Damage Location Identification of Simply Supported Steel Truss Bridge Based on Displacement

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Abstract

Bridge structure damage identification is an important step in bridge structure health monitoring system, but all kinds of damage identification method at present are all complicated and have poor applicability. Therefore, this paper will propose a simple and applicable method of damage identification based on displacement. This has important significance to realize the real-time and exact warning and forecasting the bridge structural health situation. The damage identification indexes are the change percentages of the lower chord panel points maximum deflections and the beam end maximum displacement. The identification model are established respectively using C-Support Vector Classification (C-SVC) and Probabilistic Neural Network (PNN) to identify the damage location, and the two models results are analyzed. The numerical example results show that: (1) The damage identification method based on the bridge deflection is feasible. (2) PNN model and SVC model all have good anti-noise capacity and generalization(3) SVC model is more suitable to be used in site.

Index Terms: displacement, damage location identification, SVM, PNN, railway double-track simply supported steel truss bridge

Introduction

Large-scale civil engineering structures (such as: long-span bridge, high-rise buildings, ocean platform, large span space structure and dam) are very important to the social economy development. But in their working life, because of the environment factors, human factors and natural hazard, successive damages accumulate in the large-scale civil engineering structures, these damages can cause potential safety hazard, and then impact the structure normal use. For real-time mastering the structures health condition, there are many large-scale structures established health monitoring system, such as: Tsing Ma Bridge, Sutong Bridge, Wuhu Yangtze River Bridge, etc.. Structural damage identification is the critical step in the structure health condition assessment, and is one of the research hotspot in academic world and engineering world. The bridge structure damage identification methods include two mainly methods: model-based damage identification method and no-model-based damage identification method[1]. Model-based damage identification method include: pattern matching method[2], damage index method[3], adjustment model method[4]. No-model-based damage identification method include: frequency domain identification method[5], time domain identification method[6], time-frequency analysis method[7]. These methods are initially successfully used in the damage identification of mechanical, and also have a large number of applications in the field of civil engineering in recent ten years[1]. This paper proposes a novel damage location identification method[8-9], which is combined the model-based damage identification method and no-model-based damage identification method. A number example for a 64 m railway double-track simply supported steel truss bridge is provided to verify the feasibility of the method. And the intelligence algorithms are respectively using C-Support Vector Classification (C-SVC) and Probabilistic Neural Network (PNN) to establish the damage location identification model.

Displacement-based Damage Identification Method

A. Damage identification index

There are two possibilities during the structure damaged. One is the structure mass changed, the other is the structure stiffness decreased[3]. In view of Mechanics of Materials[10] and General code for design on railway bridges and culverts [11], the structure displacement can reflect the structure stiffness. And, in Finite Element Method, the structure node displacements are calculated by equation (1).

$$\{\Delta\} = [K]^{-1}\{P\} \tag{1}$$

Where,

$\{\Delta\}$—structure node displacement vector,

$[K]$—structure stiffness coefficient matrix,

$\{P\}$—node load vector.

In equation (1), if the node load vector$\{P\}$ is constant, the structure node displacement vector$\{\Delta\}$ will be as the change of the structure stiffness coefficient matrix $[K]$. That is to say, the nodes displacement can reflect the structure stiffness.

When a train is travelling on a railway bridge, the train and the bridge compose a complicated train-bridge time-varying system. The bridge structure nodes displacement will change along with the change of the trains location. In view of the bridge structure nodes being very many, this paper constructs the damage identification index based on the bridge certain nodes maximum displacement, that is, the damage identification index is the change percentages of the bridge certain nodes maximum displacement,

$$\Delta x_i = \frac{x_{imax} - x_i}{x_i} \times 100\% \tag{2}$$

Where,

x_i—in certain load case,the maximum displacement of node i, when the structure stiffness isnt damaged,

x_{imax}—in the same load case, the maximum displacement of node i, when the structure stiffness is damaged,

Δx_i—in the same load case, the change percentages of the maximum displacement of node i.

B. Intelligent Algorithm

(A) Artificial Neural Networks

Artificial Neural Networks (ANNs) is a kind of mathematic model by simulating biology neural networks to process information. Artificial neuron is the ANNs information processing unit and the ANNs design fundamental. A large number of artificial neurons are organized by a certain topological structure to constitute a colony parallel mode processing computation structure, which is called ANNs. According to the topological structure, ANNs is divided into the forward neural network and feedback neural network. Probabilistic Neural Networks (PNN), which is used in this paper, is a forward neural network. PNN is usually applied to research pattern classification problems.

(B) Support Vector Machine

Support Vector Machine (SVM) is a powerful method to solve the tradition problems, such as Curse of dimensionality and Over learning etc. This paper use Matlab and LIBSVM, which is developed by Taiwan University PhD Lin Chih-Jen and his team members, to train the damage location identification model. The C- Support Vector Classification Machine (C-SVC)[12] algorithm flow chart, which is used in this paper, is shown in Fig.1.

In this paper, the kernel function is Gauss radial direction kernel function,

$$K(x, x') = \exp(-\|x - x'\|^2/\sigma^2) \tag{3}$$

C. Damage Location Identification

Damage identification includes 2 steps: damage location identification and damage degree identification. For the paper length limited, this paper only studies the damage location identification.

Fig. 2 shows the damage location identification flow chart.

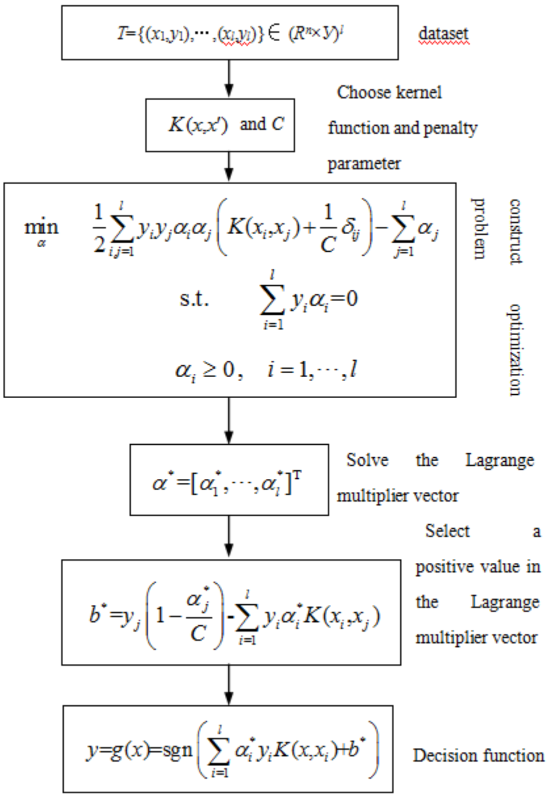


Figure 1. C-SVC flow chart

In this flow chart, there are two ways to add noise.

One way is that a certain data vector added noise according to Equation (4). This way can expand the data set. If the original data have n sets data, and $j \in [1, m]$ in Equation (4), the expanded data will have $n \times m$ data sets. The purpose is to increase the damage identification accuracy, anti-noise ability

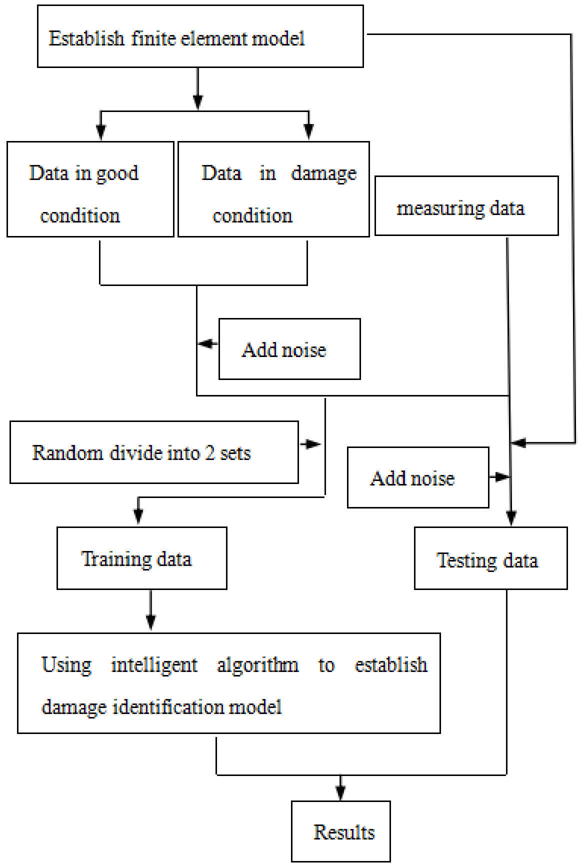


Figure 2. damage location identification flow chart

and generalization ability.

$$\{x\}_{jtest} = \{x\}_{calculate} \times (1 + \varepsilon R_j) \tag{4}$$

Where,

$\{x\}_{jtest}$—the j th simulate test data vector after a certain calculation data vector is expanded,

$\{x\}_{calculate}$—a certain calculation data vector,

R_j—the j th datum of the normal distribution random data, which the mean value is 0 and the mean square deviation is 1,

ε—noise level.

The other way is that a certain element in a certain data vector is added noise according to Equation (5) [13].

$$\{x\}_{ktest} = \{x\}_{kcalculate} \times (1 + \varepsilon R_k) \tag{5}$$

Where,

x_{ktest}—the k th independent variables simulate test data,

$x_{kcalculate}$—the k th independent variables calculation data,

R_k— the k th datum of the normal distribution random data, which the mean value is 0 and the mean square deviation is 1,

ε—the noise level.

64 m Simply Supported Steel Truss Bridge Numerical Example

A. Finite element model

This bridge is a 64 m simply supported steel truss bridge. The finite element model is established using space bar element, there are 32 nodes and 116 bar elements (Fig. 3). The x direction, y direction and z direction linear displacement are restrained on the node 1 and the node 10 to simulate fixed hinged support, and the y direction and z direction linear displacement are restrained on the node 9 and the node 18 to simulate activity hinged support. The coordinate system is shown in Fig.3.

The main truss node numbers, the upper chord unit number and the lower chord unit number are shown in Fig.4.

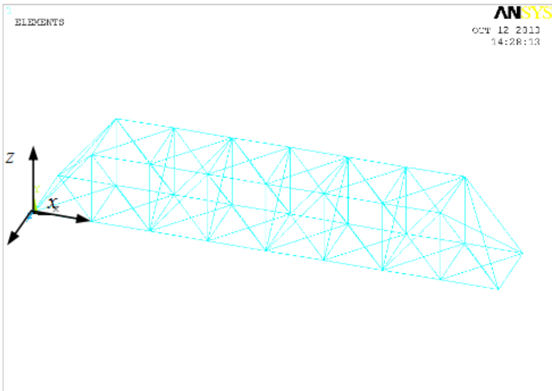
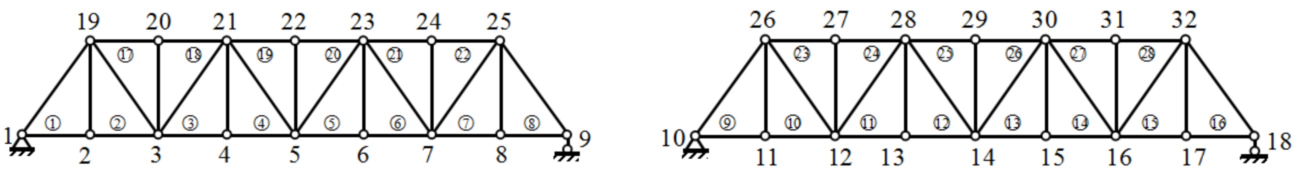


Figure 3. 64 m simply supported steeltruss bridge finite element model



（a） the main truss where y=0 （b） the main truss where y= -10

Figure 4. The main truss node numbers, the upper chord unit number and the lower chord unit numbert

B. Data preparation

The train load is considered as moving dead load. The load cases include one locomotive up-run on the bridge, one locomotive down-run on the bridge, one locomotive simultaneously from the bridge two ends run on the bridge, a train with one locomotive up-run on the bridge, a train with one locomotive down-run on the bridge and two trains with one locomotive simultaneously from the bridge two ends run on the bridge. Where, the locomotive is Dongfeng 4 locomotive, the axle load is 23 t, the vehicle is C62the axle load is 20.15 tthe wheel bases are respectively shown in Fig.5 and Fig.6[14].

Under the train loads, the upper chord and the lower chord internal forces are larger, easily damaged. Consequently, in this paper, The extensional rigidity EA of the element ①, ③,⑤ ,,⑦ ,⑨ ,⑪ ,⑬ ,⑮ ,⑰ ,⑲ ,㉑ ,㉓,㉕ and ㉗respectively discount 5%, 10%, 15%, 20%, 30%, 50% to simulate damage. When

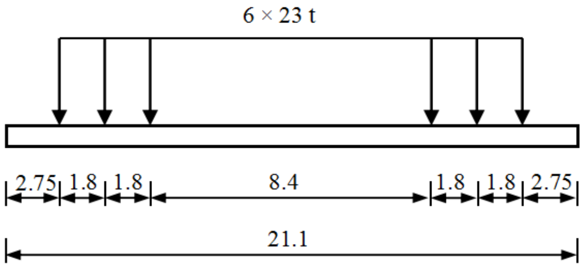


Figure 5. Dongfeng 4 locomotive axle load and wheel base (unit: m)

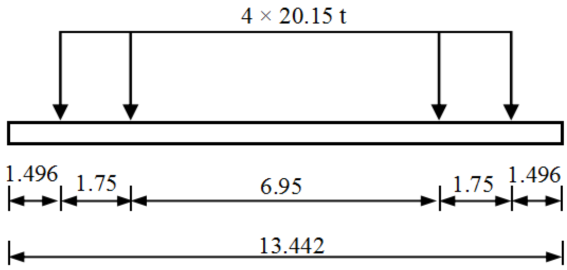


Figure 6. C62 vehicle axle load and wheel base (unit: m)

the 6 load cases are respectively on the bridge, the lower chord panel points maximum deflections and the beam end maximum displacement are calculated using the finite element model, and 504 sets data are obtained. Then according to Equation (2), the damage location identification indexes are obtained.

C. Data expand

Firstly, the 504 sets data are added noise according to Equation (4), where $\varepsilon = 1\%$, j =1,2,...,5. Then, 2520 sets data are obtained.

Secondly, the 2520 sets data are added noise according to Equation (5), where $\varepsilon = 1\%$, k =1,2,...,16.

D. Normalization processing

For increasing the classification and regression accuracy rate, and reducing the error, the indexes and the damage degrees are normalization processed. The normalization algorithm is

$$f : x_l \rightarrow y_l = \frac{x_l - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Where,

x and $y \in R^n$, $x_{min} = min(x)$, $x_{max} = max(x)$.

The normalization results is that the original data are normalized in $[0, 1]$, that is $y_l \in [0, 1], l = 1, 2, ..., n$[15].

The 2520 sets data are normalized according to Equation (6). Then the training data are obtained.

E. Testing data

In order to test the model generalization and anti-noise capacity, the testing data is obtained by the following method. Firstly, the finite element model calculation data is selected, when the element① ,③ ,⑤ ,⑦ , ⑨,⑪ ,⑬ ,⑮ , ⑰,⑲ , ㉑,㉓ ,㉕ ,㉗ are respectively damage 25% and 40% (these damage degree arent included in the training set). The load cases are a train with one locomotive up-run on the bridge, a train with one locomotive down-run on the bridge and two trains with one locomotive simultaneously from the bridge two ends run on the bridge. Then 84 sets data are obtained. Secondly, the damage identification indexes are obtained according to Equation (2). Thirdly, the 84 sets data are added noise according to Equation (5), where =0.1%, 0.5%, 1%, 5%, 10%, 20%, 30%, 50%, 80%, and k =1,2,..., 16. Last, the 84 sets data are normalized according to Equation (6). Then the testing data are obtained.

F. Damage Location Identification

(A) PNN identification model

Damage location identification model is established by MATLAB neural network toolbox function, which is newpnn(P,T,SPREAD). Where P is the input vector, T is the goal vector, SPREAD is expansion rate of the radial basis function, in this paper SPREAD=0.2.

Firstly, 2520 sets training data are used to establish and train the PNN model. Secondly, 1500 sets data are randomly selected to check the PNN model result. Lastly, the 84 sets testing data are inputted in the PNN model to check the models anti-noise ability and the generalization ability.

(B) SVC identification model

The 2520 sets training data are randomly divided into two groups, one is to train the SVC identification model, the other is to test the model. Using k–fold cross-validation method (Deng N.Y. et al., 2009), the penalty parameter C and the kernel function parameter σ are selected,$C = 32$ and $\sigma = 2$. Then, the 570 sets original data is considered as the training data to establish the damage location identification model. Then, based the 2520 sets training data, the damage location identification model is established using LIBSVM software package. Lastly, the 84 sets testing data are inputted in the SVC model to check the models anti-noise ability and the generalization ability.

(C) Damage location identification result

Table 1 shows the results of the PNN model and the SVC model, when input the testing data added various noise levels.

Fig.7 and Fig.8 respectively show the damage location identification result of the PNN model and the SVC model, when the noise level is 30%.

Table 1. The comparison results of the PNN model and the SVC model

Noise level	The number of mis- identification		Accuracy rate (%)		Elapsed time (s)	
	P NN	SVC	PNN	SVC	PNN	SVC
1%	0	0	100	100	3.85	0.35
5%	0	0	100	100	3.835	0.37
10%	0	0	100	100	3.85	0.37
15%	0	0	100	100	3.90	0.37
20%	0	0	100	100	3.91	0.36
30%	7	0	91.6667	97.619	3.72	0.36
50%	9	0	89.2857	89.2857	3.76	0.37
80%	26	0	69.0476	70.2381	3.95	0.37

From Table 1, when the noise level is less than 20%, the PNN model and the SVC model identification

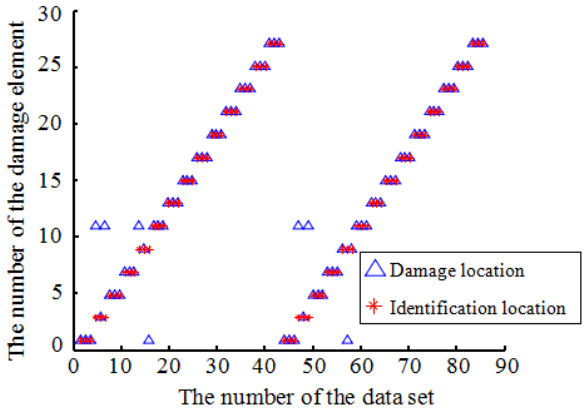


Figure 7. The damage location identification result of the PNN model, when the noise level is 30%

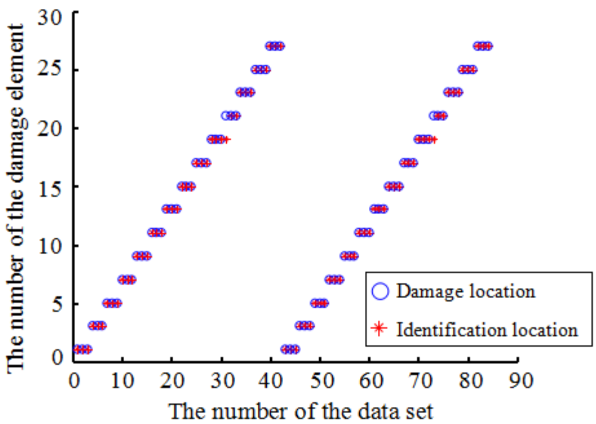


Figure 8. The damage location identification result of the SVC model, when the noise level is 30%

accuracy rates are all 100%. When the noise level is 30%, the PNN model has 7 mis-locations(Fig.7), the identification accuracy rate is 91.6667%. And, When the noise level is 30%, the SVC model has 2 mis-locations (Fig.8), the identification accuracy rate is 97.619%. And when the noise level is 50%, the identification accuracy rates decrease to 71.4%. When the noise level is 50% and 80%, these two model identification accuracy are almost equal. Meanwhile, for all noise level, the PNN model identification elapsed times are all in $3.7s \sim 4.0s$, and the SVC model identification elapsed times are all in$0.35s \sim 0.38s$, only is 10% of the PNN model. This indicates that the SVC method more can satisfy the requirement of real time, fast and accurate identification damage location, and has strong anti-noise ability and good generalization ability.

Conclusions

(1) It is feasible that the 64 m steel truss bridge lower chord panel nodes maximum deflections and the beam end maximum horizontal displacement act as the damage identification indexes.

(2) The PNN method and the SVC method all have strong anti-noise ability and good generalization ability.

(3) In the training and identification process, C-SVC algorithm is faster than PNN algorithm, more

suitable applied in damage location identification, and more can satisfy the job site requirements which require it can real-time fast and accurately identify the damage.

Acknowlegement

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