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Damage Identification of Railway Simply Supported Steel Truss Bridge Based on Support Vector Machine

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Abstract: When a train with one locomotive run on a 64 m railway simply supported steel truss bridge, the change percentages of the lower chord panel nodes maximum deflections and the beam end maximum horizontal displacement are calculated. The percentages are as the identification indexes and the identification models are established respectively using C-SVC and ε-SVR to identify 2 bars damage location and damage degree. The results show that when the noise level is to 5%, the damage location identification model begin to misidentify, the precision is 75% and when the noise level is 10%, the damage degree identification model results maximum mean square error is 0.0080, the minimum correlation coefficient is 90.50%. The identification models have good generalization and good anti-noise capability.

Key words: Damage identification, deflection, SVM, simply supported steel truss bridge

INTRODUCTION

Bridge structure is a very important infrastructure for the national economy, its health condition impacts the People's personal and property safety. So, it has significant practical significance and practical value to timely master the bridge structure's health condition and identify the damage location and the damage degree.

Now, there are many scholars devoting to the bridge damage identification field in the world. Liu and Jiao (2011) proposed a two-step method to identify the damage of the simply supported beam bridge using the modal curvature difference and the neural network technique. Hakim and Abdul-Razak (2013a) applied natural frequencies of a structure as effective input parameters used to train the ANN for predicting the severity of damage in a model steel girder bridge. Gonzalez-Perez and Valdes-Gonzalez (2011) used rigidities as output data for the Artificial Neural Networks (ANNs) and the modal strain energy differences were used as input data for the structural damage detection when the vehicular on bridge. Hakim and Abdul-Razak (2013b) developed and applied Adaptive Neuro-fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANNs) techniques to identify damage in a model steel girder bridge using dynamic parameters. Jiang *et al.* (2010) integrated intelligent information processing techniques, i.e., fractal theory, Probabilistic Neural Network (PNN) and data fusion to implement damage identification from multi-sensor data. There are also other common methods. An and Ou (2013) proposed the model updating method of damage severity identification based on correlation coefficient and correlation degree of free vibration accelerations of measured nodes to identify damage severity. Xu and Wu (2007) proposed a damage detection strategy based on acceleration responses' energy based on the relationship between the Frequency Response Function (FRF) of acceleration responses and mode shapes. Liu *et al.* (2012) a Fuzzy Logic System (FLS) for damage identification of simply supported bridge based on ratios of mode shape components between before and after damage. Zhu and Yi (2013) proposed a damage identification method using dynamic response of bridge induced by moving vehicle and static test data. Liu *et al.* (2011) proposed a Support Vector Machine (SVM) optimized by Genetic Algorithm (GA) damage identification method. All them have got good results, but these methods are all too complex and difficultly applied in *in situ* real-time health monitoring and damage identification.

Consequently, this study proposes a novel real-time damage identification method based on deflection and using Support Vector Machine (SVM) (Vapnik, 1998; Deng and Tian, 2009) algorithm to establish the damage

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identification model. The damage identification indexes are the change percentages of the certain nodes maximum deflections, when a series 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 (1998) in the early 1990s. It is a powerful method to solve the tradition problems, such as “Curse of dimensionality” and “Over learning” etc. It has successful application in many fields, where are face detection, text automatic classification, character recognition, biological information technology, three-dimension body recognition, remote sensing image analysis, network intrusion, 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) (Yuan, 2009) algorithm is used to establish the damage location identification model. And the ε-Support Vector Regression Machine (ε-SVR) (Yuan, 2009) algorithm is used to establish the damage degree identification model.

BRIDGE MODEL AND DATA PREPARETION

Bridge model: This bridge is a 64 m simply supported steel truss bridge. The finite element model is established using plane bar element, there are 16 nodes and 29 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: The load case is a train with one locomotive 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.

The extensional rigidity EA of each element is respectively discount 5, 10, 15, 20, 30, 50 to simulate damage. When the train with one locomotive run on the bridge, the lower chord panel points maximum deflections and the beam end maximum displacement are calculated using the finite element model and 174 sets data are obtained.

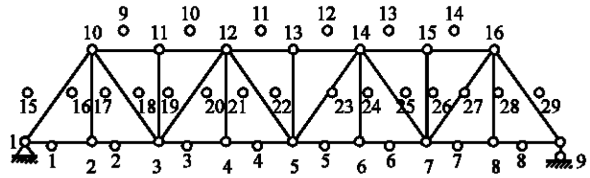

Fig. 1: Simply supported steel truss bridge finite element model

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 beam end (the node 9) maximum horizontal displacement. The function is:

$$\Delta x_i = \frac{x_{imax} - x_i}{x_i} \times 100\% \tag{1}$$

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

Data preprocessing

Data compaction: From the above 174 sets data, it can be find that:

- There are 7 pairs bars have the same axial force which are the element and the element, the element and the element, the element and the element, the element and the element, the element and the element, the element and the element, the element and the element. When one bar of the certain pair bars has one certain degree damage, the lower chord panel nodes maximum deflection change percentages are same as that when the other bar has the same degree damage. Therefore, for every pair bars, the damage indexes and the damage local data use a set data. The total data are reduced 42 sets data
- For the finite element model is a determinate structure, the element, the element and the element are all zero bars when the moving load on the lower chord. Consequently, when these bars have damage, the lower chord panel nodes maximum deflections have no change and the damage identification models can’t recognize these three bars’ damage in this study. The total data are reduced 18 sets data

In conclusion, the damage identification data are 114 sets.

Normalization processing: For increasing the classification and regression accuracy rate and reducing the error, the characteristic parameter and the damage degree are normalization processed. The normalization algorithm is:

$$f : x \to y = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

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 $y_i \in [0,1]$, I = 1, 2,..., n (Shi and Wang, 2010).

SVM DAMAGE IDENTIFICATION

Selection parameter: Firstly, the original data is random divided into two groups, one is the training set, the other is the testing set.

Secondly, the penalty parameter C and the kernel function parameter ó are selected. For the SVM parameter optimization selection, there isn't a international recognized uniform method. This paper uses a currently common method to select the parameters. First let the penalty parameter C and the kernel function parameter ó within a certain range. Next, a set of parameters are substituted into the SVM algorithm and the training data is considered the original data, the classification accuracy rate is obtained using k-fold cross-validation (Deng and Tian, 2009). Last, the highest classification accuracy rate corresponding parameters are the optimum parameters (Shi and Wang, 2010).

Bars damage location identification

Data preparation: Considering the structural distortion within linear elasticity range, the 2 bars damage location identification training sets are constructed by adding the above single bar damage data each other, where the damage data sets should corresponding different damage bar. After these data add each other, the number of the data sets is totally 6156 sets. Then, these data sets are added noise level according to the function:

$$\{x\}_{itest} = \{x\}_{calculate} \times (1 + \varepsilon R_i) \tag{3}$$

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%. To avoid the data size is too large, the value range of i is i = 1, 2,..., 5. The training sets are totally 30780 sets.

In the testing sets, the damage element group and the corresponding damage degree are showed in Table 1, there are 8 sets of data. For testing the 2 bars damage identification model anti-noise capacity, these 8 sets of data are added noise level according to the Eq. 4 (Jiang and Wu, 2011):

$$x_{itest} = x_{icalculate} \times (1 + \varepsilon R_i) \tag{4}$$

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, 0.5, 1, 2.5, 5 and 10% in this paper. Because the independent variable's number is 8, the value range of i is i = 1, 2,..., 8.

Damage location identification: Adopting C-SVC algorithm, 5000 data sets are random drown from the training sets, the optimum parameters are selected by k-fold cross-validation method. Then the 2 bars damage location identification model is established. The testing sets independent variables are substituted in the damage location identification model to check its identification results, see Table 2.

Frome Table 2, as long as the identification model parameters are selected, the elapsed time of 2 bars damage location identification is within 10 sec. When noise level is 5%, the identification model results begin to mistake. In the first damage group, the element is mistaken identified the element. And in the seventh damage group, the

Table 1: Two bars damage element group and the corresponding damage degree

Number	Damage element	Damage degree (%)	Damage element	Damage degree (%)
1	(1)	10	(3)	30
2	(3)	30	(12)	10
3	(5)	30	(20)	10
4	(23)	30	(24)	10
5	(1)	25	(3)	30
6	(3)	40	(12)	25
7	(5)	40	(20)	10
8	(23)	25	(24)	40

Table 2: Two bars damage location identification results

Noise level (%)	Accuracy rate (%)	Elapsed time (sce)
0	100.0	7.752038
0.1	100.0	8.342175
0.5	100.0	8.234281
1	100.0	7.843030
2.5	100.0	7.573090
5	75.0	8.739710
10	62.5	8.312363

element is mistaken identified the element. When the noise level is 10%, the element is mistaken identified the element in the first damage group and the fifth damage group and the element is mistaken identified the element in the seventh damage group. From Table 1, these mistaken identified elements damage degree are all small. Therefore, this damage location identification model has good identification results for the higher damage degree and has good anti-noise capacity. Meanwhile, this damage location identification model can accurately identify the damage elements which damage degrees aren't included in the training sets. So it has good generalization.

Damage degree identification

Data preparation: After the 2 bars damage location identified, the data sets of the 2 bars respectively damage with all above damage degree are added each other to construct the training sets. The element and the element simultaneously have damage for example in this paper. Then 36 sets of data are obtained. For getting enough data sets and increasing the identification accuracy rate, these 36 sets of data are added noise level according to the function (3), where the noise level is 0.1% and the value range of i is i =1, 2,..., 20. The training sets are totally 720 sets of data.

In the testing sets, the elements damage degree are showed in Table 3, there are 8 sets of data. For testing the 2 bars damage degree identification model generalization, the damage degrees include 25 and 40% in Table 3. For testing the 2 bars damage degree identification model anti-noise capacity, these 8 sets of data are added noise level according to the Eq. 4, where the noise level is 0.1, 0.5, 1, 2.5, 5 and 10%.

Table 3: Damage degree group of the element and the element are simultaneously have damage

Number	Element damage degree (%)	Element damage degree (%)
1	10	30
2	30	10
3	30	25
4	30	40
5	25	30
6	40	25
7	40	10
8	25	40

Damage degree identification: Adopting ε-SVR algorithm, the optimum parameters are selected by k-fold cross-validation method. The element damage degree identification model and the element damage degree identification model are respectively established. The testing sets independent variables are respectively substituted in the two damage degree identification models to check their identification results (Table 4 and 5).

From Table 4 and 5, the errors between the identification values and the calculation values are almost within 5%. There are only 2 errors are bigger than 5%. One is that the fifth error of the element identification results is 7.5%, when the noise level is 10%. The other is that the sixth error of the element identification results is 5.4%, when the noise level is 10%. These two sets errors corresponding damage degrees are all 25%. For this

Table 4: Element damage degree identification results when two elements simultaneously damaged

	Identification value (%)					
Calculation value (%)	Noise level (0.1%)	Noise level (0.5%)	Noise level (1%)	Noise level (2.5%)	Noise level (5%)	Noise level (10%)
10	9.8	9.6	9.7	9.7	9.6	8.6
30	30.4	30.4	30.9	29.6	31.5	31.5
30	30.3	30.2	30.1	30.1	39.0	30.8
30	29.9	29.9	30.6	29.6	28.7	26.5
25	24.7	24.6	24.4	23.7	24.3	17.5
40	41.1	41.0	41.5	41.2	43.3	38.0
40	41.4	41.1	41.5	40.5	40.6	44.1
25	24.4	24.2	24.8	24.4	23.2	19.1

Table 5: Element damage degree identification results when two elements simultaneously damaged

	Identification value (%)					
Calculation value (%)	Noise level 0.1%	Noise level 0.5%	Noise level 1%	Noise level 2.5%	Noise level 5%	Noise level 10%
30	30.4	30.5	30.3	30.3	29.8	30.4
10	9.8	9.7	9.5	9.2	10.5	12.0
25	24.8	24.7	25.1	25.3	24.6	21.6
40	42.1	42.2	42.1	41.9	41.9	42.8
30	30.7	30.8	30.9	30.5	30.7	31.5
25	22.6	22.5	22.4	21.3	21.0	19.6
10	9.0	8.9	9.0	8.1	8.9	10.5
40	42.2	42.2	42.3	42.6	42.2	41.1

damage degree excluded in the training sets, the identification errors are greater. When the noise level is 10%, the mean square error and the correlation coefficient of the element identification results are respectively 0.0080 and 90.50% and the mean square error and the correlation coefficient of the element identification results are, respectively 0.0035 and 94.76%. In conclusion, these 2 bars damage degree identification models have higher identification accuracy and good anti-noise capacity.

CONCLUSION

- It is feasible that the lower chord panel nodes maximum deflections and the beam end maximum horizontal displacement which of the 64 m simply supported steel truss bridge under a train with one locomotive, are as the damage identification indexes
- When the noise level is 5%, the 2 bars damage location identification model begin to mistaken identify. To the 2 bars damage degree identification models, the errors between the identification values and the calculation values are almost within 5%. The maximum mean square error is 0.0080 and the minimum correlation coefficient is 90.50% which of the element identification results when the noise level is 10%. These two identification model also have a certain extent anti-noise capacity and generalization

In conclusion, it is feasible that the damage identification method based on bridge deflection which is proposed in this paper. It can satisfy the job site requirements which require it can real-time fast and accurately identify the damage. For the paper length limited, this paper only propose the damage identification results of the 2 bars damage identification. In fact, this method also has satisfactory results to multi bars simultaneously damaged.

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