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Research paper

Data Mining-based Structural Damage Identification of Composite Bridge using Support Vector Machine

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Abstract

A structural health monitoring system contains two components: a data collection approach comprising a network of sensors for recording the structural responses and an extraction methodology in order to achieve the beneficial information on the structural health condition. In this regard, data mining, which is one of the emerging computer-based technologies, can be employed for extraction of valuable information from the sensor databases obtained. On the other hand, the data inverse analysis scheme, as a problem-based procedure, is developing rapidly. Therefore, the aforesaid scheme and data mining should be combined in order to satisfy the increasing demand of data analysis, especially in complex systems such as bridges. In this work, we develop a damage detection methodology based on these strategies. To this end, an inverse analysis approach using data mining is applied for a composite bridge. In order to aid the aim, the support vector machine algorithm is utilized to generate the patterns by means of the vibration characteristic dataset. In order to compare the robustness and accuracy of the predicted outputs, four kernel functions including the linear, polynomial, sigmoid, and radial basis functions are applied to build the patterns. The results obtained point out the feasibility of the proposed method for detecting damage in the composite slab-on-girder bridges.

1. Introduction

Damage can occur in any in-service structural components such as beams, pipes, and plates or complex systems, e.g. the civil infrastructures, aeronautics industry, oil and gas sector, transportation assets, and mechanical productions during the service life of the system. This is due to the fact that the structural systems are damage-prone under a number of vibrational motions involving static and dynamic forces caused by earthquakes, wind excitations, etc. [1]–[3] Consequently, these unwanted seismic impacts are one of the most significant sources in changing the structural properties such as damping, stiffness or mass and lading to shift the dynamic properties (i.e. natural frequency, mode shape, and damping ratio) [4], [5]. Besides, they can cause out-of-service conditions and catastrophic structural failure with high potential security risks for the residents. In order to overcome such difficulties, the structural health monitoring (SHM) systems have been proposed and developed in order to ensure structural safety, serviceability, and integrity as well as minimal maintenance [6], [7]. Various damage assessment methods have been applied to the structural systems. For example, visual inspection is a typical as well as popular non-destructive SHM evaluation system. However, it has many limitations including being time-consuming, costly, and with limited efficiency due to the inaccessibility of some structural damage locations. Therefore, an exceptional strategy with beneficial features is required to track the health condition and safety of the monitored structures [8].

The data mining technology is a promising innovative computational tool that is qualified for the data extraction process. It is because data mining is able to accurately find out the informative features, i.e. knowledge from the generated databases [9]. In the same line, this technology can also extract the significant relationship amongst raw sensor datasets in SHM. For the purpose of the aforementioned implementation, there is a vital requirement to have an appropriate data mining algorithm along with a well-organized model. In this regard, a number of tools exist, e.g. Knowledge Discovery in Databases (KDDs) and DMAIC that represents the Define-Measure-Analyze-Improve-Control, Cross-Industry Standard Process for Data Mining (CRISP-DM), and SEMMA that stands for Sample-Explore-Modify-Model-Assess [10]. It has been reported that CRISP-DM is the most applicable methodology [11], [12].

Over the last decade, the kernel-based machine learning algorithms, e.g. support vector machines (SVMs) have been widely used in various applications including hand-written digit recognition, image processing, object recognition, text classification, cancer diagnosis, bioinformatics, structural control systems, structural damage detection, etc. This is due to the fact that SVMs have an acceptable performance and a reliable distribution fitness. Hence, they can successfully cover a wide range of applications in terms of predictability [13].

In this work, the capability of data mining in SHM is investigated in order to develop the robustness of damage identification approaches. To do so, a composite bridge structure is considered as the test specimen of this work in order to generate a dataset. Besides, the CRISP-DM methodology and SVM are employed for implementation of the data mining procedure as a systematic methodology and applicable algorithm, respectively. In this direction, the experimental modal analysis of test structure is performed to generate the modal parameters as the input database for the data mining process. A number of damage cases are conducted in order to predict the damage severity. Then SVM is implemented in four patterns using different kernel functions, i.e. Linear SVM, Sigmoid SVM, Polynomial SVM, and RBF SVM. Furthermore, numerical simulation is implemented in order to verify the experimental findings. Then a comparison is carried out to evaluate the patterns. It is shown that among all the models, the SVM-Polynomial algorithm is able to identify the severity of damage precisely.

2. Development of Data Mining-based Models

Data mining is an exploration process with the aim of achieving an understandable and valuable information from raw data [14]. In this direction, a comparison between data mining and gold mining in rivers was made. It is because finding a pattern in datasets is quite similar to look for gold in sands. Therefore, data mining has gained increasing attention in different fields of research due to its high computation abilities. It is worth noting that according to the history of data mining, its origin starts from advances in artificial intelligence in 1950s [15].

Data mining is a hybrid process that combines the technologies of machine learning, signal processing, and statistical computing. It is driven by the demand of modern methods to analyze, identify, and visualize the datasets [16]. Overall, the data mining-based models can be divided into several categories, i.e. the descriptive, predictive, prescriptive, and hybrid paradigms. Every single category has its particular functions such as prediction, clustering, classification, association, and exploration [17]. Besides, each function has a number of algorithms to run. For example, prediction, which is one of the most applicable functions in data mining, has been frequently applied by machine learning, artificial intelligence, and statistical algorithms, i.e. artificial neural network, support vector machine, imperialist competitive algorithm, fuzzy logic, Bayesian, principal component analysis, ant colony optimization, genetic algorithm, decision tree, particle swarm optimization, and regression analysis for the structural damage identification purpose. In this direction, a comprehensive review of the latest advancements in structural damage identification through data mining has been presented by Gordan M. *et al*. [18].

3. Methodology

Data inverse analysis is eventually developing quickly [19]. By taking advantage of this fact, the SHM systems are required to be combined with the data mining technology in order to fulfil the increasing demand of data analysis, especially in complex systems, e.g. bridges. Based on this strategy, this work develops a damage detection methodology inspired by the structure of the CRISP-DM methodology. According to this model, the first step starts with introducing the laboratory work and collecting an initial data. In this manner, the modal parameters, i.e. natural frequencies acquired by a series of experimental tests are used in the function of inputs intended for data mining modeling. The next level is pre-processing the collected data through several processes such as selecting, constructing, formatting, and transforming the data in order to prepare the final dataset as the input for the modelling step. It should be noted that the dataset is divided into two partitions, i.e. 70% for the training and 30% for the testing sets. Linear SVM, Sigmoid SVM, Polynomial SVM, and RBF SVM are used in the modelling step in order to build the patterns. Then the accuracy of the patterns is evaluated to find the most precise model.

3.1. Support Vector Machine (SVM)

SVM is one of the most applicable data mining algorithms. The main novelty of this method comes from the point that SVM is able to create a reliable performance along with a respectable generalization capacity [20], [21]. Accordingly, there is a high demand to apply this algorithm in different fields, e.g. pattern recognition, classification of data, and machine learning.[22]. The reason for this comes from the fact that SVM is capable of generating valuable outputs to answer a variety of problems occurring in different applications. For example, a number of SVM applications in SHM include damaged identification-based SVM [23], wavelet-based damage identification using SVM [24], non-linear multiclass SVM–based SHM for smart structures [25], and dams crack monitoring [26].

The main goal of the simplest SVM model is to locate a linear hyperplane through the best margin. The best margin is defined as the maximum gap between two sets of data. To this end, a dataset can be considered containing circles and squares (x_i,y_i), $i = 1,\dots, N$ including input data $x_i \in R_n$ and output (class label) $y_i \in R$. R_n represents the N-dimensional vector space, and R indicates the 1D space that is $\{-1,+1\}$. The separating hyperplane, which is a linear discriminant function, is formulated as follows.

$$(w.x) + b = 0, \;\; w \in R^n, \;\; and\ b \in R \tag{1}$$

where w represents an orthogonal vector and b stands for a bias value.

It should be noted that Eq. (1) cannot be considered as an adequate solution to define the separating hyperplane individually. Therefore, the optimal separating hyperplane is required to be obtained by solving an optimization problem, as defined in Eq. (2). In the same line, the linear SVM model divides the given dataset into two parts without any data point between them. As stated earlier, this maximal space between the aforementioned parts is called margin, and can be written as follows:

$$\begin{aligned} &\text{Minimize to:} && \frac{1}{2}\|w\|^2 \\ &\text{Subject to:} && y_i(w.x_i + b) \geq 1, i = 1,2,\dots,N \end{aligned} \tag{2}$$

and the margin can be formalized as follows:

$$\text{Margin} = \frac{2}{\|w\|^2} \tag{3}$$

However, as it can be observed in Figure 1, linear SVM cannot be used when the data cannot be separated linearly. Consequently, a non-linear discriminant function $\phi(x)$ is required to map the input data x_i to a higher-dimensional feature space. The advantage of using the non-linear function is that the mapped data may be linearly separated using the following Equation instead of Eq. (1):

$$(w.\phi(x_i)) + b = 0 \tag{4}$$

Nevertheless, the non-linear mapping function does not generally allow a flexible recognition because even when the input data x_i contains a reasonable dimension, the dimension of feature space may raise extremely. Then the calculation may become impossible, which is so-called "curse of dimensionality". In order to overcome this limitation, an inner product of non-linear transformation, which is called kernel function $k(x)$, can be used in order to avoid the computational problem. This part of the modelling is well-known as the "kernel trick", and the kernel function is defined as follows:

$$k(x_i, x_j) = \phi(x_i)\phi(x_j), \;\; \forall i,j = 1,2,\dots,N \tag{5}$$

Figure 1 presents a two-feature input space, where a kernel function is implemented to map the data to a three-feature space (higher-dimensional feature space).

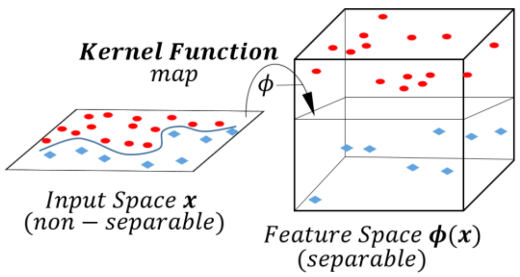

Figure 1. Mapping to higher-dimensional feature space.

The commonly used kernel functions in SVM, which are also employed in this work, are the Gaussian radial basis function (RBF) kernel, polynomial kernel, and sigmoid kernel, defined as:

$$K_{Polynomail}(x_i, x_j) = ((x_i . x_j) + 1)^d \tag{6}$$

$$K_{RBF}(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\sigma^2}\right) \tag{7}$$

$$K_{Sigmoid}(x_i, x_j) = \tanh(k(x_i . x_j) + c) \tag{8}$$

where σ is the width factor of the Gaussian radial basis function $\sigma > 0$, $d = 1, 2, \ldots, n$ and $c \geq 0$.

3.2. Experimental Test

A model of steel-concrete composite bridge was constructed and fabricated in the laboratory (see Table 1 and Figure 2). The experimental modal analysis of the composite bridge was conducted in heavy dynamic laboratory, University of Malaya (UM), in order to generate the frequency response functions of the intact and damaged specimen by means of dynamic excitation source, data acquisition system, and measurement sensors. A IMV VE-50 Electrodynamic shaker and VA-ST-03 power amplifier were employed as the dynamic excitation source. Besides, the OROS38 signal analyzer with 32 channels, a PCB 208C02 force transducer, and S100CS Wilcoxon single axis accelerometers were used as the data acquisition system and the measurement sensors, respectively. NVGate which is the OROS software platform, was employed in order to control all measurements. The setup of instruments for the experimental modal analysis is shown in Figure 3.

Table 1. Parameters of the specimen.

Element	Parameter	Value
Steel I beam	Flange width:	75 mm
	Section depth:	150 mm
	Flange thickness:	7 mm
	Web thickness:	5 mm
	Young's Modulus:	$2.1*10^{10}$ kg/m^2
	Poisson's ratio:	0.3
	Density:	7,850 kg/m^3
Concrete slab	Length:	3200mm
	Width:	1200mm
	Depth:	100mm
	Density:	2400 kg/m^3
	Strength:	37.43 MPa
	No. of beams:	3
Shear stud connector	Diameter of stud:	16 mm
	No. of studs:	16 (per beam)
	Spacing:	200 mm c/c
	Height:	75 mm
Mesh reinforcement	Diameter:	5 mm
	Spacing:	100 mm

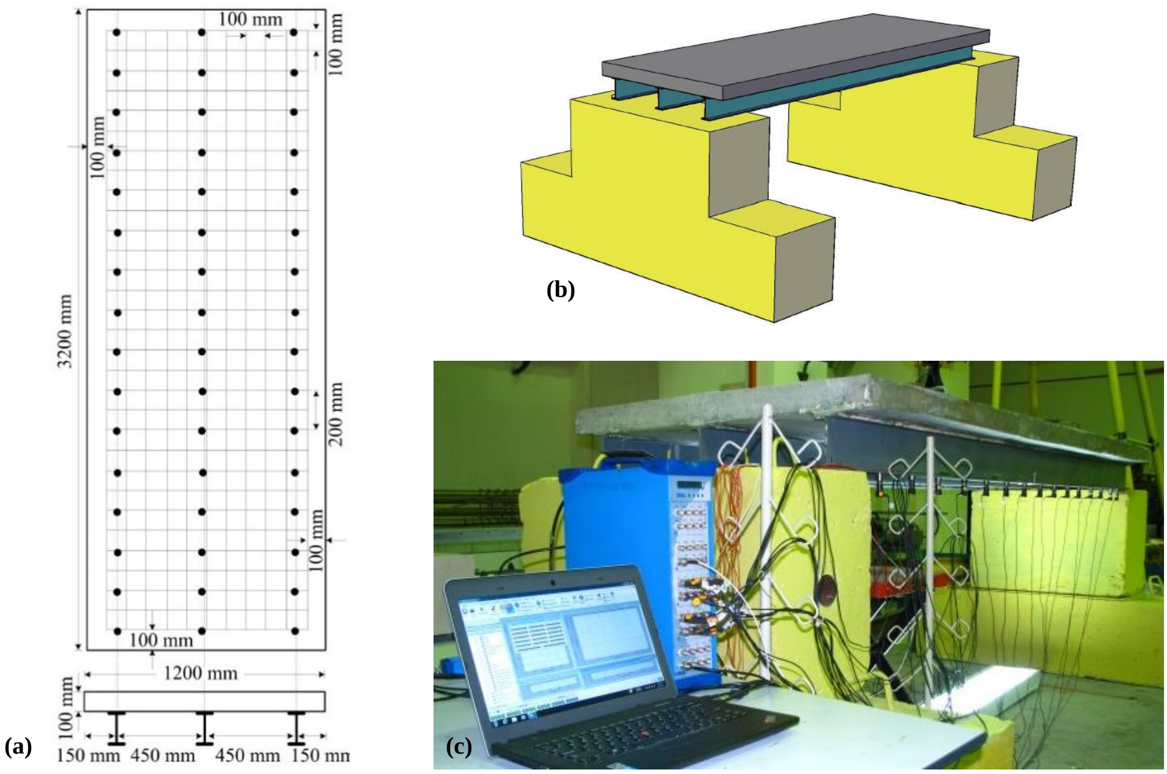

Figure 2. Experimental work: (a) layout plan of the composite bridge, (b) drawing of the experimental setup, and (c) physical observation of the vibration test.

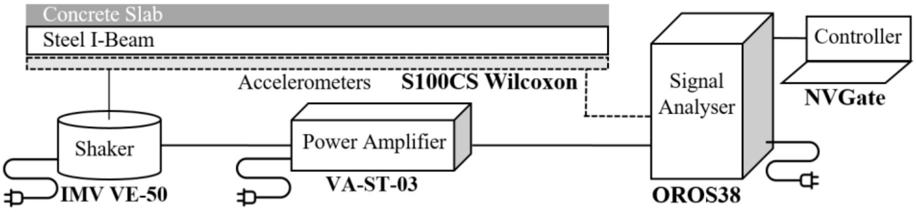

Figure 3. Illustration of the experimental modal analysis.

Figure 4(a) shows the arrangement of the accelerometers as well as the shaker location. As it can be seen in this figure, 48 nodes at the centerline of I section beams were selected in the role of sensor locations. Likewise, as it can also be observed in this figure, the shaker was located at point Number 19 due to the node points for the particular modes.

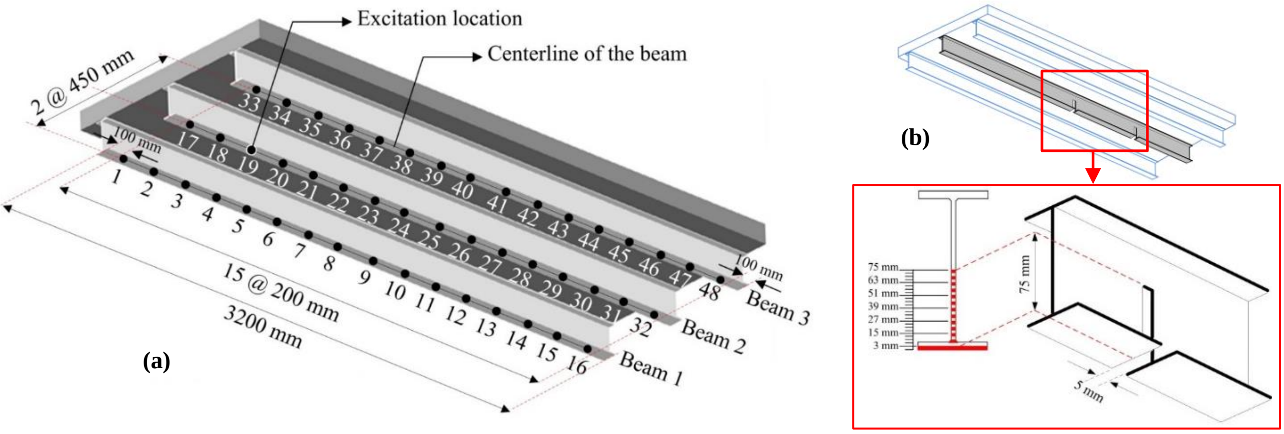

Figure 4. (a) Positions of accelerometers and shaker, and (b) conducted damage cases.

The experimental modal analysis of the intact specimen was conducted as a benchmark. Then various damage cases were imposed at two locations of the structure, i.e. mid-span and quarter-span of the middle steel I-beam (see Figure 4(b)). In this line, a total of 25 damage depths were conducted from a 3.00 mm severity up to a 75.00 mm depth. In detailed, the increment of damage depth was 3.00 mm, as shown in this figure. The outputs of the aforesaid process were employed in the function of input for modelling phase of data mining.

4. Results and Discussions

Modal parameters, i.e. natural frequencies of the intact and damaged cases of the composite bridge were collected from the experimental modal analysis. Table 2 and Figure 5 present the natural frequencies of the first mode to the fourth one in the undamaged and damaged test structure, respectively. The experimental results obtained indicate that in all modes, the natural frequencies decrease with increase in the damage severity. In this manner, the maximum drops of natural frequencies were 3.54% and 2.97% in the third and first modes, respectively. However, as it can clearly be seen in Figures 5(b) and 5(d), the changes of frequencies in modes 2 and 4 are less than the other modes. This behavior was plausible because both damage locations (mid-span and quarter-span) were the node points for the second and fourth flexural modes.

Table 2. Frequencies of the undamaged test structure.

1st Mode (f1)	2nd Mode (f2)	3rd Mode (f3)	4th Mode (f4)
31.60 Hz	255.19 Hz	389.75 Hz	558.59 Hz

A numerical simulation using the finite element package, ABAQUS, was implemented in order to verify the experimental findings deliberating the first four modes. The finite element simulation was precisely modelled as per the test specimen. I section beams have been modeled operating general-purpose 4-node shell elements, known as S4R utilizing the 432 and 371 nodes and elements, respectively. In addition, 8-node linear brick elements, i.e. C3D8R with 7533 nodes and 4800 elements were also used to build the girder deck model. For a better understanding, Figure 6 shows the experimental and numerical results in the 75.00 mm damaged state. Accordingly, the comparison of the numerical simulation and the experimental work is presented in Figure 7. It can be seen that the difference between the numerical and experimental results is less than 5%, which indicates the validity of this research work.

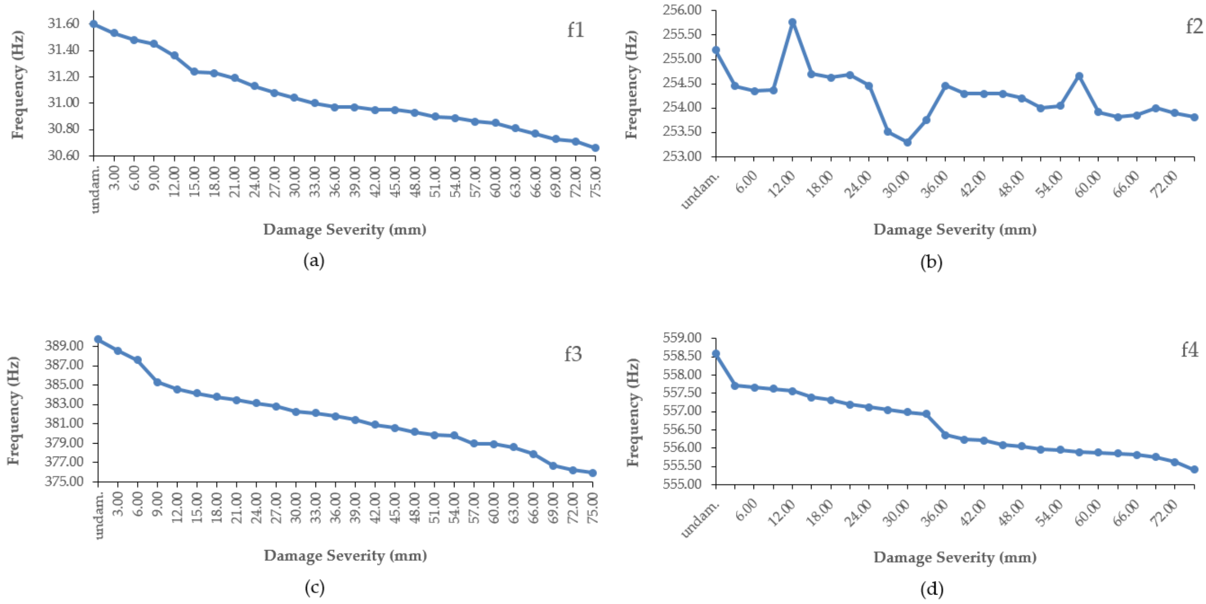

Figure 5. Natural frequencies of intact and damaged structure in the 1st four modes: (a) f1, (b) f2, (c) f3, and (d) f4.

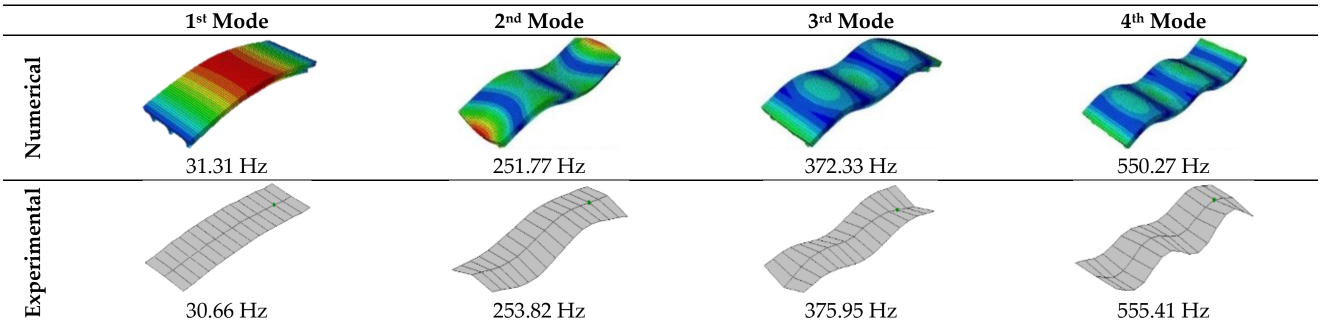

Figure 6. Experimental and numerical first four mode shapes.

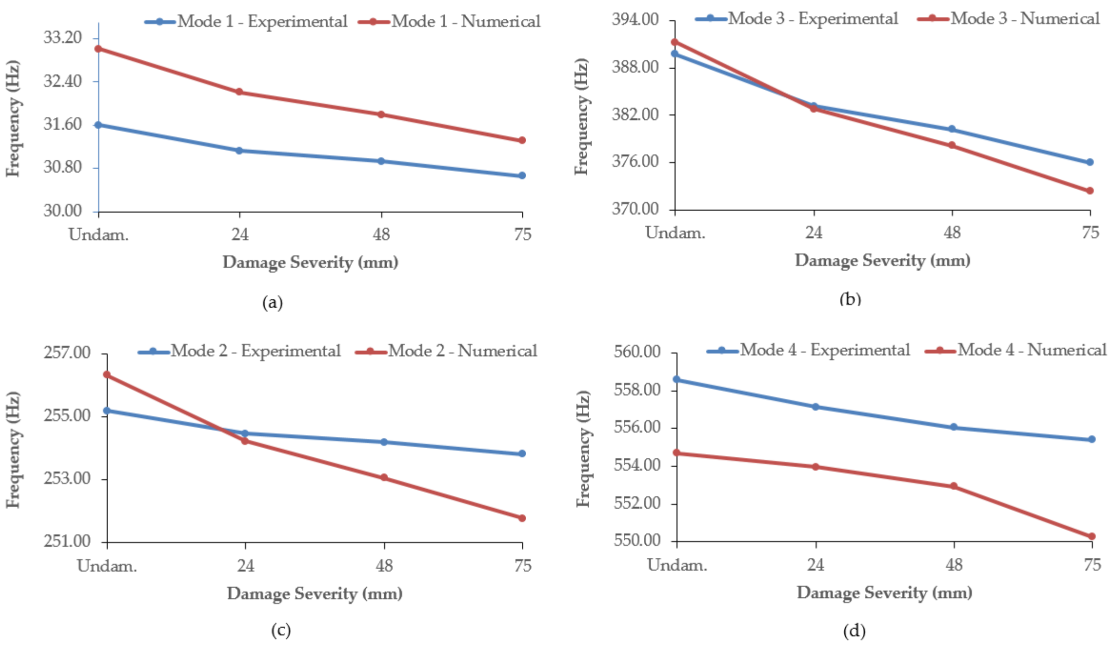

Figure 7. Evaluation of the experimental and finite element simulation findings in the (a) 1st mode, (b) 2nd mode, (c) 3rd mode, and (d) 4th mode .

As explained earlier, the SVM models were conducted by means of various kernel functions consisting of Linear, Sigmoid, Polynomial, and RBF. The first four experimental natural frequencies of the intact structure along with the damaged states (e.g. f_i, i = 1, 2, 3, 4) and the damage severities obtained from the laboratory works were considered as the inputs and the target variable of SVMs, respectively. Figure 8 demonstrates the results of four patterns, i.e. SVM-Linear, SVM-RBF, SVM-Polynomial, and SVM-Sigmoid. As shown in this figure, amongst all patterns, SVM-Polynomial achieved the most accurate predicted outputs in the first four flexural modes. In order to offer an explanation, the kernel functions were used in order to bring the data from a lower dimension to a higher dimension. To this end, the SVM classifier divided the data with a new plane, i.e. hyperplane. Therefore, despite the better learning power in the RBF kernel amongst others, this local function could not efficiency provide a satisfying dissemination. Instead, the polynomial kernel, which is a global function, performed a superior data dissemination strategy. Nonetheless, the learning process of the polynomial function experienced a lower level of learning capacity. For more clarity, Figure 9 indicates a comparison of the training and testing sets for all patterns. As it could be observed, among all the kernel functions, polynomial performed the best outputs.

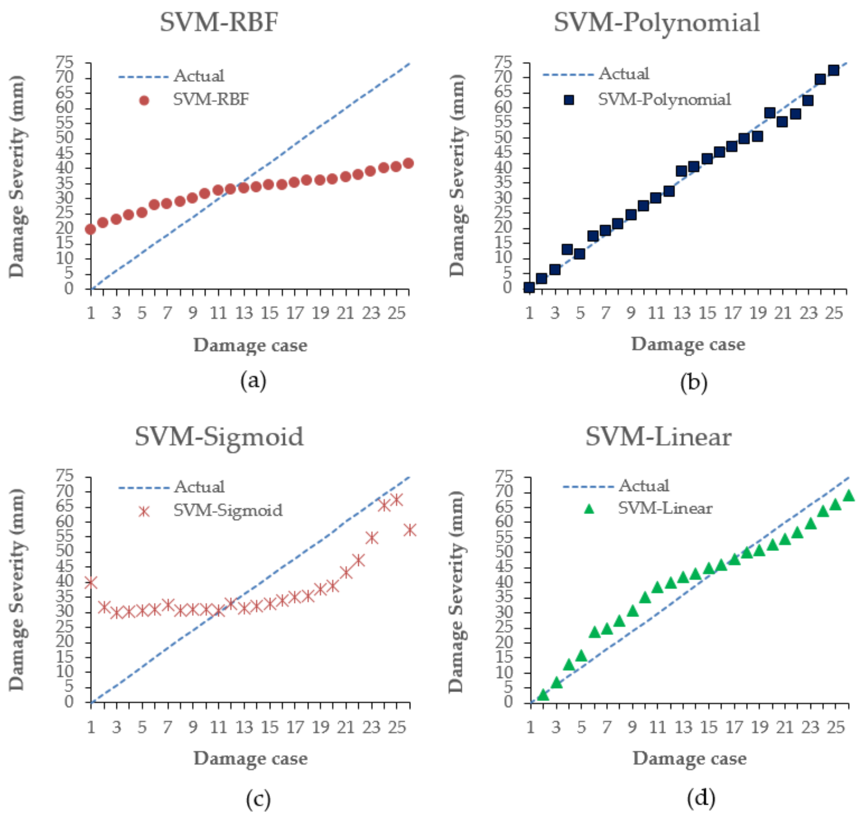

Figure 8. Comparison of outputs: (a) SVM-RBF, (b) SVM-Polynomial, (c) SVM-Sigmoid, and (d) SVM-Linear.

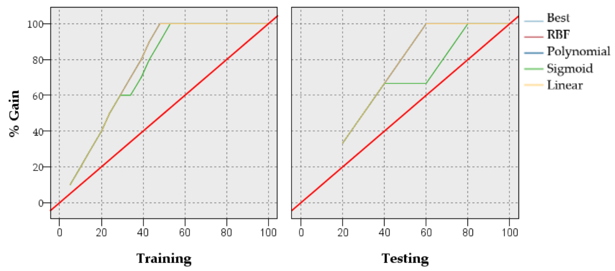

Figure 9. Comparison between different kernel functions.

Table 3 presents the predictor importance between the first four modes. According to this table, mode 1 had the most significant role in predicting process among all inputs with 28%, 33%, 30%, and 25% importance for Linear SVM, RBF SVM, Polynomial SVM, and Sigmoid SVM, respectively. Then in the second stage, the third mode showed a higher rate of importance in comparison to the fourth mode. On the other hand, mode 2 had the lowest importance in creating the patterns with importance of 23%, 19%, 18%, and 25% for Linear SVM, RBF SVM, Polynomial SVM, and Sigmoid SVM, respectively. This is due to the fact that mid-span, which was one of damage locations, was the node point for the second mode.

The performance of the patterns is required to evaluate the validity of the outcomes. To this end, the Mean Absolute Error (MAE), which is defined as bellow, was employed to determine the forecasting accuracy of all patterns.

$$MAE = \frac{\sum_{i=1}^{n} |actual_i - predicted_i|}{n} \quad (9)$$

As explained earlier, the input data was separated into the training and testing segments. Table 4 shows the modelling performance of each pattern in the training and testing sets. As it could be observed, the best MAE rates belonged to SVM-Polynomial, which were 1.265 and 2.601 for the training and testing, respectively. In addition, the outcomes of correlation values confirmed that the Polynomial kernel function gave the best prediction performance to SVM model.

Table 3. Predictor importance.

	SVM-Linear	SVM-RBF	SVM-Polynomial	SVM-Sigmoid
Mode 1	0.28	0.33	0.30	0.25
Mode 2	0.23	0.19	0.18	0.25
Mode 3	0.26	0.27	0.31	0.25
Mode 4	0.23	0.21	0.21	0.25

Table 4. Performance of patterns.

Model	Mean absolute error		Correlation	
	Training Segment	Testing Segment	Training Segment	Testing Segment
SVM-RBF	15.590	12.186	0.978	0.983
SVM-Polynomial	1.265	2.601	0.997	0.995
SVM-Sigmoid	20.714	15.600	0.764	0.811
SVM-Linear	4.981	3.994	0.977	0.982

5. Conclusions

In this work, we focused on the development of an advanced data mining-based damage detection approach suitable for continuous monitoring of the in-service structures. Different support vector machine models including linear-SVM through linear function and non-linear-SVM using kernel functions, i.e. polynomial, radial basis function, and sigmoid were conducted in this work. Based on the results obtained, it is confirmed that the proposed methodology is capable of forecasting the severity of damage in the composite bridge structures for the multiple-type damage scenarios.

The effectiveness of the kernel-based patterns was examined by the vibration characteristics of the test structure obtained from the laboratory tests. It should be highlighted that the experimental work was verified by the numerical simulation. The results obtained showed that the SVM-Polynomial and SVM-Linear patterns with the 1.265 and 4.981 MAE values in the training phase could provide the best solution, respectively. Likewise, the testing segment of the patterns proved the same result. It should also be emphasized that SVM-Polynomial delivered the most precise outcomes. It could also provide a good result for the minor damaged data. In contrast, SVM-Sigmoid and SVM-RBF performed the less accurate outputs with the 20.714 and 15.590 MAE values in the training process, respectively. It is because the local kernel-based functions are capable of a lower dissemination ability in comparison with the global-based kernel functions.

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شناسایی آسیب سازه ای در پل کامپوزیت مبتنی بر داده کاوی با استفاده از ماشین بردار پشتیبان

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چکیده:

یکی از سیستم‌های پایش سلامت سازه شامل دو جزء می‌باشد: رویکردی جهت جمع آوری داده‌ها متشکل از شبکه ای از حسگرها برای ثبت پاسخ‌های سازه و روش تحقیقی برای کسب اطلاعات مفید در مورد وضعیت سازه. در این راستا، داده کاوی بعنوان یکی از جدیدترین فناوری های محاسباتی، قادر به استخراج داده جهت کشف اطلاعات ارزشمند از داده‌های جمع آوری شده توسط حسگرها می‌باشد. از طرف دیگر، روش‌های تجزیه و تحلیل معکوس داده، بعنوان یک مکانیسم مبتنی بر مسئله، به سرعت در حال توسعه است. بنابراین لازم است که مکانیسم فوق الذکر و داده کاوی برای برآوردن تقاضای روزافزون تجزیه و تحلیل داده‌ها، بخصوص در سیستم‌های پیچیده مانند پل ها، ترکیب شود. در این مقاله، ما روش تحقیقی برای تشخیص آسیب مبتنی بر استراتژی های مذکور ارائه کردیم. بدین منظور، روش تجزیه و تحلیل معکوس داده‌ها با استفاده از داده کاوی برای یک پل کامپوزیت اعمال می‌شود. جهت رسیدن به هدف، الگوریتم ماشین بردار پشتیبان با استفاده از مشخصات ارتعاش برای تولید الگوها بکار رفته است. برای مقایسه انسجام و دقت خروجی‌های پیش بینی شده، از چهار تابع کرنلی، از جمله توابع خطی، چند جمله ای، سیگموئید و گوسین برای ساخت الگوها استفاده شده است. نتایج بدست آمده بیانگر امکان‌پذیری روش پیشنهادی برای تشخیص آسیب در پل‌های کامپوزیتی دال برروی تیر می‌باشد.

کلمات کلیدی: داده کاوی، پایش سلامت سازه، ماشین بردار پشتیبان، آنالیز مودال تجربی.