, N., and Chakrabartty, Sh. 2010. Calibration and Characterization of Self-powered Floating-Gate Usage Monitor with Single Electron Per Second Operation Limit. *IEEE Trans. Circuits and Systems*, 57(3): 556-567.

Huo, Q., Rao, J., and Biswas, S. 2013. Pulse Switching: Towards a Packet-less Protocol Paradigm for Event Sensing. *IEEE Transactions on Mobile Computing*, 12(1): 35-50.

Jain, A. K., Duin, R. P., and Mao, J. 2000. Statistical Pattern Recognition: A Review. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 22(1): 4-37.

Lankewicz, L. and Benard, M. 1991. Real-time anomaly detection using a nonparametric pattern recognition approach. *Proceedings. Seventh Annual Computer Security Applications Conference*, 80–89.

Li, M., Yuan, B. 2005. 2DLDA: A Statistical Linear Discriminant Analysis for Image Matrix. *Pattern Recognition Letters*, 26: 527-532.

Li, Y. Y., Cheng, L., Yam, L. H., and Wong, W. O. 2002. Identification of Damage Locations for Plate-like Structures using Damage Sensitive Indices: Strain Modal Approach. *Computer and Structures*, 80: 1881-1894.

Lynch, J. P., Loh, K. J. 2006. A Summary Review of Wireless Sensors and Sensor Networks for Structural Health Monitoring. *The Shock and Vibration Digest*, 38: 91-128.

Yang, J., Zhang, D., Frangi, A. F., Yang, J. 2004. Two Dimensional PCA: A New Approach to Appearance-based Face Representation and Recognition. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 26(1): 131-137.