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Railway Simply Supported Steel Truss Bridge Damage Identification Based on Deflection

[1,2]Jian-ying Ren, [3]Mu-biao Su and [1]Qing-yuan Zeng
[1]School of Civil Engineering, Central South University, 410075, Changsha, China
[2]Department of Engineering Mechanics, Shijiazhuang Tiedao University, 050043, Shijiazhuang, China
[3]Structural Health Monitoring and Control Institute, Shijiazhuang Tiedao University, 050043, Shijiazhuang, China

Abstract: To propose a novel damage identification method, this study firstly used deflections and SVM to establish the damage identification model. It has significant theoretical significance and practical value to timely master the bridge structure's health condition and identify the damage location and damage degree. There are five load cases, such as, one locomotive run on the bridge, two locomotives coupling run on the bridge, three locomotives coupling run on the bridge, a train with one locomotive run on the bridge, a train with two locomotives run on the bridge. When the load cases respectively act on the 64 m railway simply supported steel truss bridge, the change percentages of the lower chord panel points maximum deflections and the beam end maximum displacement are calculated. The percentages are independent variables, the damage location and the damage degree are dependent variables, the identification models are established respectively using C-SVC and ε-SVR to identify the damage location and the damage degree. These two models all have good anti-noise ability and good generalization.

Key words: Deflection, damage identification, simply supported steel truss bridge, SVM

INTRODUCTION

Now, many scholars are devoting to the bridge damage identification field in the world. The main damage indexes are the modal curvature difference (Liu *et al*., 2011), natural frequencies (Hakim and Abdul-Razak, 2013), the modal strain energy differences (Gonzalez-Perez *et al*., 2011), correlation coefficient and correlation degree of free vibration accelerations (An and Ou, 2013), natural frequency and vibration mode measurements (Dilena *et al*., 2011), displacement energy damage index (Zhu and Yi, 2013), train-induced responses and sensitivity analysis (Zhan *et al*., 2011), strain responses (Xu *et al*., 2011), etc. The damage identification methods are Artificial Neural Networks (ANNs) (Hakim and Abdul-Razak, 2013; Jiang *et al*., 2010), adaptive neuro-fuzzy inference system (ANFIS) (Gonzalez-Perez *et al*., 2011), fractal theory and data fusion (Jiang *et al*., 2010), the model updating method (An and Ou, 2013; Dilena *et al*., 2011), sensitivity analysis (Zhan *et al*., 2011), genetic algorithm-support vector machine (GA-SVM) (Liu and Jiao, 2011), etc. All of them have gotten good results, but these methods are all too complex and difficultly to be applied in in-situ real-time health monitoring and damage identification.

This study proposes a novel real-time damage identification method based on deflection and using Support Vector Machine (SVM) (Naiyang and Yingjie, 2009; Yuan, 2009) algorithm to establish the damage identification model. The damage identification indexes are the change percentages of the certain nodes maximum deflections and the beam end maximum horizontal displacement, when a series of moving load run on the bridge. A numerical example for a 64 m simply supported steel truss bridge is provided to verify the feasibility of the method.

SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a youngest machine learning method which is proposed by Vapnik (Vladimir, 1998) in the early 1990s. It is a powerful method to solve the tradition problems, such as "Curse of dimensionality" and "Over learning" etc. This study 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 and the damage degree identification model. The C- Support Vector Classification Machine (C-SVC) (Naiyang and Yingjie, 2009) algorithm and the ε-Support Vector

Corresponding Author: Jian-ying Ren, Department of Mechanical Engineering, Shijiazhuang Tiedao University, 050043, Shijiazhuang, China

Regression Machine (ε-SVR) (Naiyang and Yingjie, 2009) algorithm is below.

C-SVC algorithm:

- If the training set is T = $\{(x_1,y_1),\ldots,(x_l,y_l)\}$ $(R^n\times Y)^l$, where $x_i R^n, y\ Y = \{1,-1\}$, i = 1, ..., l
- The suitable kernel function K(x, x') and penalty parameter C>0 are selected, optimization problem is constructed and solved

$$\min_{\alpha} \quad \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j \left(K(x_i,x_j) + \frac{1}{C}\delta_{ij} \right) - \sum_{j=1}^{l}\alpha_j \tag{1}$$

$$\text{s.t.} \ \sum_{i=1}^{l} y_i \alpha_i = 0 \tag{2}$$

$$\alpha_i \geq 0, \quad i = 1,\cdots,l \tag{3}$$

Where:

$$\delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \tag{4}$$

Lagrange multiplier vector $\alpha^*=[\alpha_1^*,\cdots,\alpha_l^*]^T$ is gotten. The element is the Lagrange multiplier.

- A positive element $\alpha_j^* > 0$ is selected in the Lagrange multiplier vector α^*, then:

$$b^* = y_j\left(1-\frac{\alpha_j^*}{C}\right) - \sum_{i=1}^{l} y_i \alpha_i^* K(x_i,x_j) \tag{5}$$

- The classification model is constructed as:

$$y = g(x) = \text{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i K(x,x_i) + b^* \right) \tag{6}$$

where, $K(x_i,x_k)$ is the kernel function. It is the important step to generalize the linear SVM to common nolinear SVM.

The kernel function is defined as: supposing that there is a transformation from R^n to Hilbert space

$$\Phi: \begin{matrix} R^n \to H \\ x \mapsto \Phi(x) \end{matrix} \tag{7}$$

Then:

$$K(x,x') = (\Phi(x)\cdot\Phi(x')) \tag{8}$$

where, (.) represent the inner product in H space. The function $K(x,x')$ is the kernel function which is defined in $R^n\times R^n$. This study use Gauss Radial Basis Function kernel function (RBF kernel), that is:

$$K(x,x') = \exp(-\|x-x'\|^2/\sigma^2) \tag{9}$$

The nolinear ε-Support Vector Regression Machine (ε-SVR) algorithm:

- If the training set is T = $\{(x_1, y_1), \ldots, (x_l, y_l)\}$ $(R^n\times Y)^l$, where $x_i\ R^n, y\ Y = R$, i = 1, ..., l
- The suitable kernel function $K(x,x')$, precision ε>0 and penalty parameter C>0 are selected, optimization problem is constructed and solved
- Convex quadratic programming problem is constructed and solved

$$\begin{aligned} \min_{\alpha^{(*)}\in R^{2l}} \quad & \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)K(x_i,x_j) \\ & +\varepsilon\sum_{i=1}^{l}(\alpha_i^*+\alpha_i)-\sum_{i=1}^{l}y_i(\alpha_i^*-\alpha_i) \end{aligned} \tag{10}$$

$$\text{s.t.} \ \sum_{i=1}^{l}(\alpha_i^*-\alpha_i)=0 \tag{11}$$

$$0 \leq \alpha_i^{(*)} \leq C, \ i=1 \text{ and}, \ l \tag{12}$$

Lagrange multiplier vector is $\bar{\alpha}^{(*)}=[\bar{\alpha}_1,\bar{\alpha}_1^*,\cdots,\bar{\alpha}_l,\bar{\alpha}_l^*]^T$,the element is the Lagrange multiplier

- Calculate $\bar{b}$: The $\bar{\alpha}_j$ or $\bar{\alpha}_k^*$ in the Lagrange multiplier vector $\bar{\alpha}^{(*)}$, which is a positive element in the open internal (0, *C*), is selected. If $\bar{\alpha}_j$ is selected, then

$$\bar{b} = y_j - \sum_{i=1}^{l}(\bar{\alpha}_i^*-\bar{\alpha}_i)K(x_i,x_j)+\varepsilon \tag{13}$$

If $\bar{\alpha}_k^*$ is selected, then:

$$\bar{b} = y_k - \sum_{i=1}^{l}(\bar{\alpha}_i^*-\bar{\alpha}_i)K(x_i,x_k)-\varepsilon \tag{14}$$

- The regression function is constructed as:

$$y = g(x) = \sum_{i=1}^{l}(\bar{\alpha}_i^*-\bar{\alpha}_i)K(x_i,x_k)+\bar{b} \tag{15}$$

where, $K(x_i,x_k)$ is kernel function.

DATA PREPARATION

Bridge model: This bridge is a 64 m simply supported steel truss bridge. The finite element model is established

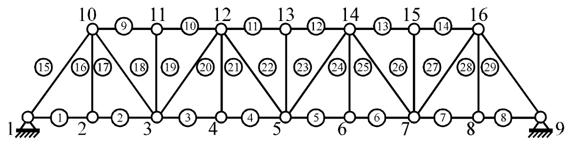

Fig. 1: Simply supported steel truss bridge finite element model

using plane bar element, there are 16 nodes and 29 bar elements (Fig. 1). The vertical linear displacement and horizontal direction linear displacement are restrained on the node 1 to simulate fixed hinged support and the vertical linear displacement is restrained on the node 9 to simulate activity hinged support.

Data preparation: There are five load cases which are one locomotive run on the bridge, two locomotives coupling run on the bridge, three locomotives coupling run on the bridge, a train with one locomotive run on the bridge, a train with two locomotives run on the bridge. The locomotive is Dongfeng 4 locomotive, the axle load is 23 t, the vehicle is C62,the axle load is 20.15 t,the wheel base can be find in related standard (Ge, 1996)

The extensional rigidity EA of each element is respectively discount 5, 10, 15, 20, 30 and 50% to simulate damage. When the 5 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 570 sets data are obtained.

The damage identification indexes are the change percentages of the 7 lower chord panel nodes (there have no deflections for hinged support on the node 1 and the node 9, then there are 7 nodes which have deflections) maximum deflections and the 1 beam end (the node 9) maximum horizontal displacement. The function is

$$\Delta x_i = \frac{x_{imax} - x_i}{x_i} \times 100\% \tag{16}$$

where, Δx_i is the change percentage of the node i maximum deflection under a certain load case. x_{imax} is the node i maximum deflection, when some bar have some degree damage under the certain load case. x_i is the node i maximum deflection, when the bridge is perfect under the certain load case.

Data preprocessing

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:

Table 1: The identification accuracy rate and elapsed time of the damage location identification model for various noise levels

Noise level (%)	Accuracy rate (%)	Elapsed time(s)
0.1	100	0.179396
1	100	0.198322
10	100	0.176812
20	100	0.178450
30	100	0.179227
40	92.9	0.182678
50	71.4	0.175612

$$f : x \to y = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{17}$$

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 $y_j \in [0,1]$, j = 1, 2, ..., n(Feng and Wang, 2010).

SVM DAMAGE IDENTIFICATION

Damage location identification: The 570 sets original data is random divided into two groups, one is the training set, the other is the testing set. Using k-fold cross-validation method (Naiyang and Yingjie, 2009), the penalty parameter C and the kernel function parameter Y are selected. Then, the 570 sets original data is considered as the training data to establish the damage location identification model. In order to test the model generalization and anti-noise capacity, the testing data is obtained by the following method. First the finite element model calculation data is selected, when the element, the element, the element, the element, the element, the element and the element are respectively damage 25% and 40% (these damage degree aren't included in the training set). Next, these data are added a mutual independence and normal distribution random sequence to simulate the test data. The function is (Jiang and Wu, 2011):

$$x_{itest} = x_{icalculate} \times (1 + \varepsilon R_i) \tag{18}$$

where, x_{itest} is the ith independent variable's simulate test data. $x_{icalculate}$ is the ith independent variable's calculation data. R_i is the ith datum of the normal distribution random data which the mean value is 0 and the mean square deviation is 1. ε is the noise level, it is 0.1, 1, 10, 20, 30, 40 and 50% in this study. Because the independent variable's number is 8, the value range of i is i = 1, 2, ..., 8.

Table 1 Shows the identification accuracy rate and elapsed time of the damage location identification model for various noise levels.

From Table 1, when the noise level is less than 30%, the identification accuracy rates are all 100%. When the noise level is 40%, the identification accuracy rate is

92.9%. And when the noise level is 50%, the identification accuracy rates decrease to 71.4%. Once the parameters are selected, the identification elapsed times are all within 0.2 sec. It is indicate that this method can satisfy the requirement of real time, fast and accurate identification damage location. And the damage location identification model has strong anti-noise capacity and good generalization.

Damage degree identification: The element has damage as an example to identify the damage degree. The five load cases are also considered and the damage degree include 5, 10, 15, 20, 30 and 50%, then 30 sets data can be calculated. According to the function (19), these data can be added noise level.

$$\{x\}_{itest} = \{x\}_{calculate} \times (1 + \varepsilon R_i) \tag{19}$$

where, $\{x\}_{itest}$ is the ith simulate test data vector after a certain calculation data vector is expanded. $\{x\}_{calculate}$ is a certain calculation data vector. R_i is the ith datum of the normal distribution random data which the mean value is 0 and the mean square deviation is 1. ε is the noise level, it is 0.1, 0.5, 1,3, 5,7 and 10% in this study. In order to get enough training set and increase the identification accuracy rate, the value range of i is i = 1, 2, …, 10. That is, every set calculation data is expanded to 10 set simulation test data after it is added a certain noise level. These added noise data sets are considered as training sets, there are totally 3000 sets data. These data sets are random divided into two groups, one is the training set, the other is the testing set. Using k-fold cross-validation method, the penalty parameter C and the kernel function parameter Y of theε-SVR algorithm are selected. Then, the damage degree identification model is established.

In order to test the model generalization and anti-noise capacity, the testing data is obtained by the following method. First the finite element model calculation data is selected, when the element is respectively damage 25 and 40% (these damage degree aren't included in the training set) and the load case only consider 2 case which are one locomotive run on the bridge and a train with one locomotive run on the bridge. Then 4 sets data are obtained. Next, these data are added noise level according to the function (19), the noise level are 0.1, 0.5, 1, 3, 5, 7 and 10%. In order to get enough testing set and increase the identification accuracy rate, the value range of i is i = 1, 2, …, 20. The data are totally 80 sets. Corresponding to every noise level the data sets are considered as the testing set to test the degree damage identification model accuracy rate.

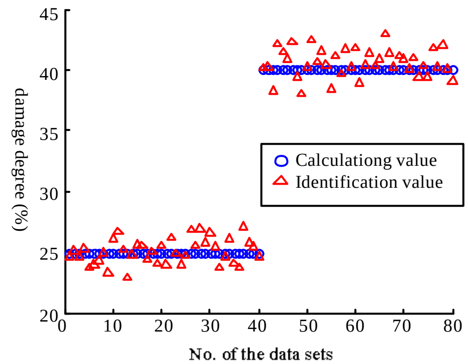

Fig. 2: The comparison diagram of the identification values and the calculation values, when the testing sets noise level is 5%

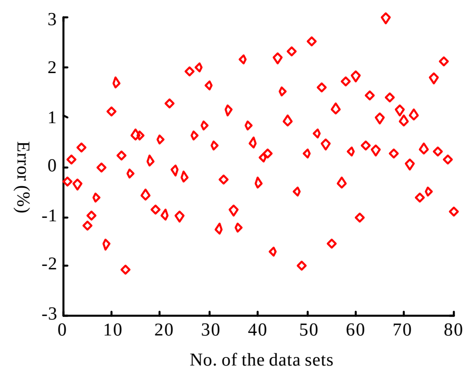

Fig. 3: The error diagram of the identification values and the calculation values, when the testing sets noise level is 5%

Table 2 shows the mean square error and the correlation coefficient of the degree damage identification model for all noise levels testing set.

From Table 2, when the testing set noise level is higher, the mean square error of the damage degree identification model results is bigger and the correlation coefficient is smaller. This indicate that the noise level impact the damage degree identification results. The noise level is higher, the identification error is bigger. When the noise level is under 7%, the mean square errors are all small, the maximum is 9.31992e-4, the correlation coefficient are all over 97%, the minimum is 97.2035%. When the noise level reach 10%, the maximum mean square error is 2.09579e-3, the correlation coefficient is also over 90%, it is 93.3990%.

For the study length limited, Fig. 2 and 3 only show the comparison diagram and the error diagram of the damage degree identification model identification values

Table 2: The mean square error and the correlation coefficient of the degree damage identification model for all noise levels testing set

Noise level (%)	Mean square error(e-4)	Correlation coefficient (%)
0.1	1.54669	99.8919
0.5	1.60741	99.8571
1	1.7744	99.8328
3	3.88865	99.2012
5	6.81937	98.0569
7	9.31992	97.2035
10	20.9579	93.3990

and the calculation values, when the testing sets noise level is 5%. The error function is:

$$\Delta = y_{\text{identification}} - y_{\text{calculation}} \tag{20}$$

where, $\Delta$is the identification error. $y_{\text{identification}}$ is the identification damage degree. $y_{\text{calculation}}$ is the calculation damage degree.

From Fig. 2 and 3, when the damage degrees are 25% and 40%, the identification values all wave around the calculation values, the errors are all within ±3%.

Form Table 2, Fig. 2 and 3, the damage degree identification model has higher accuracy rate, good generalization and anti-noise capacity.

CONCLUSIONS

It is feasible that the lower chord panel nodes maximum deflections and the beam end maximum horizontal displacement act as the damage identification indexes.

To the damage location identification model, the identification accuracy rates are all 100%, when the noise levels are within 30%. To the damage degree identification model, the mean square error is 2.09579e-3 and the correlation coefficient is 93.3990%, when the noise level is 10%. These two identification model have good anti-noise capacity and generalization.

In conclusion, the damage identification method based on bridge deflection which is proposed in this study, can satisfy the job site requirements which require it can real-time fastly and accurately identify the damage.

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