Enhancement of Structural Health Monitoring Framework on Beams based on k-Nearest Neighbor Algorithm

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ABSTRACT

The aiming of this work is to enhancement the structural health monitoring (SHM) framework of beams structure for damage detection to treatment the drawbacks of poor detection efficiency in traditional of beams monitoring algorithms, the improvement framework on beams SHM is based on novel data classification technique through designing the k-Nearest Neighbor (k-NN) algorithm. First, the beam finite element model under impact load is analysis, and the cumulative damages are considered and introduced to beam model. The datasets of beam SHM are compiled from the sensors installed in beam structure, and then processed using kernel principal component analysis to remove the unnecessary features and reduce the scale of classification features. The k-NN algorithm parameters of beam SHM are determined by the genetic optimization algorithm (GOA) to establish the optimal SHM classification model of beam. Finally, a comparison between the present damage detection results via k-NN and traditional models via convolutional neural network (CNN) and supper vector machine (SVM) results available in literatures is established through the most significant indexes of testing to check the effectiveness and superiority of suggested method. The results show that the presented SHM model are gave higher precision, reduced the time of modeling, and improvement the total performance of damage detection model in beams. The current performance are recorded 95.3%, 91.8%, and 89.7%, for accuracy rate, recall rate, and F-score respectively.

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INTRODUCTION

In recent years, the construction of beam structures has developed rapidly, and the health monitoring of beam structures has become a research hotspot at home and abroad. Reasonable configuration of sensors is the premise to ensure the quality of beam structure health monitoring, and it is very important to obtain accurate and real-time information on the health status of beam structures and realize the monitoring and evaluation of beam structures [1-6]. Nowadays, more and more use intelligent and digital means to automatically capture various structural safety-related data such as environmental temperature and humidity, expansion joint displacement, etc. through the beam and plate structural health monitoring system, identify and record the development of existing diseases in real time, Discover new diseases and report it, assist in decision-making and judgment, reduce maintenance costs, and improve monitoring efficiency and quality [7-12].

At present, the main use of neural networks to model the SHM of the beam structure, and the neural network is a learning algorithm based on minimizing experience risk. State training samples make the cost of the SHM of the beam structure high [13-19]. k-NN is a classification algorithm based on minimizing structural risk. There is no large sample condition limit for the sample requirements of beam structure health. The classification ability is also better than the neural network. It provides a new construction for the health state of the beam structure model method [20-24].

In order to obtain better beam structure health state classification results, there are problems such as large classification errors and poor efficiency such as the health state classification model of the current beam structure, and a beam structure health state classification model (k-NN) based on data classification technology is designed. Test the effectiveness and superiority of the present beam structure health model is analyzed by using the most significant indexes.

BEAMS SHM-BASED CLASSIFICATION MODEL BY K-NN ALGORITHM

A k-Nearest Neighbor (k-NN) Algorithm

k-NN is the supervised machine learning algorithm used for classification and regression. It manipulates the training data and classifies the new test data based on distance metrics. It finds the k-nearest neighbors to the test data, and then classification is performed by the majority of class labels. Selecting the optimal k value to achieve the maximum accuracy of the model is always challenging for a data scientist. Figure1 presents the k-NN algorithm principal in classification.

Beam Description

Consider a beam subjected to an impact force, as shown in Figure 2 as an example, the beam length is $20m$, $E = 210\ GPa$, $\rho = 7850\ kg/m^3$, $A = 1m^2$, $I = 0.083m^4$. An impact exciting force of $1000\ N$ is applied at the midpoint of the beam. Figure 3 introduced the force-time relation. Various sensors were installed on the longitudinal direction of the beam at total of 20 orders element, 21 nodes, as shown in Figure 2 the sensors positions ate each node. Use ANSYS performs a transient analysis, simulating damage with stiffness drop at each element.

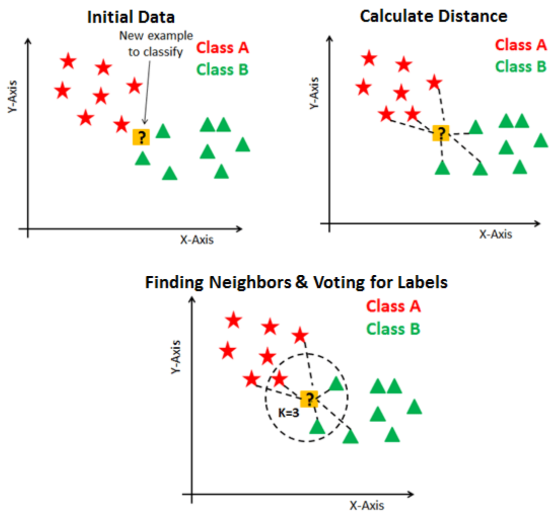
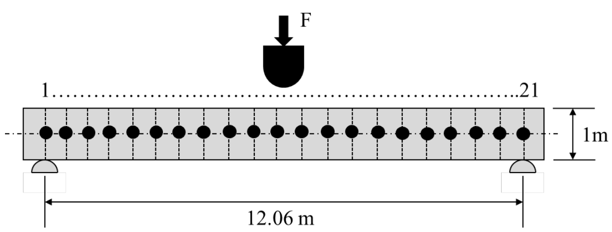


Figure 1. A k-NN algorithm principal.



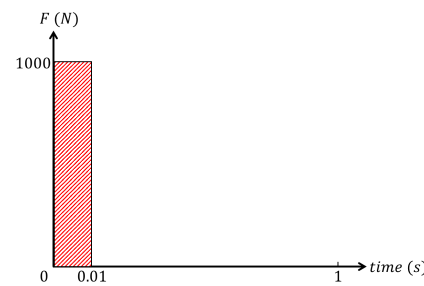


Figure 2. Beam General View.

Figure 3. Random Excitation.

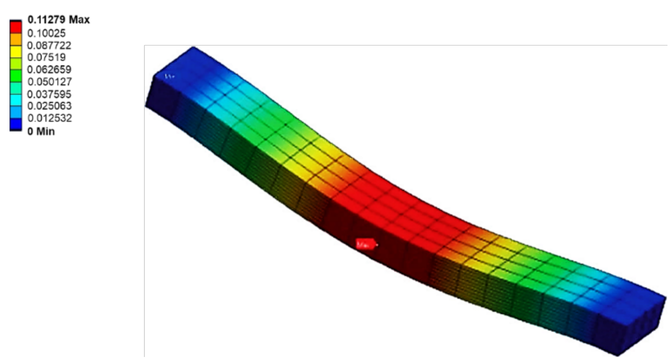


Figure 4. Finite Element Modeling of Beam.

The suitable finite elements were selected, i.e. for simulating structural characteristics is used BEAM3 element with material model EX 210000, PRXY: 0.3, and DENS: 7.85e-6. The displacement of the 21 nodes before and after the damage under the action of the exciting force is shown in Figure 4.

RESULTS AND DISSECTIONS

The Sensor Network Collection Beam SHM Data

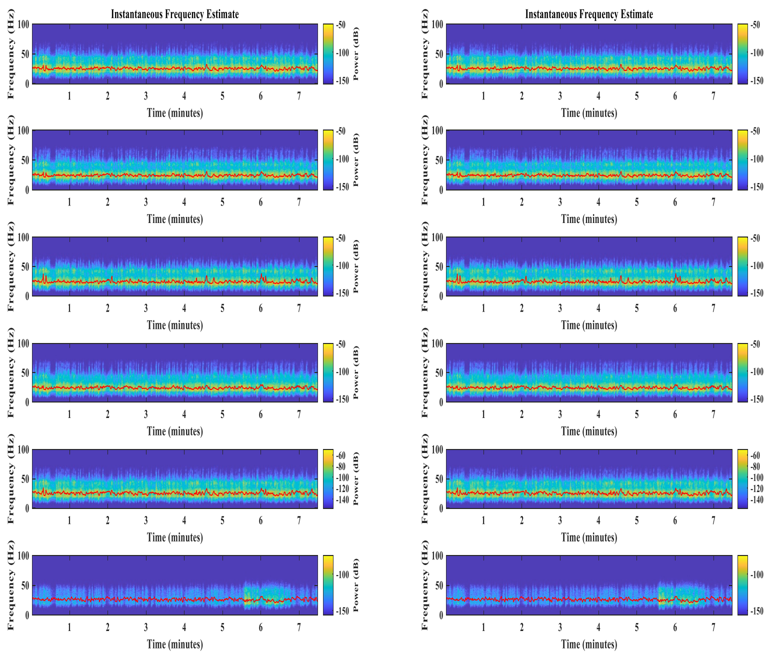


Figure 5. The instantaneous frequency (IF) of sensors response due to impact exciting force.

For nonstationary signals of the distributed sensors installed on the each node in beam, the frequency concept misses its effectiveness, so it is necessary to use a parameter that takes into account the time-varying nature such as Instantaneous frequency (IF). In this work, IF is an important index to reflect the structure stability in the context of analysis of time-varying functions as shown in Figure 5.

Steps of Beams SHM-Based on Data Classification Technology

The work frame and main steps of the beam SHM-based on data classification technology is shown in Figure 6.

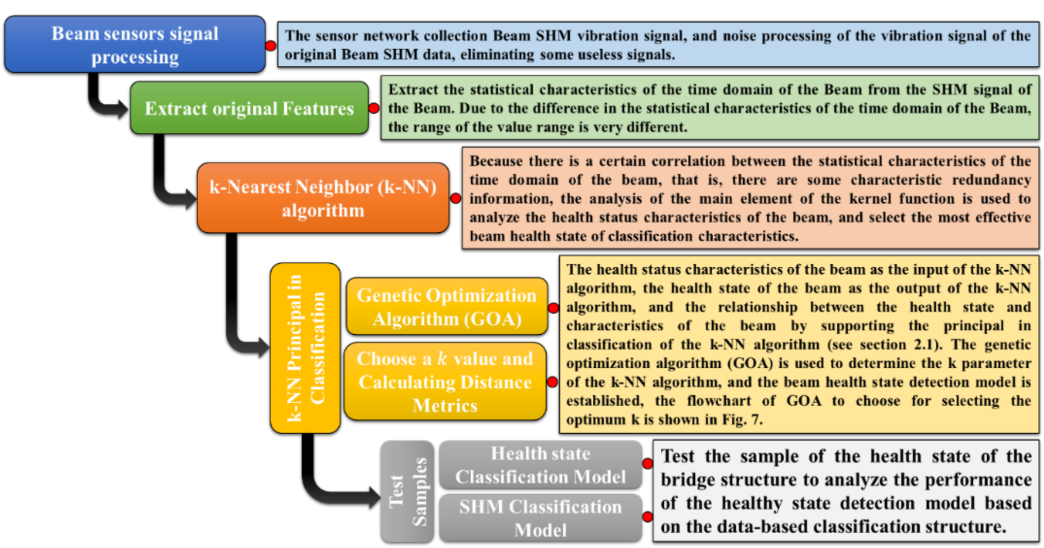


Figure 6. The Work frame and main steps of the beam SHM-based on data classification technology.

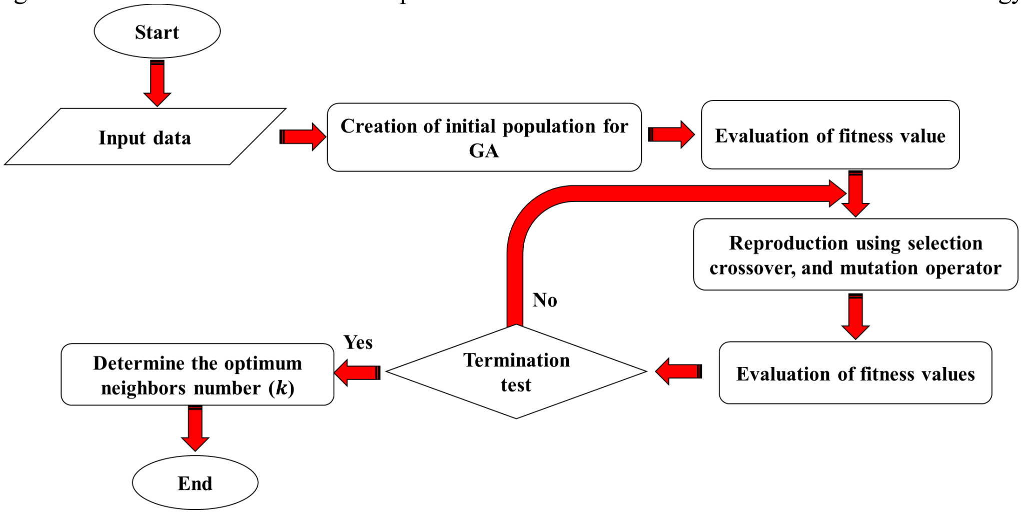


Figure 7. GOA flowchart for selecting the optimum k.

K-NN Data Classification Technology

Choose a k Value

A k value indicates the count of the nearest neighbors. We have to compute distances between test points and trained labels points. Updating distance metrics with every iteration is computationally expensive. As shown in Figure 8, if we proceed with $k = 3$, then we predict that test input belongs to class B, and if we continue with $k = 7$, then we predict that test input belongs to class A. That's how you can imagine that the K value has a powerful effect on k-NN performance.

The following Figure 9 illustrates more generally how the decision boundary (depicted by a dashed line) is affected by larger or smaller k values. Smaller values allow more complex decision boundaries that more carefully fit the training data. The problem is that we do not know whether the straight boundary or the curved boundary better represents the true underlying concept to be learned.

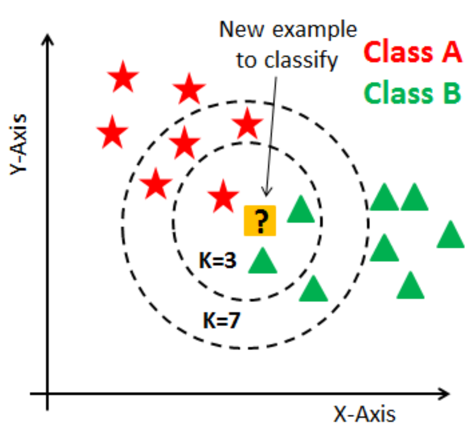


Figure 8. Choose a k value.

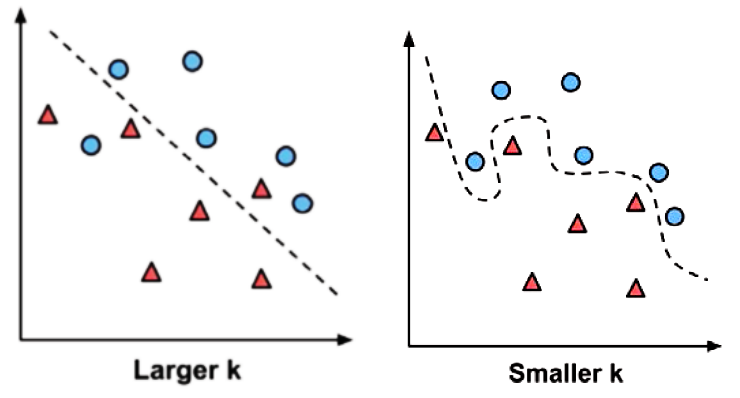


Figure 9. Different between large k and smaller k in classification accuracy.

As the aiming of this work, the response of acceleration sensor will be used as the input for SHM classification of the beam. After select the optimum value of parameter k. The sensors datasets pass through min-max normalization and z-score standardizations, as shown in Equations:

$$Min - Max\ normalization\ (X) = \frac{(X - \min(X))}{(\max(X) - \min(X))} \tag{1}$$

$$z - score\ standardization\ (X) = \frac{(X - \text{main}\ (X))}{\text{StdDev}\ (X)} \tag{2}$$

Calculating Distance Metrics

The distance metric is very important for accurate classification because when a pair of features is inputted, the k-NN searches the nearest k-pair of features using Euclidean distance on the same scale, we can measure the distance from Equation (3). We measure the distance along a straight line from point (x_1, y_1) to point (x_2, y_2).

$$Euclidean\ Destance = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

Table 1 presents the k-NN internal parameters of the current study.

TABLE I. K-NN INTERNAL PARAMETERS.

Parameters	**Value**
Optimum Neighbors number (k)	73
Optimization method	GOA
Distance	$Euclidean$
Bucket size	50
Include ties	0
Distance weight	equal
Break ties	smallest
Standardize data	1
Type	Prediction
$\min(X)$	$[3.735E-3, 8.684E-3]$

StdDev (X)	[0.656,1.008]
Weight (W)	$106.58E-03$

Accuracy and Reliability Evaluation of Suggested Algorithm

To evaluate the suggested algorithm of SHM of beam structure, we computed the most significant indexes of performance measures for k-NN output of data classification sets that include the true-positive rate (TPR), true-negative rate (TNR), false-positive rate (FPR), and false-negative rate (FNR). The performance indicators of suggested algorithm of SHM of beam structure can be found by calculating the accuracy rate ($P\%$), regression rate ($R\%$), and F-score ($F\%$) from the following equations:

$$P\%, = \frac{N_{TPR}}{N_{TPR}+N_{FPR}} \tag{4}$$

$$R\% = \frac{N_{TPR}}{N_{TPR}+N_{FNR}} \tag{5}$$

$$F\% = \frac{2N_{TPR}}{2N_{TPR}+N_{FNR}+N_{FPR}} \tag{6}$$

Used a convolutional Neural Network (CNN), Supper Vector Machine (SVM), and K-NN for training the samples of the health state of the beam structure, then establish the corresponding beam structure health state classification model, and then test the sample of the health state of the beam structure to assess the present beam structure health state. Figure 10 Comparing and analyzing the test results of the beam structure from where classification time, accuracy rate, regression rate, and F-score.

In general for all indexes ($P\%$, $R\%$, $F\%$, and Classification time), using CNN over the input datasets obtains a lower average accuracy than the SVM configuration, present approach k-NN achieve better results than the SVM and CNN. As a general conclusion, the proposed approach k-NN consistently outperforms the SVM, and CNN with all indexes.

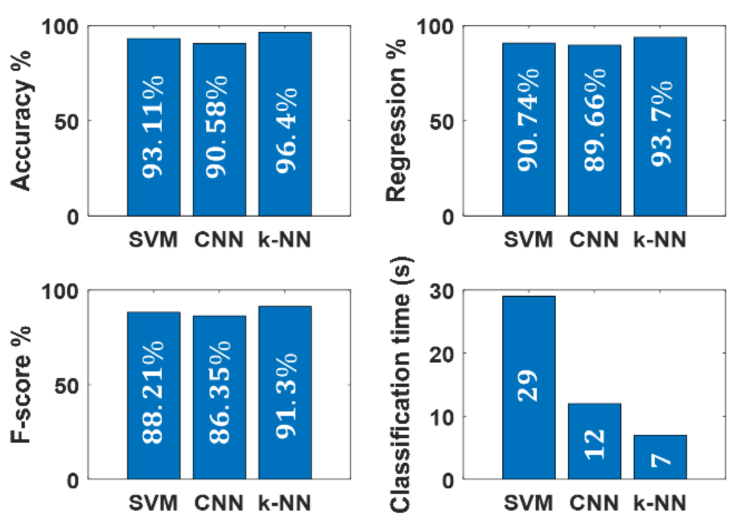


Figure 10. Comparison of the test results of the beam structure.

CONCLUSIONS

SHM is an important technology to ensure beam safety. There is a large amount of excessive information data in the original beam SHM data, which affects the beam SHM performance. To improve the accuracy of SHM, The model of a beam SHM based on data classification technology was proposed through designing the k-Nearest Neighbor (k-NN). Firstly, the datasets of beam SHM were compiled from the sensors installed in beam structure, and then processed using kernel principal component analysis to remove the unnecessary features and reduce the scale of classification features. The k-NN algorithm parameters of beam SHM model were determined by the genetic optimization algorithm (GOA) to establish the optimal SHM classification model of beam. Finally, to test the effectiveness and superiority of the current beam SHM model, a comparison between the current model of SHM using k-NN and another two algorithms such as a CNN and SVM were established, the indexes of P%, R%, F%, and Classification time were computed and compared. The results show that the current model has obtained the results of the beam SHM with higher accuracy, the time for current beam SHM modeling was reduced, the efficiency of beam SHM is improved, and the overall performance of the beam SHM is significantly better. The current performance were recorded 95.3%, 91.8%, and 89.7%, for accuracy rate, recall rate, and F-score respectively.

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