Expert Systems With Applications 135 (2019) 259–273

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Data mining methodology employing artificial intelligence and a probabilistic approach for energy-efficient structural health monitoring with noisy and delayed signals

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ARTICLE INFO

Article history:
Received 14 August 2018
Revised 7 April 2019
Accepted 29 May 2019
Available online 31 May 2019

Keywords:
Structural health monitoring
Data mining
Artificial intelligence
Probabilistic approach
Signal time delay

ABSTRACT

Numerous methods have been developed in the context of expert and intelligent systems for structural health monitoring (SHM) with wireless sensor networks (WSNs). However, these techniques have been proven to be efficient when dealing with continuous signals, and the applicability of such expert systems with discrete noisy signals has not yet been explored. This study presents an intelligent data mining methodology as part of an expert system developed for SHM with noisy and delayed signals, which are generated by a through-substrate self-powered sensor network. The noted sensor network has been demonstrated as an effective means for minimizing energy consumption in WSNs for SHM. Experimental vibration tests were conducted on a cantilever plate to evaluate the developed expert system for SHM. The proposed data mining method is based on the integration of pattern recognition, an innovative probabilistic approach, and machine learning. The novelty of the proposed system for SHM with data interpretation methodology lies in the integration of the noted intelligent techniques on discrete, binary, noisy, and delayed patterns of signals collected from self-powered sensing technology in the application to a practical engineering problem, i.e., data-driven energy-efficient SHM. Results confirm that the proposed data mining method employing a probabilistic approach can be effectively used to reconstruct delayed and missing signals, thereby addressing the important issue of energy availability for intelligent SHM systems being used for damage identification in civil and aerospace structures. The applicability and effectiveness of the expert system with the data mining approach in detecting damage with noisy signals was demonstrated for plate-like structures with an accuracy of 97%. The present study successfully contributes to advance data mining and signal processing techniques in the SHM domain, indicating a practical application of expert and intelligent systems applied to damage detection in SHM platforms. Findings from this research pave a way for development of the data analysis techniques that can be employed for interpreting noisy and incomplete signals collected from various expert systems such as those being used in intelligent infrastructure monitoring systems and smart cities.

1. Introduction

Energy-efficient wireless sensor networks (WSNs) for structural health monitoring (SHM) have emerged due to progress in self-powered sensors and low-power data communication protocols. One such network is the through-substrate ultrasonic self-powered sensor network (Das et al., 2017), which employs ultrasonic pulses to communicate binary signals (from self-powered sensors) through the material substrate. However, the noted network creates time-delay on the generated signals due to the power budgeting required for sensing and data transmission. This study presents an expert system with a data mining approach for SHM in order to deal with such discrete noisy and delayed signals.

Signal time-delay estimation/reconstruction is a problem that has attracted considerable attention in the SHM community. Numerous techniques have been developed for signal delay estimation for SHM and damage identification (Giurgiutiu, 2005; Giurgiutiu & Cuc, 2005; Nichols, 2003; Sun, Chaudhry, Rogers, Majmundar, & Liang, 1995; Yan, Royer, & Rose, 2010). Ultrasonic techniques (e.g., lamb wave methods) have been used for time-delay

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https://doi.org/10.1016/j.eswa.2019.05.051
0957-4174/

estimation for SHM (C. H. Dib & Udpa, 2016; Park, Farrar, di Scalea, & Coccia, 2006; Petculescu, Krishnaswamy, & Achenbach, 2007; Wang, Rose, & Chang, 2004). Aranguren, Monje, Cokonaj, Barrera, and Ruiz (2013) proposed a piezoelectric-based SHM system for damage detection using lamb waves and delayed signals. Kudela, Radzienski, Ostachowicz, and Yang (2018) developed an SHM approach based on lamb waves to increase damage imaging resolution, where the effectiveness of the approach for damage detection with time-delayed signals was demonstrated on a structural plate. Lamb wave methods have also been incorporated into techniques called delay-and-sum algorithms for signal delay reconstruction. Qiu, Liu, Qing, and Yuan (2013) introduced a quantitative multi-damage monitoring algorithm using delay-and-sum imaging algorithms for large-scale composites in order to deal with delayed signals coming from the actuator-sensor channels. Sharifkhodaie and Aliabadi (2014) presented a damage detection method based on lamb waves, and evaluated the applicability of the proposed delay-and-sum algorithms for SHM of aircraft panels with delayed signals.

Time synchronization approaches have also been used for SHM employing WSNs for dealing with delayed signals (Araujo et al., 2012; Chae, Yoo, Kim, & Cho, 2012; Kim et al., 2007; Lei, Kiremidjian, Nair, Lynch, & Law, 2005; Paek, Chintalapudi, Govindan, Caffrey, & Masri, 2005; Wang & Law, 2011). Linderman, Mechitov, and Spencer (2013) presented a high-throughput real-time wireless data acquisition on an advanced smart sensor platform used for SHM with time-delayed signals. In addition, Pyayt et al. (2014) proposed a data-driven SHM approach combining time-frequency feature extraction, wavelet analysis, and classification techniques for damage assessment in concrete dams; in which analysis of phase delay between sensors was performed based on Fourier transforms. Although the noted studies showcase the applicability of different techniques to reconstruct signal time-delay for SHM with WSNs, such methods mainly dealt with small amounts of delay, i.e., few milliseconds, where it has been shown that such small delay values have little impact on the performance of SHM systems. However, the delay in the noted through-substrate sensor network is large, and thus the effect of time-delay cannot be disregarded.

Numerous techniques have been developed within the context of expert and intelligent systems for SHM with sensor networks (Brownjohn, 2006; Ecke, Latka, Willsch, Reutlinger, & Graue, 2001; Jiang, Zhang, & Zhang, 2011; Loutas, Panopoulou, Roulias, & Kostopoulos, 2012; Wu et al., 2010; Zhao, Yuan, Yu, Ye, & Cao, 2008; Zhu, Deng, & Zhang, 2013). Chen & Zang (2011) proposed a hybrid model for structural damage PR based on combination of fuzzy clustering and artificial immune PR, where the model was tested on a benchmark structure. Oliveira, Araujo, Inman, and Vieira Filho (2018) developed a strategy using fuzzy network with particle swarm optimization, where the effectiveness of the approach was demonstrated for SHM of composite structures. Yet, the applicability of the noted expert systems for SHM was evaluated based on the interpretation of continuous time-history sensor data. This is while, as noted, the nature of data/signals from a self-powered sensing technology are discrete binary and delayed (i.e., not continuous in time), and therefore such expert systems cannot be effectively used when dealing with discrete noisy and delayed signals. Further, no efficient approach has yet been proposed within the context of expert and intelligent systems that can be considered for SHM with large values of delay. The above-mentioned issues evidently imply the necessity to develop a new class of expert and intelligent systems for data-driven SHM that are able to interpret and analyze discrete, noisy, and delayed/missing signals.

To tackle the problems associated with discrete binary signals generated by the through-substrate network the authors previously presented a damage identification methodology employing pattern recognition (PR) (Salehi, Burgueño, Das, Biswas, & Chakrabartty, 2016; Salehi, Das, Chakrabartty, Biswas, & Burgueño, 2015, 2018), for which it was hypothesized that damage detection with binary signals can be treated within the context of PR. Further, to take into account the effect of time-delay the authors previously proposed a framework incorporating PR and matrix completion for damage identification in aircraft structures (Salehi, Das, Chakrabartty, Biswas, & Burgueño, 2017). Yet, the noted framework was found to be computationally intensive for SHM purposes. Further, the effectiveness of the framework highly depended on the optimal parameters of a learning algorithm. To address these issues, this paper presents a novel SHM system within the context of expert and intelligent systems for damage detection with discrete noisy and delayed binary signals. An expert system employing an intelligent data mining methodology that efficiently deals with delayed/noisy signals is presented based on integration of PR, an innovative probabilistic approach, and machine learning using a support vector machine (SVM) algorithm. The image-based PR approach is used to represent sensor nodes responses as a pattern. Another contribution of the study presented herein is the development of a probabilistic approach as part of the SHM system to reconstruct delayed signals. The SVM algorithm is also used to detect the presence of damage and to determine damage detection accuracy with the reconstructed signals. The novelty of the proposed intelligent SHM system lies in the incorporation of artificial intelligence techniques (i.e., PR and machine learning) and a probabilistic approach on discrete noisy and delayed patterns in the application to a practical engineering problem. The developed intelligent SHM system could effectively address the important issue of energy availability for SHM. This significantly improves safety and decreases maintenance costs of civil and aerospace structures.

It is to be noted that the integrated self-powered sensor with communication technology is under design, fabrication, and testing. Further, experimental validation of the self-powered sensor and through-substrate communication protocol has been done separately in prior studies (Das, Lorenz, Dong, Huo, & Biswas, 2015; Huang & Chakrabartty, 2012; Huang, Lajnef, & Chakrabartty, 2010; Zhou & Chakrabartty, 2017; Zhou, Abraham, Tang, & Chakrabartty, 2016). Thus, this study contributes to the development and evaluation of expert systems for SHM by using intelligent data mining methodologies for delayed signals through experimentally calibrated numerical simulations on a dynamically loaded cantilever plate. The proposed SHM system promotes the development of new class of data interpretation techniques for analysis of noisy and delayed signals provided by intelligent systems being used in domains of smart infrastructure monitoring, aerospace monitoring, and smart cities. Finally, the presented research, through development of the expert SHM system, successfully contributes to advance data mining and signal processing techniques in the data-driven SHM domain, further showing a practical application of expert and intelligent systems for energy-efficient SHM and smart infrastructure monitoring.

2. Nature of signals generated by the through-substrate sensor network

The expert and intelligent SHM system presented in this research is based on a novel energy-aware through-substrate sensor network aiming to minimize energy consumption for SHM. The method's objective is to interpret the binary (i.e., 1 or 0) and time-delayed signals provided by self-powered analog wireless sensors (Das et al., 2017; Huo, Dong, & Biswas, 2014; Huo, Rao, & Biswas, 2013), used to measure the structural response, along with an energy-efficient pulse switching architecture (Huang et al., 2010), employed for signal communication through the material's

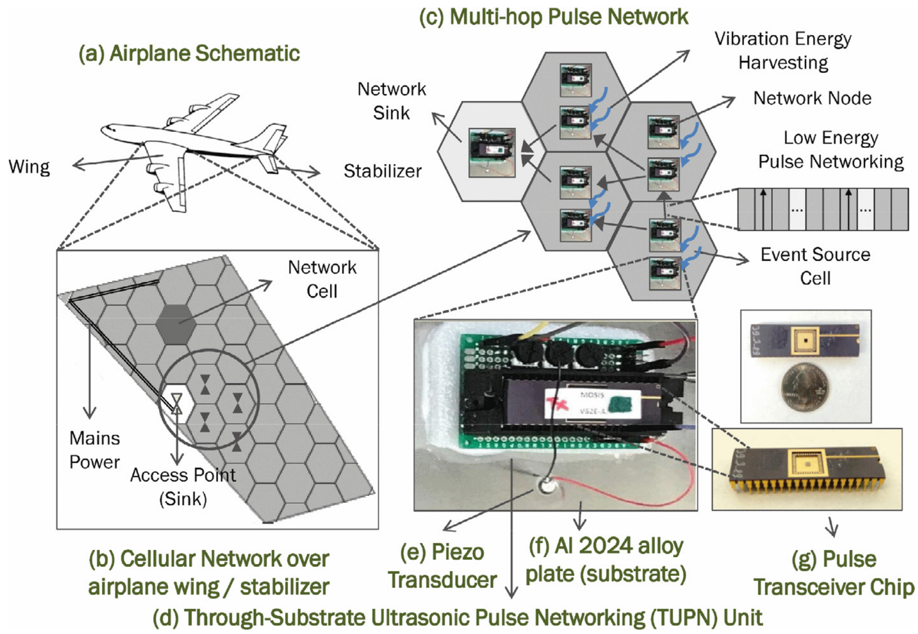

Fig. 1. Structural health assessment and performance monitoring employing a through-substrate self-powered sensing technology.

substrate. The uniqueness of the analog wireless sensor is that it operates on gates with a non-volatile memory that demands very low energy; thus logging/recording data in a discrete and asynchronous manner. The communication part employs the pulse switching protocol in which a minimal number of ultrasonic pulses are used to encode event location and forwarding information. A schematic of the through-substrate ultrasonic self-powered sensor network for SHM of an aircraft wing stabilizer is shown in Fig. 1. A significant characteristic of such network is that it consists of a system of low-power through-substrate ultrasonic pulse networking (TUPN) units communicating with each other using the noted energy-lean pulse switching architecture, and powered by energy harvested from the substrate's (i.e., structural) vibrations. The generated pulses are communicated via multi-hop transmission between TUPNs to a data logger/sink node, where information received from sensors across the structure is accumulated and used to assess the structure's condition.

The cellular pulse networking (CPN) protocol is used for the energy-aware self-powered sensor network. Such protocol is well-suited for SHM applications where the information to be transmitted is small, i.e., essentially binary information indicating the occurrence or absence of a structural event. There can be multiple factors contributing to the latency of event information delivery at the sink when CPN is employed in a self-powered sensor network for SHM, such as distance from the source to the sink, energy availability, event merging policy, and frame size. As shown in Fig. 2, energy availability depends on the harvested energy as well as its consumption due to communication, idling leakage, and sensing. An event merging/processing policy determines how the generated events will be accumulated in a data buffer based on available buffer size and the pending event processing status. The frame size is important in terms of the event buffering time because events from any cell can be transmitted in only one slot per frame.

3. Simulation of time-delayed binary signals

The development and validation of the proposed SHM system employing intelligent data mining approach is based on data obtained through experiments on a cantilever plate. To this aim, vibration tests using conventional strain gages were conducted on a plate cantilevered from one side. The plate geometry and locations of output locations (i.e., strain gages) are shown in Fig. 3. The plate was made of aluminum 2024-T4 with $E = 73{,}100$ MPa and $\nu = 0.33$. Damage on the experimental plate was introduced by means of a circular hole (see Fig. 3) of varying diameter (13 mm, 19 mm, and 25.5 mm.) Testing consisted on subjecting the plate's clamped edge to a dynamic harmonic motion (5 mm in amplitude at a frequency of 2.3 Hz) using a universal testing frame. Strain data was collected during 10 s with a time step of 0.01 s; therefore, the size of dataset is 1000.

The continuous experimental response (strain) from the vibration tests was post-processed to extract binary signals based on response thresholds. Consequently, strain responses were collected from the strain gages. However, the acceleration response is needed to simulate the through-substrate sensor network. To this aim, an experimentally calibrated finite element (FE) model of the cantilever test plate was used to extract the acceleration responses at the stain gage locations. The key idea is that binary signals are generated based on strain at a local level (i.e., sensor nodes or strain gages), saved in the sensor cell memory, and communicated if enough power is available based on accumulated harvested energy (from acceleration at sensor nodes). Accordingly, experimental strain responses were used to generate binary signals using a threshold concept, and acceleration responses extracted from the FE simulations were used to determine harvested energy. The acceleration response and binary signals were thus used in a simulation algorithm of the through-substrate sensor network employing an energy-aware pulse switching protocol to generate the time-delayed binary signals. The generated time-delayed binary signals were finally the input to the SHM methodology.

The strain responses from the vibration tests were used to calibrate the FE model. Simulated and experimental strain histories (for the first 4 s of the experiment) at nodes 1 and 4 are plotted in Fig. 4, from which it can be observed that they are in good agreement in spite of the experimental uncertainties and noise. Similar results were observed for other strain gages (nodes), indicating that the numerical and experimental strain responses were essentially equal. With such validation of the numerical simulation, the

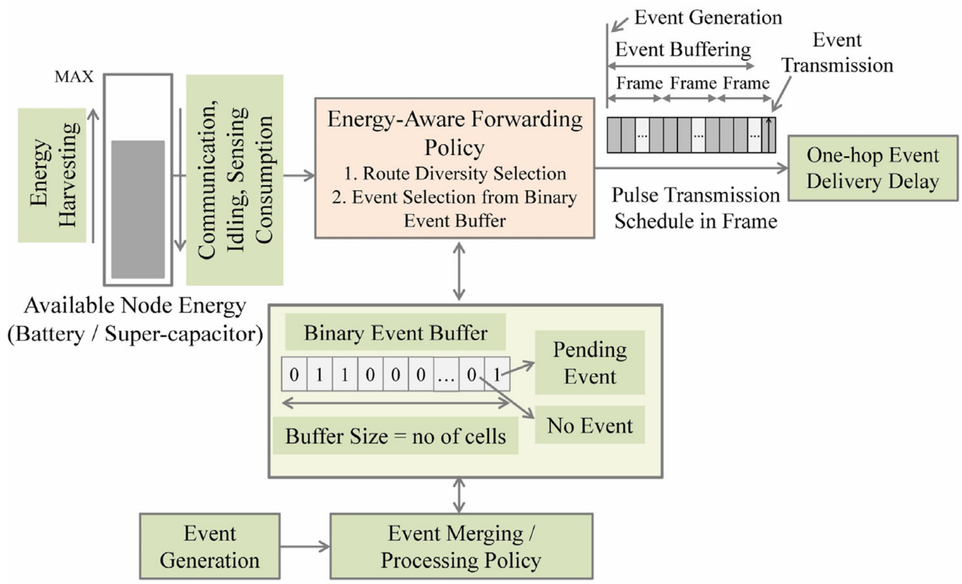

Fig. 2. Factors affecting one-hop event delivery delay when using CPN in energy-harvesting-powered wireless sensor networks.

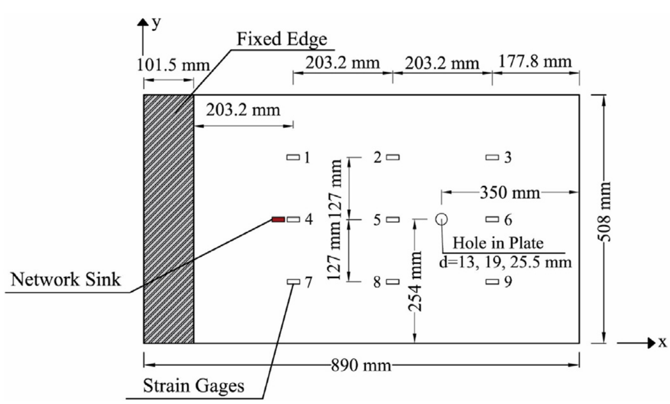

Fig. 3. Geometry and strain gages layout of a cantilever plate for vibration testing.

acceleration responses at the strain gage locations were extracted from the FE model and used in the simulated pulse communication protocol for generating energy-dependent timed-delayed binary signals corresponding to the experiments.

4. Proposed SHM methodology with delayed signals

The time-delayed signals considered in this study are crucial to the SHM system, and therefore a new SHM system is presented within the context of expert systems to efficiently deal with such signals. The SHM platform with the proposed data mining methodology, schematically presented in Fig. 5, is designed upon merging an image-based PR approach, an innovative probabilistic approach, and machine learning with SVM algorithm. Theoretical considerations for each of the noted techniques are provided in following sub-sections.

4.1. Representation of sensor nodes responses using an image-based PR approach

Detailed information of the proposed image-based PR approach is reported in prior works (Salehi et al., 2015; Salehi et al., 2016; Salehi et al., 2018). However, a brief summary is presented here to highlight its implementation. To apply the PR approach, the arrangement of sensor nodes (and consequently the distribution of binary signals generated from structural response) was considered as a pattern/image. Consistent with image data analysis techniques, each pattern (image) was treated as a matrix and represented by specific features (binary signals according to local rules). The dimension of the generated matrix, which herein is the dimension of the PR problem, depends on the number of time steps and distribution of sensor nodes; while each of the matrix elements denotes a pattern's feature (binary signal) at each sensor. In other words, sensor node responses for the entire simulation time were

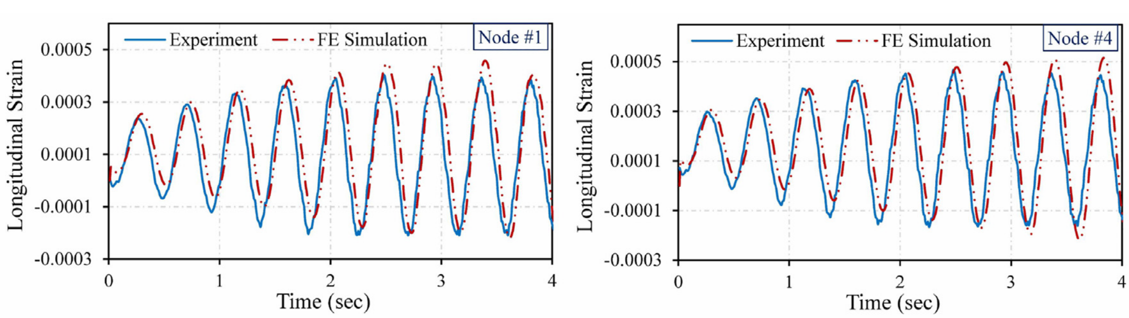

Fig. 4. Strain response of the cantilever plate: (a) Node #1, and (b) Node #4.

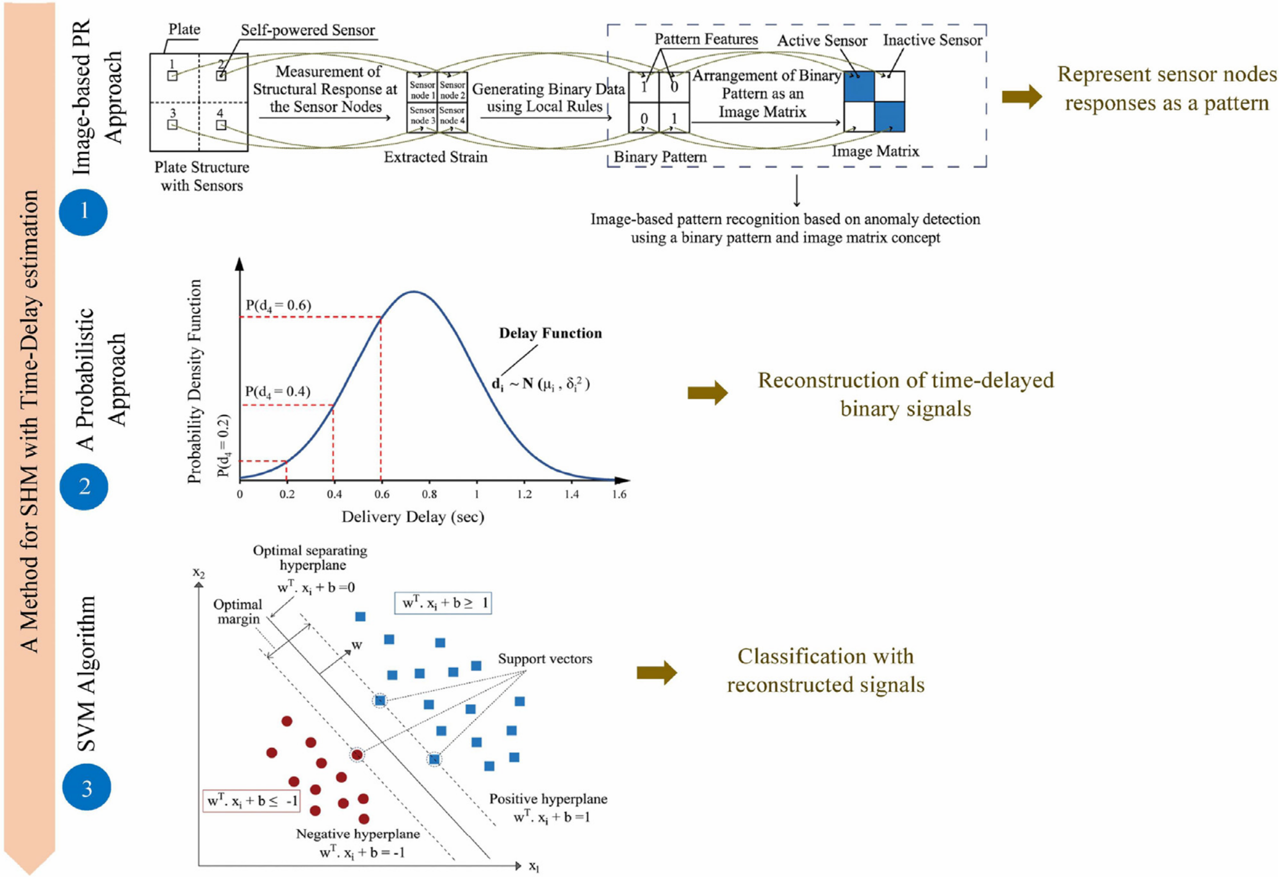

Fig. 5. Proposed data mining methodology for intelligent SHM system using noisy and delayed signals.

arranged in m rows and n columns, where m denotes number of time steps and n refers to the number of sensor nodes in the network. Accordingly, if the number of sensors is n, each pattern was represented by n features at each time step.

Once sensor node responses were arranged as a pattern, a PR approach employing anomaly detection (Basharat, Gritai, & Shah, 2008; Moshtaghi, Leckie, Karunasekera, & Rajasegarar, 2014) was used to identify patterns as normal or damaged. A schematic illustration of the proposed image-based PR approach for damage detection of a simply supported plate with 9 sensor nodes is presented in Fig. 6. The resulting patterns from the structures' regular (in-service) response are memorized and used as benchmarks for damage detection model. A change in structural response is expected when damage or decay occurs under consistent loading, which leads to a different pattern because the binary-event thresholds are exceeded at different locations (see Fig. 6). If a pattern resulting from the noted material/structural changes is recognized as new, with respect to the benchmark, it is thought to be representative of damage.

4.2. Reconstruction of time-delayed signals with probabilistic approach

Binary signals at the sensor nodes were created based on a threshold concept. A simple pilot-type local rule for binary signal generation was defined in terms of a strain threshold R1, namely 120 micro-strains, at the sensor nodes (i.e., strain gages locations). Consequently, a binary signal was generated if the value of the longitudinal strain at the strain gage location exceeded threshold R1. Preliminary results indicated that the layout shown in Fig. 3(a) provided adequate information for robust data analysis. Thus, the number of sensors for the cantilever plate was set at 9, and therefore each pattern was represented with 9 features (binary values).

Preliminary results show that the variation of signal delay with respect to the number of event readings has a Gaussian distribution. Thus, the probability density functions (PDF) of delivery delay values at the sensor nodes were determined. The PDF plots of delivery delay for strain gages 1 to 6 obtained from experiments of the intact plate are shown in Fig. 7(a) and (c); while those for the damaged plate with a hole diameter of 19 mm are presented in Fig. 7(b) and (d). The variations in the PDF plots of the noted sensing nodes/strain gages confirm that the distribution of event delivery delay values is Gaussian.

Given the Gaussian distribution of signal delay, the PDF of each sensor node was determined. Thereafter, it was decided to develop a statistical approach using a conditional probability concept. That is, the probability that sensor node S_i observes binary signal (1) at time t_j should be combined with the anticipated delay function d_i, as shown in Eq. (1).

$$P\left(t_j^i = 1 | d_i\right) \tag{1}$$

In Eq. (1), $d_i \sim N(\mu_i, \sigma_i^2)$, where μ_i and σ_i are average and standard deviation of signal delay for sensor node S_i.

The key idea behind the proposed probabilistic approach is to use the PDF values of the sensor nodes to determine the probabilities that can be further used for classification. Assuming that a binary signal is received at time t_j, the aim is to determine what would be the probability that such signal comes from $t_{j\text{-}1}$, $t_{j\text{-}2}$, etc. For such purpose, a time lag factor parameter (l) is introduced to

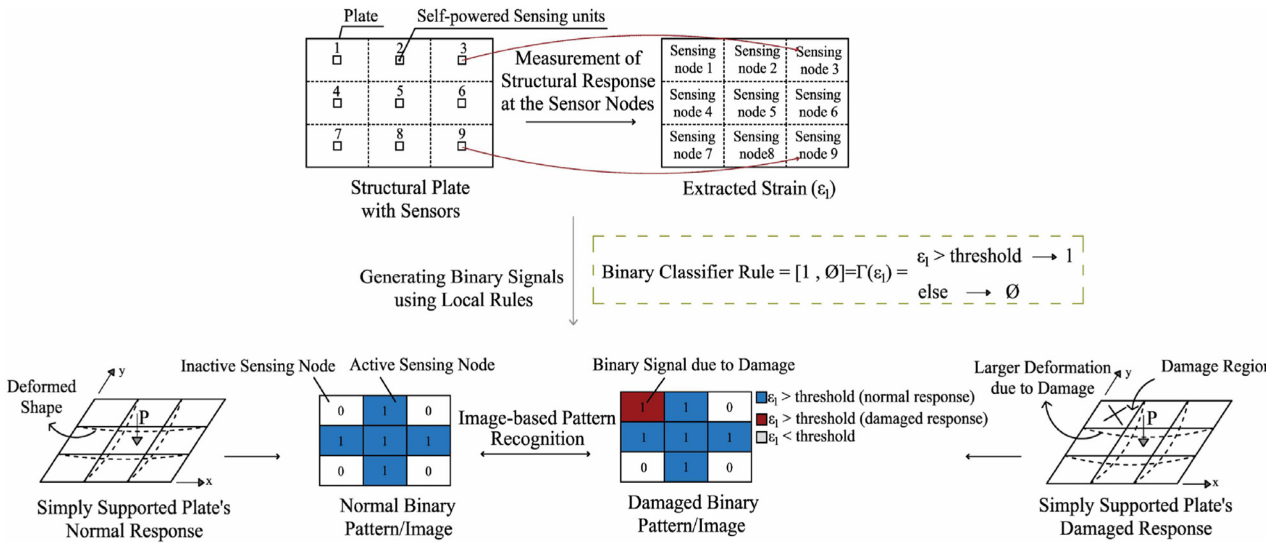

Fig. 6. Schematic illustration of image-based PR approach.

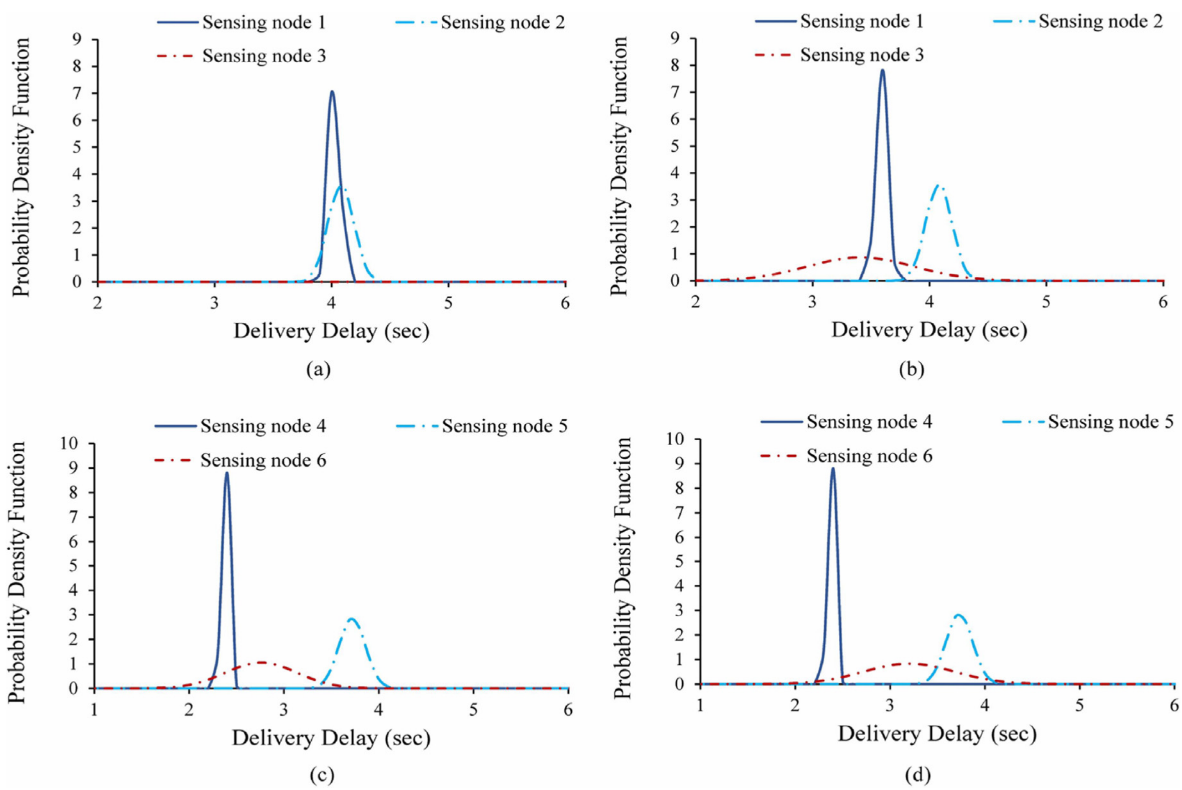

Fig. 7. The PDF plot of delivery delay for sensors/strain gages 1 to 6 for experimental plate: (a) and (c) intact plate, (b) and (d) damaged plate.

designate the time (i.e., number of readings) that we should go behind the current time t_j to capture a delay. Fig. 8 schematically illustrates the proposed probabilistic approach. The figure illustrates a situation in which the binary signal is observed by sensor node 4 at time $t = 0.7$ s. The goal is to determine the probabilities that such binary signal was actually generated at times $t = 0.6$, 0.5, 0.4, 0.3, 0.2, and 0.1 s, given the time lag is 0.6 s. The time lag of 0.6 s refers to the six previous readings, indicating the probabilities that the signal comes from one of the six previous readings need to be determined. The noted probabilities are written in Eq. (2). Further, *Pi,tj* in Fig. 8 refers to the probabilities obtained from the PDF of sensor node *i* at time step *tj*.

$$\begin{array}{ll} P(V_4 = 1|j = 0.1) \approx P(d_4 = 0.6) & P(V_4 = 1|j = 0.2) \approx P(d_4 = 0.5) \\ P(V_4 = 1|j = 0.3) \approx P(d_4 = 0.4) & P(V_4 = 1|j = 0.4) \approx P(d_4 = 0.3) \\ P(V_4 = 1|j = 0.5) \approx P(d_4 = 0.2) & P(V_4 = 1|j = 0.6) \approx P(d_4 = 0.1) \end{array} \tag{2}$$

The implementation and different steps of the proposed algorithm are presented in Fig. 9. Once the time delay is reconstructed

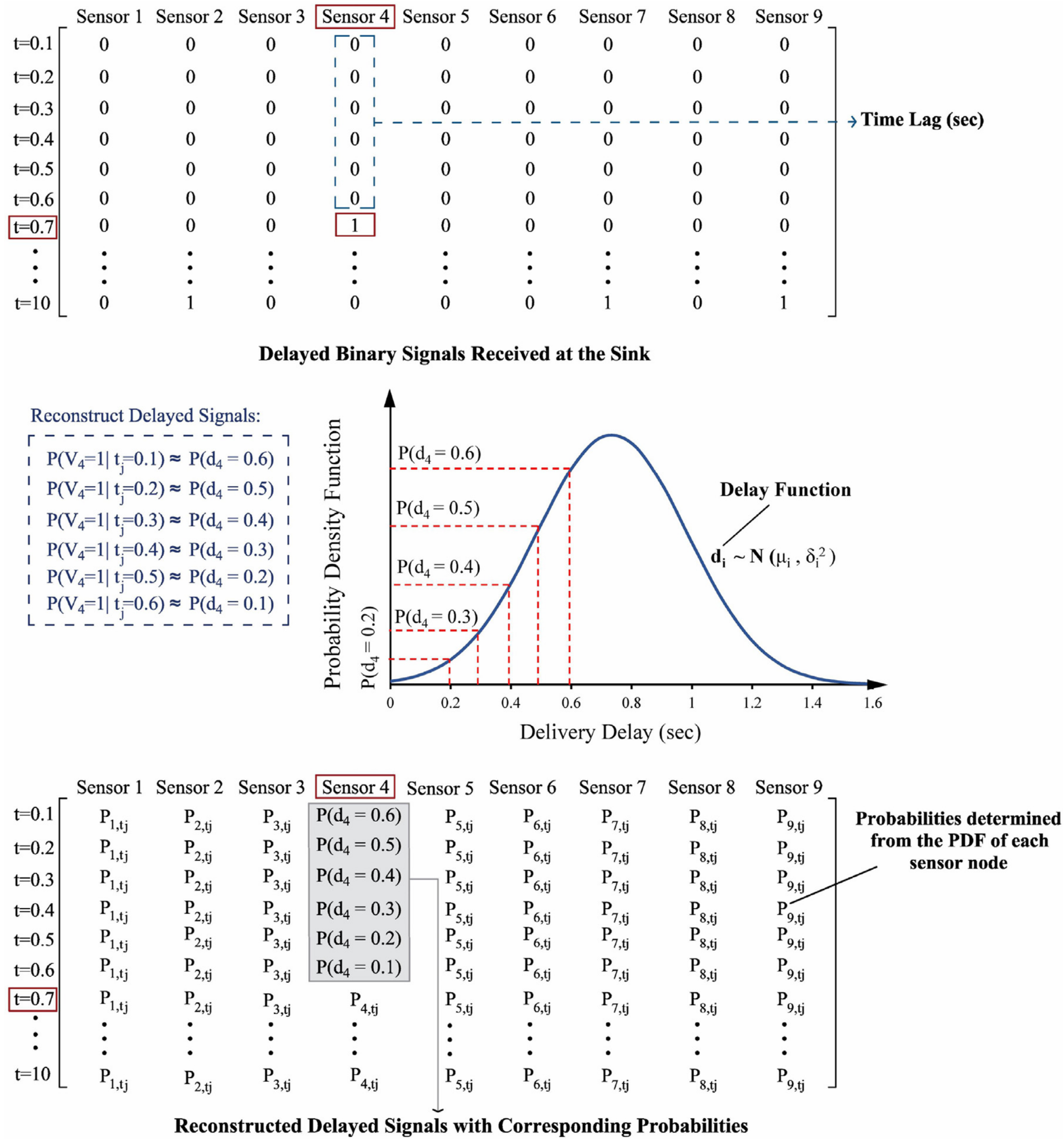

Fig. 8. Schematic of a proposed probabilistic approach for delayed signal reconstruction.

using the proposed probabilistic algorithm, support vector machine (SVM) is employed to detect damage and to classify the reconstructed signals. It is noted that the classification with SVM is based on probability values and not binary signals.

4.3. Classification with SVM algorithm

Support vector machine (SVM) is one of the well-established learning algorithms for pattern classification (Cortes & Vapnik, 1995). SVM is able to achieve good performance as it uses the structural risk minimization principle, while it introduces a kernel trick (Salehi & Burgueño, 2018). SVM is attractive for structural damage identification due to its effectiveness and robustness when dealing with insufficient information, noise, and uncertainty. Yan et al. (2014) reported on the use of back-propagation neural networks and SVM for damage assessment in beams mounted on ocean platforms. Liu, Liu, & Liu (2009) studied SVM for damage detection of a long span cable-stayed bridge and demonstrated that SVM is more accurate compared to a back-propagation neural network. Therefore, SVM was used in this study to detect damage due to the following main reasons:

- SVM has a regularization parameter to avoid over-fitting, while it generalizes new samples well if appropriate parameters are chosen
- Unlike other AI methods (e.g., neural networks), which produce multiple solutions based on local minima, SVM is guaranteed to converge to a unique global solution.
- The SVM optimization technique is based on convex optimization to prevent local minima problems.
- If linear decision hyperplanes are not adequate to separate the classes SVM projects the input data into a high dimension feature space, thus resulting in a nonlinear classifier.
- SVM uses a kernel trick, thus making the user able to design different kernels for the decision function via an engineering approach.

Algorithm A Probabilistic Approach for Reconstruction of Delayed Signals

Input: An $m \times n$ matrix A which includes delayed binary signals, where m is the number of time steps and n is the number of sensors in the network.

1. **for** each sensor S_i (i=1,2,…,n) **do**

   Compute the average delivery μ_i and standard deviation σ_i of delay function d_i.

   Given a Gaussian distribution for delivery delay values, determine the probability density function (PDF) using a Gaussian distribution for each sensor node S_i.

   if ($A(m,n)=0$) at time t

   Assign a probability of 0.05 for a probability value, $A(m,n)=0.05$.

   end

   if ($A(m,n)=1$)

   Introduce a *lag factor (l)* to determine the time that we need to go behind the current time t_j (j=1,2,…,m) to capture the delay and to combine the probability of getting binary event (1) with delay that we anticipate.

   Determine the probability that the value of sensor i at time $t=j$ is 1 given a delay function d_i as $P(t_j^i=1|d_i)= P(S_i=1|j=1)$ in order t to model delay.

   Compute the probability that the binary signal (1) observed at time j comes from time j to $j-(l-1)$; calculate $P(S_i=1\backslash d_i=0)$, $P(S_i=1|d_i=1)$,.., $P(S_i=1|d_i=l-1)$ using the PDF values determined for each sensor S_i.

   end

   end

2. Output an $m \times n$ matrix V including the determined probabilities which are used for classification.

Fig. 9. Implementation of the proposed algorithm for signal reconstruction.

The SVM problem originated from a supervised binary classification, in which most of the solutions are evaluated by obtaining a separating hyperplane among classes. To express the SVM it can be assumed that $T=\{(x_i, y_i):\ i=1,\ldots,N\}$ denotes a training data set consisting of an N number of m-dimensional extracted feature vectors $x_i \in R^{m\times 1}$, and the corresponding labels of these feature vectors are $y_i \in \{-1,\ 1\}$). It is noted that N is the number of training samples. The goal of the SVM model is to find the separating boundary between two data classes by maximizing the margin between the decision/separating hyperplane and the datasets, as illustrated in Fig. 10, while minimizing the misclassification. The decision hyperplane can be defined as (Vapnik, 1998):

$$w^T x + b = 0 \tag{3}$$

where w and b denote the weight vector defining the direction of the separating boundary and bias, respectively. The constraint for classification in the original feature space can be stated as:

$$y_i(w^T x_i + b) \geq 1 \tag{4}$$

For the SVM, the decision function is expressed according to the following equation:

$$f(x) = \mathrm{sgn}(w^T x_i + b) \tag{5}$$

Accordingly, $\mathrm{sgn}(\alpha)$is defined as:

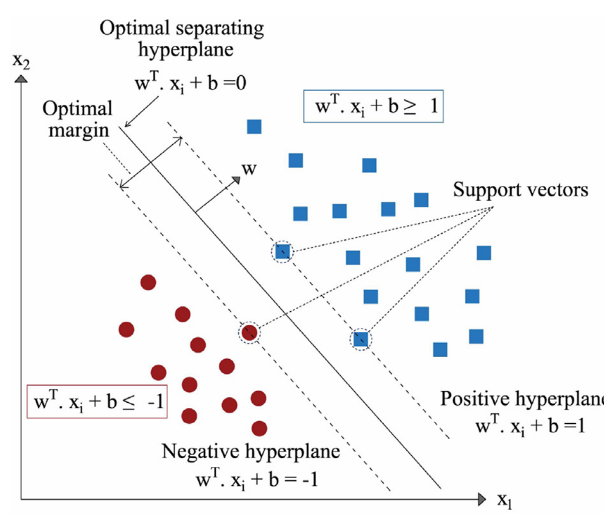

Fig. 10. Schematic illustration of the SVM with optimal margin and separating hyperplane.

$$\mathrm{sgn}(\alpha) = \begin{cases} 1, & \alpha \geq 0 \\ -1, & \alpha < 0 \end{cases} \tag{6}$$

SVM attempts to maximize the margin by minimizing $\|w\|$, thus resulting in the following constrained optimization problem:

$$\min_{w,\xi} \tau_1(w,\xi) = \min_{w,\xi} \left[\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \right]$$

$$\text{subject to } y_i(w^T x_i + b) \geq 1 - \xi_i\ ,\ \xi_i > 0,\ C > 0,\ i = 1, \ldots, N \quad (7)$$

where $\tau_1(.)$, $\|.\|^2$, and ξ_i refer to the objective function, L_2-norm, and slack variable, respectively.

Misclassification is decreased by minimizing the non-negative slack variables in Eq. (7). Further, C denotes the regularization parameter that balances the significance between the maximization of margin and the minimization of the misclassification error. Introducing a Lagrange multiplier α leads to following optimization problem:

$$\min_{\alpha} W(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j \left(x_i, x_j\right) - \sum_{j=1}^{N}\alpha_j$$

$$\text{Subject to } \sum_{i=1}^{N}\alpha_i y_i = 0,\ 0 \leq \alpha_i \leq C \quad (8)$$

Accordingly, the corresponding decision function can be written as:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i (x_i^T x) + b \right) \quad (9)$$

SVM is able to offer an alternative solution for pattern classification when the data is linearly inseparable. In this regard, SVM uses a kernel trick method that projects the data into a higher dimensional feature space, such that the data becomes divisible. If $\Phi(.)$: $R^o \to R^h$ represents the projection/mapping from the original into the high dimensional feature space, the inner product of the original space $x_i^T \cdot x$can be substituted by the inner product of the transformed space $\Phi^T(x_i) \cdot \Phi(x)$. Yet, it is computationally inexpensive to evaluate the inner product of the transformed space. Therefore, a kernel function provides an effective path to overcome this difficulty, such that a kernel function $K(\cdot)$ satisfies the Mercer theorem as shown in Eq. (10):

$$K(x_i, x_j) = \Phi^T(x_i) \cdot \Phi(x_j) \quad (10)$$

There after, the decision function can be defined as:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \right) \quad (11)$$

In fact, the kernel function defines the nonlinear mapping from the input space into a high dimensional feature space. Typical kernel functions include linear, polynomial, radial basis, and sigmoid functions. In the present study, SVM is used for damage classification using the probabilities determined as the output of the algorithm presented in Fig. 9.

5. Results and discussion

To examine the effectiveness of the SHM system on a realistic structure, experimental validation was conducted using event-based time-delayed binary signals. The experimental dataset for the analysis was randomly divided into three subsets: training, validation, and testing. Further, k-fold cross validation was used to prevent overfitting problems. In this research, 10-fold cross-validation (assuming $k = 10$) was used. Vibration tests were conducted for 10 s with a time step of 0.01; therefore, the size of dataset was 1000. To implement the SVM algorithm, the dataset (patterns) was classified into 7 classes. Classes 4 to 6 represented patterns due to normal condition of the plate, classes 1 and 3 denoted patterns due to damage, and class 2 represented noisy and time-delayed patterns. Matlab (2014) was utilized for implementing the method and algorithms. The damage detection accuracy with SVM was determined according to Eq. (12). Results are presented in terms of different measures, namely: confusion matrices, the receiver operating characteristic (ROC) curve, and the cumulative match characteristic (CMC) curve.

$$\textit{Damage Detection Accuracy} = \frac{\textit{Number of patterns correctly classified}}{\textit{Total number of patterns}} \quad (12)$$

5.1. Results of PR approach

An image-based PR was used to recognize patterns representing different conditions of the experimental plate. The identified patterns are presented in Fig. 11, where patterns 1 and 2 denote normal conditions, pattern 3 was due to noise and time delay, and patterns 4 to 6 were recognized due to damage (i.e., damaged plate with varying hole diameters). The blue and grey regions in the figure denote active and inactive sensor nodes, respectively, whereas red regions represent the binary signals generated due to damage (hole) in a cantilever plate.

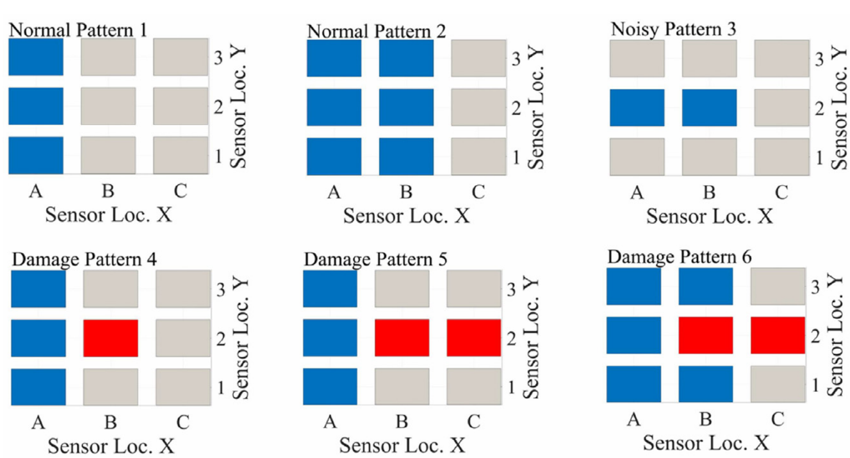

Fig. 11. Identified patterns on experimental plate using image-based PR approach. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

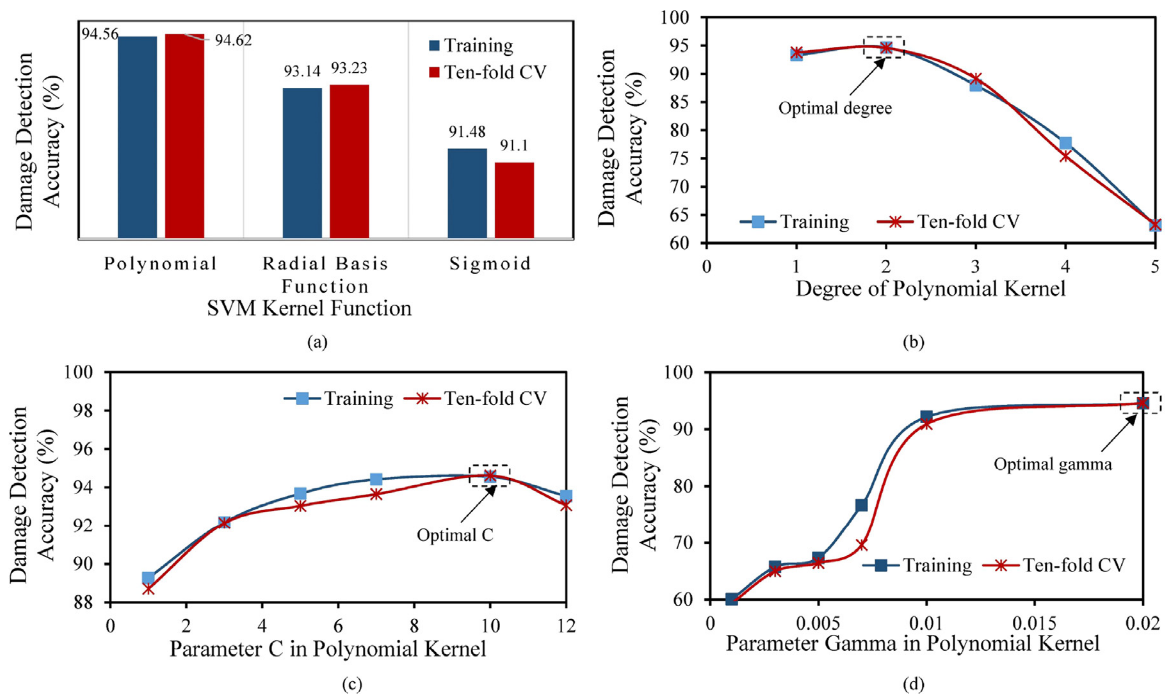

Fig. 12. (a) Selection of optimal kernel parameter, (b) Tuning optimal kernel degree, (c) optimization of the kernel parameter C, and (d) Optimization of the kernel parameter γ.

5.2. Results of SVM classification

It is of importance to select the optimal hyper-parameters of the SVM algorithm. On this basis, grid-search on C and γ (i.e., kernel parameters) was conducted in this study using 10-fold cross-validation. Several pairs of (C,γ) were thus used, and the pair with best cross-validation accuracy was selected as optimal hyper-parameters. The training and validation data sets were used to optimize the regularization and kernel parameters. Different kernel functions, i.e., polynomial, radial basis function (RBF), and sigmoid, were utilized for implementing the SVM method. However, as shown in Fig. 12(a), performance with the polynomial kernel was found to be superior compared to other kernels; where the maximum accuracy (polynomial kernel) was 94.62% and 94.56% for the validation and training data set, respectively. The optimal degree of the polynomial kernel function was determined through the optimization process, with the best degree value found being 2 (see Fig. 12(b)).

Once the polynomial kernel was selected as the optimal kernel, the grid-search with 10-fold cross validation for different pairs of (C,γ) was conducted to determine the optimum kernel parameters. Consequently, the noted hyper-parameters were tuned through the optimization process. Results from the grid-search in terms of the variation of the damage detection accuracy as a function of the kernel parameters C and γ are presented in Fig. 12(c) and (d). As can be seen, the best damage detection accuracy was achieved for a polynomial kernel with $d=2$, $C=10$, and $\gamma=0.02$. The noted values were thus selected and used as the optimal SVM hyper-parameters.

As previously noted, the dataset was randomly divided into three subsets. In addition, the effectiveness of the approach with respect to size of the subsets was also explored. In this context, the dataset was divided to four different cases as follows:

- Case 1: training & 10-fold cross validation (70%), test (30%)
- Case 2: training & 10-fold cross validation (75%), test (25%)
- Case 3: training & 10-fold cross validation (80%), test (20%)

Table 1
Damage detection accuracy for different time lags.

Time lag (sec)	Data pre-processing	Damage detection accuracy (%)		
		Training	Ten-fold CV	Test
3	Case 1	71.64	69.93	78.19
	Case 2	73.74	72.15	79.96
	Case 3	75.18	73.58	83.09
	Case 4	75.4	74.20	85.86
4	Case 1	94.56	94.62	95.41
	Case 2	94.89	94.74	96.40
	Case 3	95.23	94.58	97.63
	Case 4	95.51	95.17	97.30
5	Case 1	92.40	92.30	92.63
	Case 2	92.24	91.97	93.14
	Case 3	92.36	91.73	94.02
	Case 4	92.33	91.64	96.24

- Case 4: training & 10-fold cross validation (85%), test (15%)

Confusion matrices for the actual/target and predicted/output classification results using SVM were determined for different data subset sizes and shown in Fig. 13. Results reveal that SVM is able to identify damage with good classification accuracy. Nonetheless, the best classification accuracy was achieved based for Case 2 (97.6%), where the error for damage class 1 was 8.2%.

The effect of time lag parameter on the performance of the SHM method was also assessed. As previously noted, the size of data set was 1000. Therefore, time lags of 3, 4, and 5 s imply that 300, 400, and 500 readings, respectively, were considered. Results of damage detection accuracy with different time lags based on noted cases are presented in Table 1, from which it can be observed that by damage detection accuracy increases by increasing the number of samples in the test set (e.g., from 92.63% to 96.24% for cases 1 to 4 and a time lag of 5 s.) The best classification result was for the time lag of 4 s, which was 97.63% for case 3.In other words, the highest classification accuracy was achieved when, after a sensor received a binary signal, the probabilities of the previous 400 readings are computed and used to reconstruct the signals.

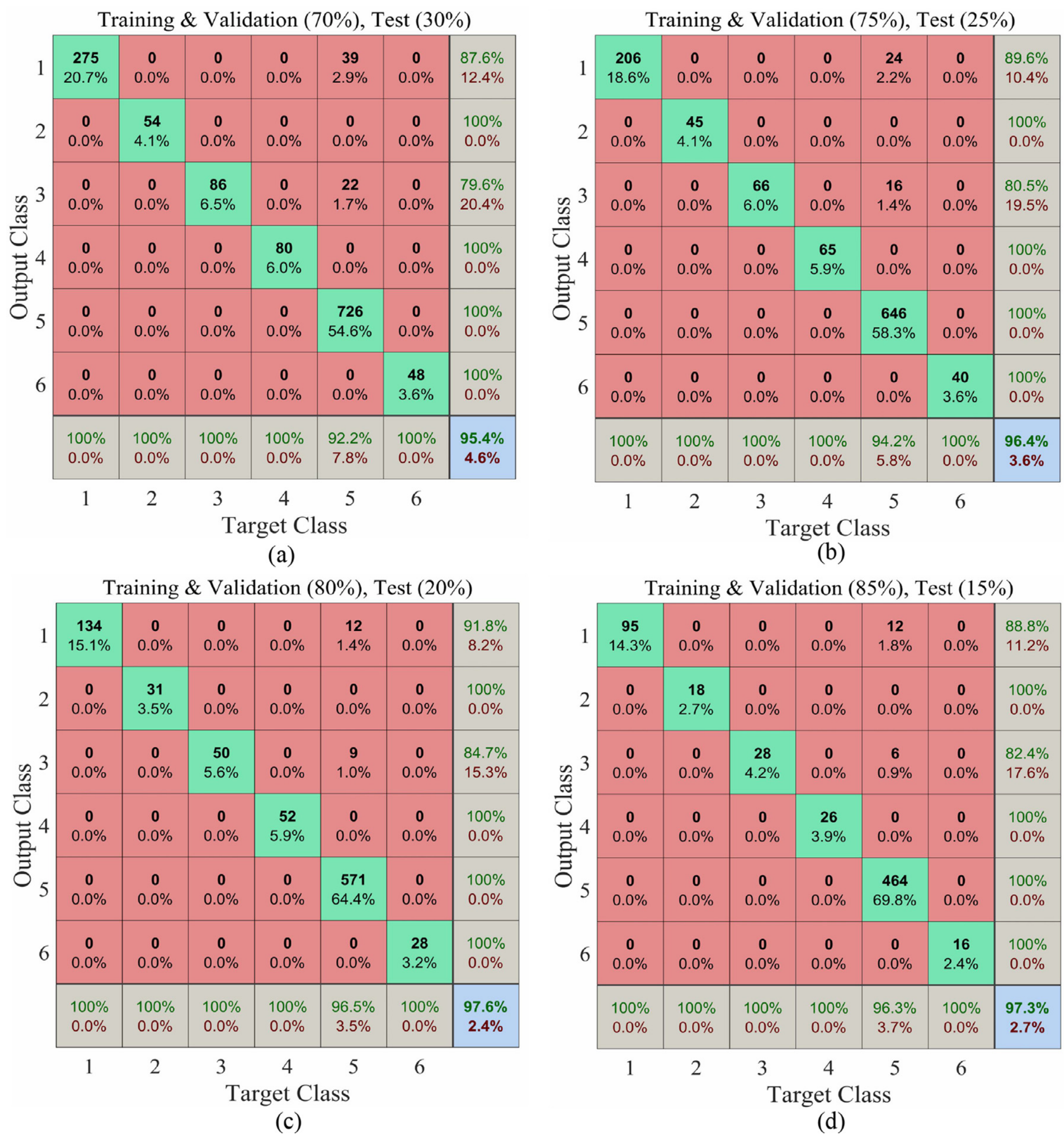

Fig. 13. Confusion matrix using SVM for different size of data subsets.

The receiver operating characteristic (ROC) (Bradley, 1997; Fawcett, 2006) based on SVM was determined and plotted. The area under the ROC curve (AUC) is a metric used to assess a classifier's performance; such that an AUC value close to 1 indicates better classification performance. ROC curves for all cases (1 to 4) and damaged classes are shown in Fig. 14 for a time lag of 4 s. Although good damage classification accuracy was obtained for all cases, case 3 (training & validation (80%), test (20%)) had the best performance, as its UAC value was slightly higher than the other cases. In summary, classification results, i.e., confusion matrices and ROC curves, indicate good performance of the proposed SHM methodology, even with time-delayed data.

The cumulative match characteristic (CMC) curve (Bowyer, Chang, & Flynn, 2006), a rank-based metric, was computed. To determine a CMC curve, each test data is compared to each class, and the resulting scores are ranked. The rank at which a true match occurs is determined, while the probability of observing the correct classification within top ranks is computed. Plotting the noted probabilities against ranks yields a CMC curve that represents the accuracy of the SVM classifier with different ranks. To this aim, multinomial logistic regression was utilized to compute the predicted probabilities for the model. CMC curves for different size of data subsets and damaged classes are presented in Fig. 15. Results indicate that the accuracy for the first rank for all of the cases is good, further confirming the satisfactory performance of the damage identification approach.

6. Conclusions and future studies

This paper presented a methodology for structural health monitoring (SHM) within the context of expert and intelligent systems with delayed signals from a novel through-substrate self-powered sensor network. The proposed expert system for energy-efficient SHM employs an intelligent data mining method merging an image-based pattern recognition (PR) approach, a probabilistic approach, and machine learning with a support vector machine

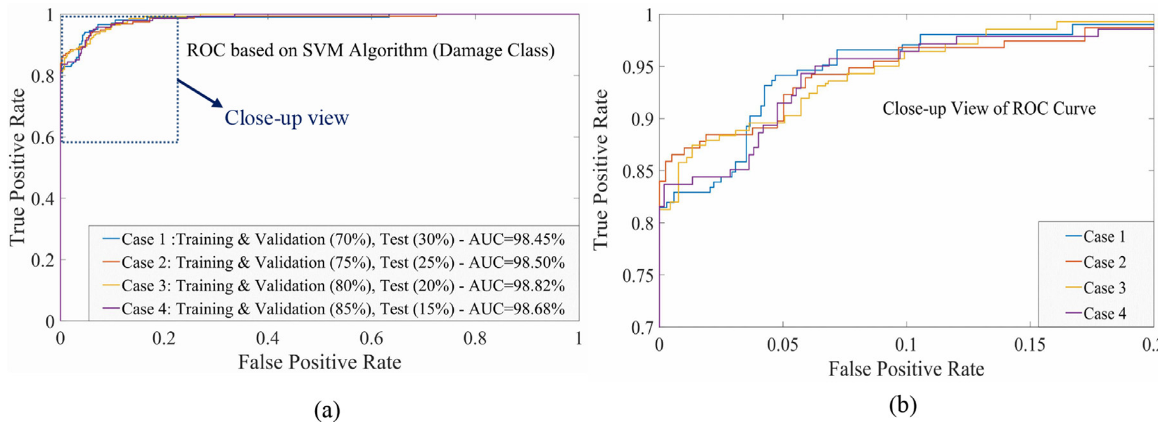

Fig. 14. (a) ROC curves based on SVM classification algorithm for different size of data subsets, (b) a close-up view of the ROC curves.

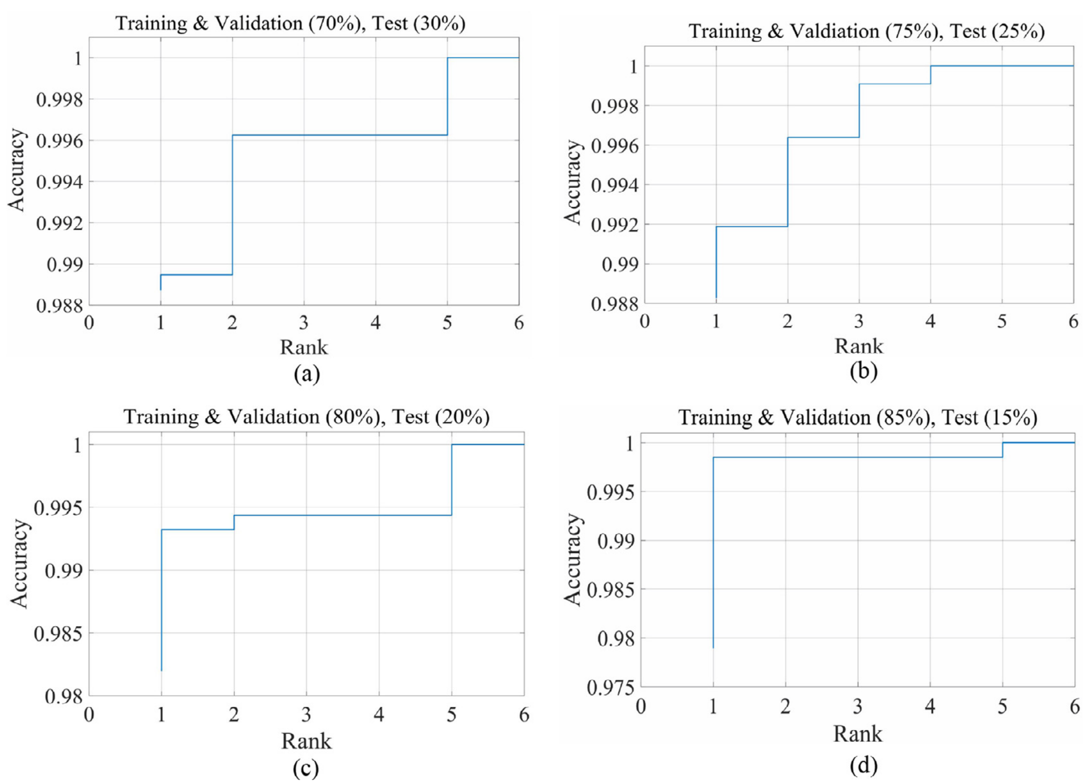

Fig. 15. CMC curve with SVM for different size of data subsets.

(SVM) algorithm. The PR approach is used to represent sensor node responses as a pattern, while a proposed probabilistic approach allows reconstruction of the time-delayed signals. SVM is used for damage classification with the reconstructed signals. The effect of size of the data subsets and time lag parameter, defined within the probabilistic approach on the SHM system's performance, was evaluated. Experimental vibration tests were conducted to explore and validate the applicability of the intelligent SHM system. The following conclusions were reached:

1) The distribution of the delayed signals is Gaussian. Further, results confirmed that the proposed probabilistic approach can be successfully used as part of the developed expert system to reconstruct delayed signals.
2) The time lag parameter has an effect on the performance of the approach. However, such effect was found to be minimum for the set up presented in this study.
3) Results of classification, confusion matrices, ROC, and CMC curves indicated that SVM led to acceptable damage detection accuracy with noisy and delayed signals.
4) Damage classification accuracy on the test set increased with an increase in the number of data in the set.

The presented study demonstrated that the proposed SHM system can be effectively used within the context of expert and intelligent systems for damage identification with noisy and delayed binary signals. Results evidently indicated that the developed expert system for SHM can be employed to reconstruct delayed and noisy signals in the application to a practical engineering problem, i.e., data-driven SHM. Development of the expert system presented in this paper significantly addressed the important issue of energy availability for intelligent systems being used for structural/infrastructure health monitoring and aerospace monitoring. This study also contributed to promote data mining and signal processing techniques in the SHM domain, demonstrating a practical application of expert and intelligent systems in such domain. Unlike other expert systems studied for SHM, for which the performance of the system strongly depends on continuous data/signal availability, the developed intelligent SHM system shows satisfactory performance, even with noisy and incomplete signals. This clearly indicates the significance of the proposed expert system for data-driven SHM. However, there are still some challenges that are the focus of on-going studies. Particularly, the proposed intelligent SHM system should be evaluated in full-scale experiments using the through-substrate sensor network to validate its efficiency.

The PR approach used in this study is a supervised learning algorithm based on the labeled patterns. A future research topic will focus on evaluating the applicability of unsupervised machine learning methods for an intelligent SHM platform for the cases where target classes are unknown. To this aim, an investigation on unsupervised learning algorithms is being conducted to select the best algorithm leading to highest damage classification accuracy. Besides, future work should be done using dimensionality reduction techniques such as principal component analysis and independent component analysis to reduce the dimension of the feature space, thereby optimizing the required time consumption. Finally, future research topics should incorporate feature extraction techniques with the developed expert system to extract the most significant features and generate an optimal subset of features, which will lead to a notable improvement in the SHM system's performance and an increase in computational efficiency of such intelligent systems.

Conflict of interest

None.

Credit authorship contribution statement

Hadi Salehi: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing - original draft, Writing - review & editing. **Saptarshi Das:** Investigation. **Subir Biswas:** Funding acquisition, Project administration. **Rigoberto Burgueño:** Conceptualization, Methodology, Funding acquisition, Project administration, Investigation, Resources, Supervision, Writing - review & editing.

Acknowledgment

The research described in this paper was carried out with funding from the U.S. National Science Foundation under grant number CNS-1405273. The auhors thank Prof. Arun Ross (MSU) for his suggestions on the probability approach for delayed signal reconstruction.

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