ISSN 1330-3651 (Print), ISSN 1848-6339 (Online) https://doi.org/10.17559/TV-20240104001243
Original scientific paper

Research on Damage Detection of Civil Structures Based on Machine Learning of Multiple Vegetation Index Time Series

Jianling TAN*, Xuejing ZHANG, Dan LI, Hanzheng SUN

Abstract: On the basis of analyzing the natural frequency of the structure, the identification quantity of each process is constructed with modal parameters and input into the machine learning as characteristic parameters to realize the damage identification. By extracting the median curve of vegetation index time series after 5G filtering in the damaged area of typical civil structures, and comparing it with the actual growth curve of crops in the area, the vegetation index time series monitoring model was constructed, and 10 was selected as the best threshold. The accuracy of the result is verified, and the iteration time is 0.18 hours. A damage detection method based on machine learning is proposed. Good prediction results are obtained for three common surface damage of concrete cracks, spalling and exposed steel bars, which verify the ability of this method to accurately identify and detect structural surface damage at pixel level.

Keywords: civil structure damage detection; machine learning; multiple vegetation index time series; structural damage identification

1 INTRODUCTION

For engineering structures, the dynamic response of structures is easy to realize and measure. The structural dynamic detection method is not limited by the size and concealment of the structure, as long as the response sensor is installed in the accessible structural position [1]. At present, efficient modular and digital structural dynamic response measurement technology provides solid and effective technical support for structural dynamic testing methods. Therefore, how to use the vibration characteristics of the structure to detect global damage and structural damage has become an urgent problem to be solved.

Generally, the damage identification method based on mathematical model is the optimization of structural parameters. There are various optimization algorithms [2, 3], but these algorithms consume time and cannot realize real-time identification of structural damage. In addition, for cases with many degrees of freedom, the results can be unstable. In recent years, artificial neural networks have been widely used in damage recognition. The relationship between structural damage and structural mechanical properties is established by using neural networks to identify structural damage. Local damage occurs continuously during the use of civil structures, and when the local damage accumulates to a certain extent, it will pose a threat to the safety and reliability of the structure. The problem of structural damage identification is highly nonlinear and complex system, so it is difficult to identify damage by traditional methods. Neural network has great advantages in knowledge acquisition, adaptive learning, error correction ability and so on. It has become a new method to study damage recognition. The key to solving problems of neural networks is the reasonable selection of network input parameters [4], and the modal property is a function of the physical parameters of the structure.

Generally speaking, the health monitoring of complex structures is divided into four stages: abnormal detection of structures, location of damage types, assessment of damage degree and prediction of residual life of structures [5]. Structural damage monitoring and detection technology has been described in detail in many pieces of literature, and can be divided into structural parameter identification technology, modal parameter identification technology and non-physical model technology from the perspective of structural parameter identification. The core technology of civil structure damage detection is pattern recognition, which is difficult to be solved by traditional pattern recognition technology. The neural network itself has the ability of pattern matching and memory, and the effect of pattern recognition with certain noise is better. A component of the covariance matrix in the pattern category is represented by a weight of a variety of vegetation index time series, and the damage detection of pattern recognition can be realized by machine learning. The first part is the introduction, the second part is related work, and the third part is research method of damage detection of civil structures based on machine learning. The fourth part is simulation verification, and the fifth part is conclusion.

2 RELATED WORK

Compared with the natural frequency of the structure, the natural vibration mode of the structure contains more damage information, especially when locating the structural damage. It is more accurate to use the natural vibration mode of the structure [6, 7]. A large number of tests have shown that it can be used to determine the possible location of structural model errors and damages [8, 9]. Once the structure is damaged, it means that the stiffness of the structure will decrease, that is, the flexibility of the structure will increase. It is precisely based on this characteristic of flexibility that many researchers have studied the damage of structures by using the flexibility of structures as the damage indicator of structures [10, 11]. In general, since the observed flexibility matrix is proportional to the inverse matrix of the observed frequency, the observed flexibility matrix is more sensitive to changes in the lower-order modes of the structure and is suitable for structure identification using the lower-order modal data [11, 12]. Research on structure recognition based on flexibility matrix [13]. However, data incompleteness is still relatively rare. The research of structure recognition based on flexible matrix shows that flexible matrix contains rich information about structure characteristics under low order modal conditions, which provides a new and effective method for structure recognition under low order modal conditions. However, under the condition of incomplete and imprecise data, the number of researches on the flexible method of structure recognition is still relatively small, and further research on the structure recognition based on flexible matrix is needed.

The local damage detection method calculates the residual stress method, so that the specific situation of damage can be accurately judged. Method for measuring existing stresses in concrete structures is by borehole core surface strain gauge [14, 15]. The drilling ring method was used to measure the residual stress on the surface of concrete and a machine learning damage detection model for civil structures was established [16, 17]. The comparison with the experimental results of the US (United States) Federal Aviation Administration verified that the drilling ring method could be used to measure the residual stress. Machine learning civil structure damage detection method was used to analyze the variation law of the slotted structure's released stress with depth [18], and a correction method was proposed based on the slotted structure detection results.

The accuracy of local damage detection method will be affected by the test environment, cutting factors, external environment (temperature and humidity, etc.) and other factors. However, the local damage detection method cannot be used as a regular inspection method. Non-destructive testing methods involve the use of various detection techniques to detect any defects or damage of structures or buildings [19], and are widely used in the detection of various civil engineering projects such as concrete, steel structures, pipelines and roads. Non-destructive testing methods generally include ultrasonic, electromagnetic wave, ray (X-ray and gamma line) detection, magnetic particle detection, acoustic emission detection, radar and other technologies [20, 21]. 7 groups of concrete specimens have been tested by ultrasonic wave [22], but its detection accuracy is low and its speed is slow, which cannot meet the requirements of large-scale structure detection. In general, the traditional detection method requires the inspection personnel to inspect the structure in a close distance on the site, which is too time-consuming. The accuracy of the detection results is affected by the subjective experience of the inspection personnel and the operation level of the instrument, and it is easy to obtain an incorrect safety grade result of the evaluation of the structure. At the same time, the site environment and weather changes will also affect the development of normal traditional detection work. Therefore, the traditional detection methods can no longer adapt to the large-scale multi-type and multi-scene detection environment.

Machine learning uses mathematical and statistical methods to enable computers to learn rules and knowledge from data, allowing them to complete specific tasks on their own. Traditional machine learning is to extract features manually and then use various algorithms (decision trees [23], random forests [24], artificial neural networks [25], support vector machines [26]) for training and prediction. A three-layer neural network and backpropagation algorithm [27] were proposed to classify cracks, joint displacement, cross-sectional area reduction and fall off on the surface of underground sewage pipes, and the recognition accuracy reached 98.2%. A comprehensive crack imaging system based on artificial neural network was proposed [28], and the crack type classification accuracy reached 95.2% on the artificially made pavement crack image dataset. A backpropagation neural network is proposed to identify cracks on the surface of concrete structures [29]. Then, 120 images are used for image classification test, and the recognition rate of crack image is 90%, and the recognition rate of non-crack image is 92%. However, its simple structure cannot be applied to more advanced tasks such as semantic segmentation and object detection.

Machine learning structural damage detection based on big data can not only detect local damage such as cracks, spalling and exposure of steel bars commonly seen in engineering structural components, but also identify structural components such as beams, columns and walls globally. On this basis, the damage degree detection model of component is constructed to realize the end to end damage degree assessment. The image recognition method based on machine learning can better adapt to various engineering structure detection scenarios, and has higher accuracy and robustness in practical engineering damage detection. Based on this, this paper mainly uses the method of machine learning to study the automatic identification of surface damage and disease of engineering structural components and common structures.

3 RESEARCH METHOD OF DAMAGE DETECTION OF CIVIL STRUCTURES BASED ON MACHINE LEARNING

3.1 Application of Machine Learning in Damage Detection of Civil Structures

Once it is found that there are damage or quality problems in the upper timber engineering structure, it is necessary to use the damage identification method to determine the damage type and damage degree, so as to evaluate the overall performance of the structure. Machine learning model correction method is a damage identification method that optimizes constraint conditions and dynamic tests by constructing upper timber engineering structure model. It can modify damping, mass, stiffness and other characteristics of upper timber engineering structure to some extent. Then compare the two methods, in order to complete the identification and judgment of the structural damage of the upper timber project. In addition, the model modification method can also divide the unit in the structure and deal with the substructure model in the structure. However, due to its insufficient sensitivity to the parameters in the test process, it will cause strong noise in the measurement process or a large error in the measurement results. In addition, the modal information obtained from modal tests in the model modification method is still lacking in maturity, which also makes it less stable when solving the characteristic equation. Its frame diagram is shown in Fig. 1.

Gaussian process has the advantage of being easy to implement. Another advantage of the algorithm is its flexible non-parametric inference. The algorithm parameters of Gaussian process can be obtained adaptively in the process of model construction. Probabilistic interpretation of the forecast output can be made, and the modeler can evaluate the uncertainty of the model forecast output through the confidence interval [30]. This paper proposes a damage detection model for civil structures based on machine learning, and predicts the stability of actual civil structures, which provides a new way to realize fast, economical and safe civil engineering design.

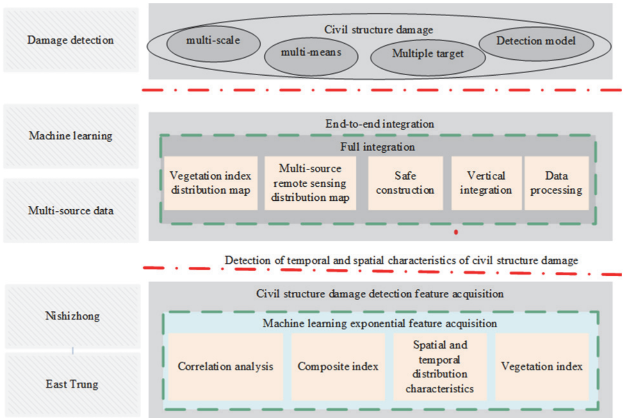


Figure 1 Research diagram of damage detection of civil structures by machine learning

Civil structure data set $D=(x_i, y_i)$, where x is the input vector, y is the output value, and for a given latent function, the observed value is an independent Bernoulli distribution variable whose likelihood function is:

$$p(y)=\sum_{i=1}^{m} p(y_i \mid f_i) \tag{1}$$

The prior distribution N of the potential function is:

$$p(f \mid X)=N(0,\lambda) \tag{2}$$

Covariance function k of machine learning model:

$$k_y=\lambda^2 \exp\frac{(x_i-x_{i-1})^2}{(y_i-y_{i-1})^2} \tag{3}$$

3.2 A Machine Learning Model for Damage Detection and Estimation of Civil Structures

The damage of civil structure is affected by many factors. According to engineering experience, the main factors affecting the stability of civil structure include rock weight, internal friction Angle, civil structure Angle, civil structure height, pore water pressure ratio, rock structure type, joint, the relationship between joint plane and civil structure Angle, and groundwater. The main factors considered in this paper are rock weight, internal friction coefficient, civil structure Angle, civil structure height and pore pressure ratio. N-dimensional vectors of damage factors of civil structures represent rock weight Y, cohesion force C, internal friction coefficient P, civil structure Angle r, civil structure height H and pore pressure ratio d, respectively. Examples of the composition of the sample set can be seen in Tab. 1.

Table 1 Training samples of machine learning

No.	Y	C	P	r	H	d	status
1	12.28	0	32.3	34.6	7	0.46	–1
2	23.48	0.3	31	36	216	0.41	–1
3	16.92	70.53	22.5	42.3	114.8	0.343	1
4	20.43	25.6	14	21	10.76	0.35	1
5	19.44	11.77	21.6	23.5	12.38	0.34	1
6	21.78	8.56	33	29	12.9	0.45	–1
7	20.45	32.46	12.6	17.8	12.68	0.43	–1
8	18.68	14.45	32.6	24.6	45.87	0.57	–1
9	18.39	0.83	26.8	21.6	10.68	0.36	1

When the order of magnitude difference between the control factors affecting the stability of civil structures is large or the dispersion of the same control factor is large, it will not be conducive to learning to standardize processing:

$$p_i=\frac{x_i}{s}, s=\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1} \tag{4}$$

By maximizing the log-likelihood function of the potential function 1 of the training sample, the optimal hyperparameters of the covariance function are obtained.

Synthesize prior information and adjust the posterior distribution of each random variable. EP algorithm is used to obtain the potential function f of the prediction sample. Approximate posterior Gaussian distribution;

The prediction probability of civil structure being stable state is obtained. When the prediction probability of civil structure stability is greater than 0.5, the state of civil structure is judged to be "stable". When the predicted probability value of civil structure stability is less than 0.5, the state of civil structure is judged as "failure".

The average absolute error of the five model training sessions is in the range of 7-11, with an average of 8.9, while the average for R-square is about 0.47. From the running point of the whole program, the total time of five model training and verification is only 0.11 s. As can be seen from the above, the experimental results basically reflect the advantages of high accuracy and short prediction time of machine learning. According to the training results, it can be seen that the fourth training model in this experiment has the strongest generalization ability, and the cement content in concrete and the culture time have a great influence on the final compressive strength, while the water content is negatively correlated with the compressive strength. The comparison between the real and predicted values of this training is shown in Fig. 2.

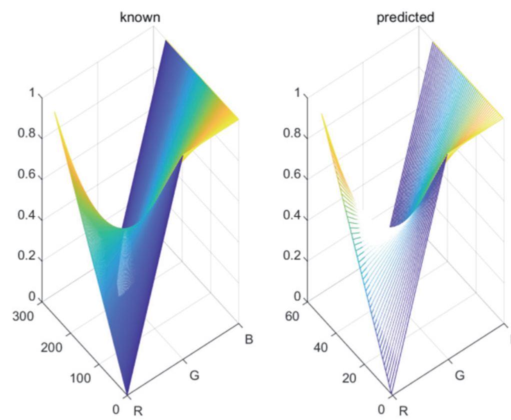


Figure 2 Comparison between the real value and the predicted value

3.3 Remote Sensing Retrieval of Civil Structure Damage Using Machine Learning Algorithm

In order to further improve the prediction accuracy of various models, synthetic learning models began to appear in various algorithm competitions and industrial fields. It improves the accuracy of the final prediction result, and has the advantages of high flexibility and strong generalization ability. Integrated learning model. In terms of improving the accuracy of organic carbon, total nitrogen, salinity, pH value and attribute map of civil structures, this paper combined multiple single machine learning models with integrated learning algorithms, and proposed remote sensing inversion methods based on multiple differentiated models under integrated learning architecture. Firstly, variable data, including microwave variables, vegetation variables, temperature variables, albedo variables, terrain variables, etc., were obtained. Secondly, models were established, including measured soil composition and parameter optimization, and models were established for training. Finally, models were compared to analyze the ability and spatial distribution of soil composition inversion of different models, as shown in Fig. 3.

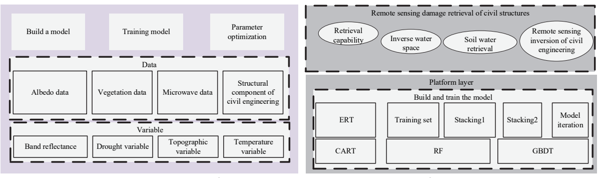


Figure 3 Technical route of remote sensing retrieval of civil structure damage based on machine algorithm

Firstly, the change of modal strain energy of each element before and after structural damage is used to detect the location and magnitude of structural damage. The main steps are as follows:

(1) Obtain the frequency, modal shape and stiffness matrix of each element of the undamaged structure;

(2) When measuring incomplete mode, the mode expansion method is used to expand;

(3) The possible damage element of the structure is determined by changing the modal strain energy ratio of the element;

(4) The damage coefficient of the damage element is obtained, and the size of the structural damage is obtained.

In practical application, the damage of structural stiffness is varied, and how to simulate the damage will directly affect the determination of the damage size.

The equation of structural vibration is as follows:

$$(T - w^2 * N) \times \delta = 0 \tag{4}$$

In the formula, "T" and "N" represent the stiffness matrix and mass matrix of the structure respectively, the δ mode matrix, and the w is the eigenvalue. After the structure is damaged, the stiffness and mass will change slightly, then δ and w will produce a small change, and the structural motion equation after damage becomes:

$$[T + \rhd T] - (w + \rhd w)^2 (\delta + \rhd \delta) = 0 \tag{5}$$

The damage significantly reduces the stiffness of the structure, but the mass distribution hardly changes, so the equation can be further simplified as:

$$[T + \rhd T] - (w^2 + 2 \times w \times \rhd w)(N + \rhd N)(\delta + \rhd \delta) = 0 \tag{6}$$

where: $\rhd T, \rhd N, \rhd \delta$ is the change of the global stiffness matrix, mass matrix and mode respectively.

When the structure is damaged, its stiffness decreases while the structure mass does not change, and the L-order natural frequency change r caused by damage can be regarded as a function of the stiffness reduction k and the damage position vector t:

$$\delta w_i = f(0, \delta) + \frac{\partial(0, \delta)}{\partial(T)} \tag{7}$$

where, f is the natural frequency before structural damage, and the change of ∂w_i structural damage frequency.

3.4 Damage Detection of Civil Structures with Multiple Vegetation Index Time Series

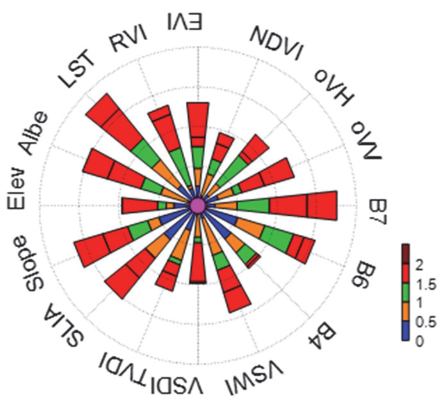
The study roughly divides them into three categories: visible light, short-wave infrared, and short-wave infrared. Its name and calculation formula are shown in Tab. 2.

Table 2 VI adopted in this study and its calculation formula

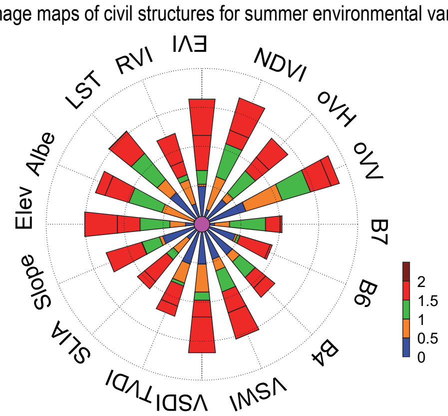
Spectral band	VI Name	Calculation formula
Visible light	Vegetation index	$\frac{T_N - T_R}{T_N + T_R}$
	Improved vegetation index	$\frac{T_N - T_G}{T_N + T_G}$
	Differential vegetation index	$\frac{T_N - T_G}{T_N + T_G}$
	Return to differential vegetation index	$\left(\frac{T_N - T_R}{T_N + T_R}\right)^{\frac{1}{2}}$
Near infrared	Trigonometric index	$\frac{T_N - T_{SR}}{T_N + T_{SR}}$
Short-wave infrared	Difference index	$\frac{T_N - T_{SG}}{T_N + T_{SG}}$

Therefore, in order to comprehensively analyze the relationship between soil water and environment, the best prediction model of soil water content in the study area was constructed. A total of 18 spatial environment variables, including remote sensing image band T, terrain factor N, vegetation factor R and drought factor G, were selected as the spatial prediction modeling variables of soil water. The relationship between soil moisture factors and SMC is not linear. In fact, most of the influencing factors, if not screened, can easily produce synergistic or inhibitory effects on soil water inversion, thus reducing the inversion efficiency of the algorithm. A good feature set should contain fewer features and contribute as much to model accuracy as possible. Fig. 4 shows the importance (z-one score) of the 18 environmental covariates (parts) of the SMC.

The classification accuracy of 7 kinds of VI was investigated to determine the best and worst VI in crop classification. As can be seen from Fig. 5, for the other 6 kinds of VI except NDSVI, the damage prediction of civil engineering by machine learning is better than the other 2 algorithms. The accuracy of DT (Data Technology) is higher than RF (Radio Frequency), NDSVI (Normalized Difference Vegetation Index) has the lowest classification accuracy, the accuracy of the three ML algorithms is lower than 81.5%, and the accuracy of RF+NDSVI is the lowest (73.7%) among all the results. The accuracy of machine learning civil engineering damage prediction + EVI was the highest (95.5%), followed by machine learning civil engineering damage prediction +NDVI (94.8%). The accuracy of EVI, GNDVI, NDVI, RDVI and TVI is high, and the accuracy of different algorithms is different. For TVI, the difference between the three algorithms is the smallest, and the accuracy is above 91%, which is the VI with the highest average accuracy. As can be seen from Fig. 5, NDSVI has the worst classification effect, and TVI has the best classification effect, although the highest accuracy is obtained by machine learning civil engineering damage prediction +VI. For the case of a single VI input, RF is the least effective, and machine learning is the best for civil engineering damage prediction.



(a) Damage maps of civil structures for summer environmental variables



(b) Damage maps of civil structures with winter environmental variables

Figure 4 Importance of damage environment variables of civil structures

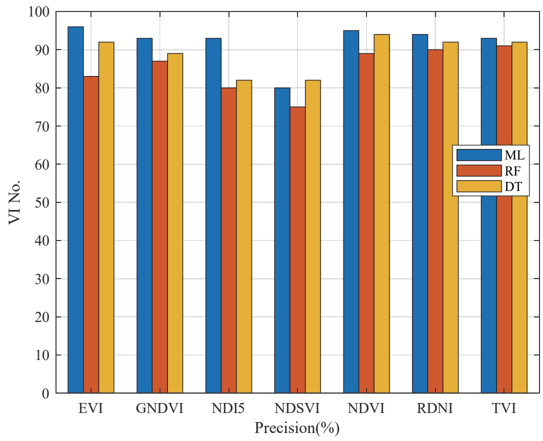


Figure 5 Classification accuracy of civil structure damage single VI as input

5 SIMULATION VERIFICATION

82 engineering examples of circular slope were collected. For the slope stability prediction model, 67 sample examples were randomly selected as learning samples, among which 36 were damaged samples, 31 were stable samples, and another 10 sample examples were randomly selected as prediction samples to test the prediction effect of the model (Tab. 1). For the unknown pore-water pressure ratio of some instances, the average of the known pore-water pressure ratio of all other instances can be replaced by 0.31.

According to the established machine learning civil structure damage detection model of slope stability safety factor, the prediction model is set to (0, 0) as the initial value of the hyperparameter by learning the training sample and taking the maximum likelihood of the training sample as the target. By learning the training sample, the conjugate gradient optimization algorithm is adopted, and the convergence standard is set as the maximum iteration step of 200. The calculation was performed on an Intel Celeron 2.5 GHz PC and took a total of 68 s after 136 iterations.

The prediction results of the machine learning civil structure damage detection model on the test samples are shown in Tab. 3. According to the basic principle of machine learning civil structure damage detection model, the slope stability state belongs to Class 1 (stable) when the prediction probability of slope stability is higher than 0.5. On the contrary, when the prediction probability of slope stability is less than 0.5, the slope stability state belongs to Class 2 (failure). As can be seen from Tab. 3, the prediction results of slope stability state of 10 test samples are completely consistent with the actual situation, indicating that the model has strong self-learning ability and extrapolation ability, and high prediction accuracy.

Table 3 Comparison between the predicted results of the machine learning civil structure damage detection model and the measured values

ID	Y	C	P	r	H	d	Stability probability	Predicted state	Actual state
1	31.5	67	36	49.3	203.5	0.35	0.45	destroy	destroy
2	20.5	21	34	45.5	52	0.35	0.09	destroy	destroy
3	25.4	46	37	56.3	26	0.36	0.94	stabilize	stabilize
4	31.4	69	35	46.3	35	0.35	0.24	destroy	destroy
5	25.4	46	37	44.5	26	0.36	0.97	stabilize	stabilize
6	27.4	11	39	42.3	45	0.35	0.94	stabilize	stabilize
7	25.2	47	42	43.5	35	0.35	0.93	stabilize	stabilize
8	25.2	49	41	46.3	34	0.35	0.93	destroy	destroy
9	31.7	68.7	36	48.7	21.5	0.35	0.97	destroy	destroy

The specimen was calculated with the eighth order of damage depth of 10, 30, 50 mm on the rectangular beam as the parameter, which was used to train the network, and small damage was used to detect whether the location and degree of damage were accurate. Limited by space, this paper only gives the first five natural frequencies of rectangular beams with different damage degrees at 100, 200, 300 mm positions, as shown in Tab. 4.

Table 4 Natural frequencies at different damage locations and damage degrees

	Damage degree	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
undamaged	0	219.85	224.18	708.93	729.87	901.56
100	10	219.56	224.23	702.67	729.56	901.78
100	30	219.75	221.65	643.75	726.64	899.51
100	50	213.56	219.13	518.93	718.34	893.34
200	10	219.78	223.57	702.34	728.67	892.78
200	30	217.67	219.56	655.67	721.78	901.56
200	50	198.67	219.34	560.54	703.45	899.89
300	10	219.68	223 .57	705.78	725.76	893.54
300	30	212.87	218.45	677.46	716.78	900.56
300	50	186.67	216.24	618.78	698.89	896.67

The modal frequency of the beam changes before and after damage. The modal change of the beam at the damaged place of 100, 300 mm is shown in Fig. 6.

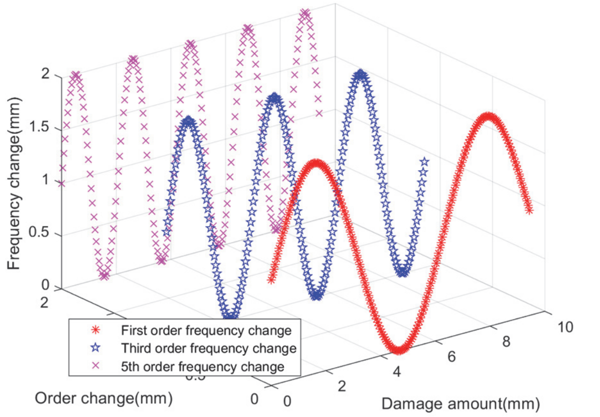


Figure 6 Modal frequency change of the beam at 100 mm

Only a small number of lower-order modes are retained for each substructure to set up the vibration equation of the polycondensation, and then the dynamic displacement of the whole structure is calculated. An additional term is added to the vibration equation to consider the contribution of the abandoned higher-order modes. The number of retained modes affects the accuracy of the substructure method, and the more retained modes, the higher the accuracy. However, the greater the number of preserved modes, the computational efficiency will be greatly reduced. The closer the model correction is to the optimal solution, the higher the precision of displacement and displacement sensitivity is required. Therefore, in order to ensure the accuracy and efficiency of substructure model modification, different number of modes are preserved in different model modification stages. For the first 6 iterations, 35 modes are retained. As the correction process of machine learning civil structure damage detection model is approaching convergence, the number of retained modes is increasing. In the last 3 iterations, the order 20 modes are retained, as shown in Fig. 7.

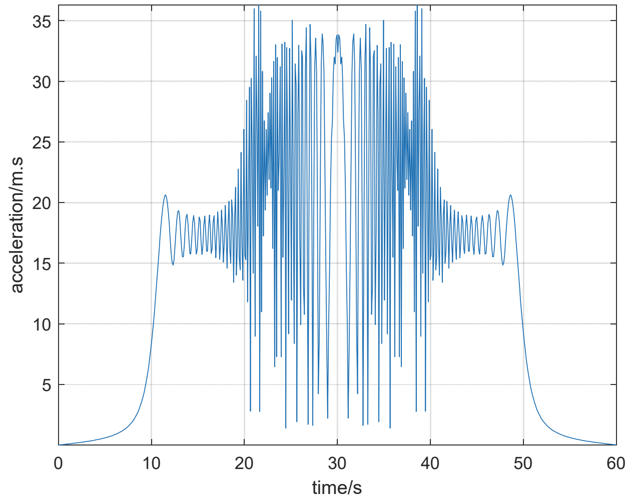


Figure 7 Seismic load excitation

The changes of loss value and average crossover ratio of the machine learning model and comparison model in the training process are shown in Fig. 8 and Fig. 9. It can be seen that after 60 rounds of training, the loss value is reduced to a low enough level, and the average crossover ratio also reaches a high value, indicating that each network model has been fully trained.

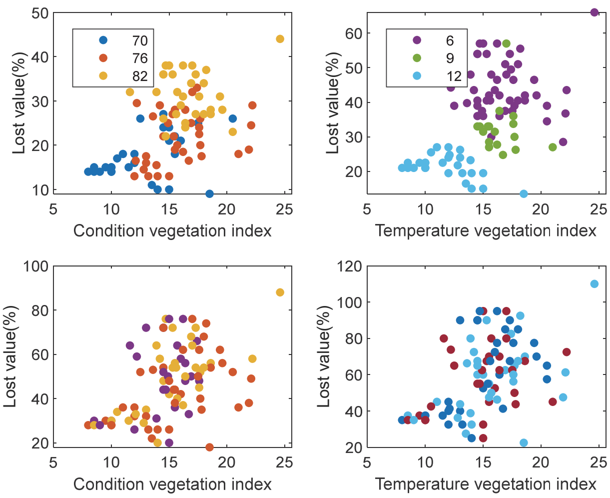


Figure 8 Change of loss value of machine learning civil structure damage model

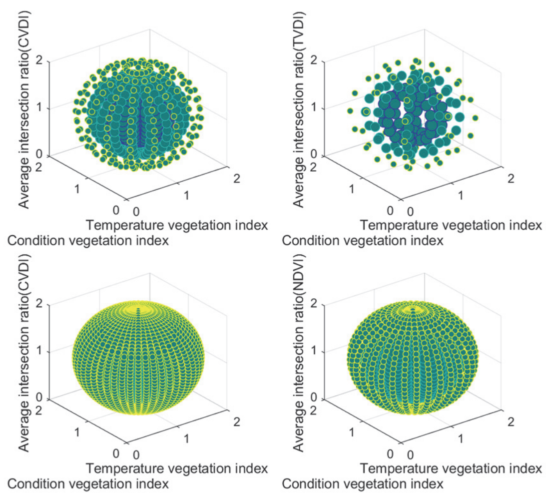


Figure 9 Change of average intersection ratio of machine learning civil structure damage model

Tab. 5 shows the crack prediction performance of these semantic segmentation models in post-earthquake UAV road images. U-Net-light-CBAM, the machine learning model proposed in this study, has the best performance in F1 and mIoU indicators, with scores of 98.73% and 99.43%, respectively. Although the crack accuracy index is slightly lower than that of PSP-Net, the accuracy of background pixel segmentation has been improved, and the phenomenon of background pixel being wrongly divided into cracks has been significantly improved.

Table 5 Comparison of UAV image performance after civil structure damage with multiple vegetation index

Model	Accuracy	Precision	Recall	F1
FCN	0 .5408	0.9811	0.9751	0 .9870
SegNet	0 .5428	0.9797	0.9741	0 .9861
PSPNet	0 .5932	0.9807	0.9868	0 .9883
DeepLabV3	0.4227	0.9699	0.9629	0 .9867
Machine learning	0.6987	0.9902	0.9943	0 .9873

The comparison of the time-history curve of the online recognition value is shown in Fig. 10, and the time-history response of the restoring force is shown in Fig. 11. The real value of model parameters, the recognition value of machine learning civil structure damage detection model, the recognition value of least square method and the initial guess value were compared respectively.

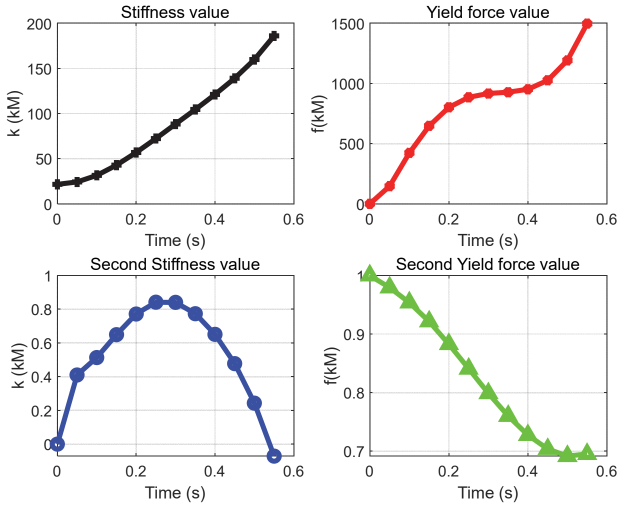


Figure 10 Online recognition curve

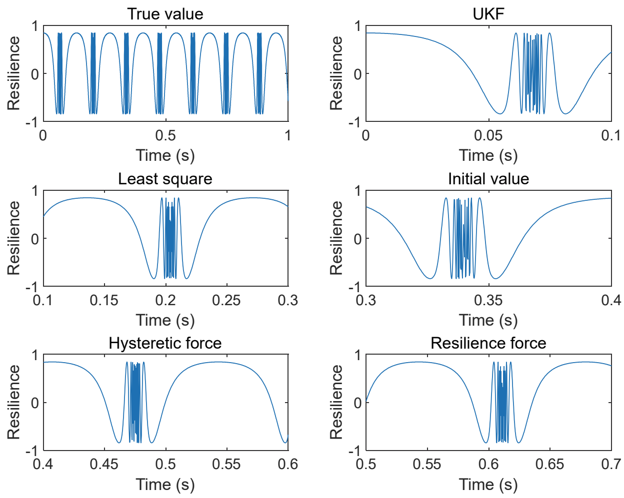


Figure 11 Results of parameter identification and model update

The results show that compared with the initial value and least square method, the parameter estimation of the machine learning civil structure damage detection model is more accurate, and the relative errors of the final value and the true value are 0.365 and 0.092, respectively. In the 0.7 s time history, all parameters can converge to the true value at about 0.6 s, indicating that the machine learning civil structure damage detection model has a fast convergence speed. Using Intel dual-core CPU(2.33 GHz) for a common desktop computer, the numerical simulation time is 0.6 s, indicating that the machine learning civil structure damage detection model has high computational efficiency.

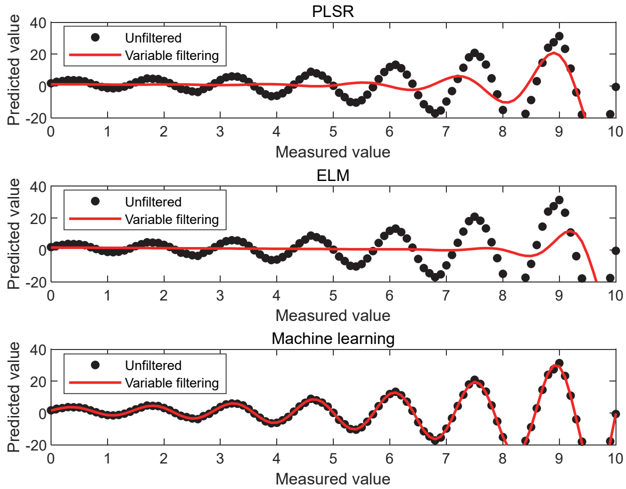


Figure 12 Convergence curve of the corrected civil structure damage detection model

Fig. 12 compares the damage identification method modified based on the machine learning damage detection model for civil structures. When the mode is retained for 30 orders, the dimensions of the vibration equation and the sensitivity equation are condensed to 270 × 270, and the time spent for each iteration is 0.18 h. For the last 3 iterations, the vibration equation/sensitivity equation has a size of 1170 × 1170, and each iteration takes 0.9 h. The substructure method requires a total of 23 iteration steps and 9.78 h convergence. The dynamic response and sensitivity of the whole model were calculated by the whole structure method. The size of the vibration equation/sensitivity equation was 23364 × 23364. Each iteration step took 14.17 h, and it took a total of 10 iteration steps and 198.38 h to reach convergence.

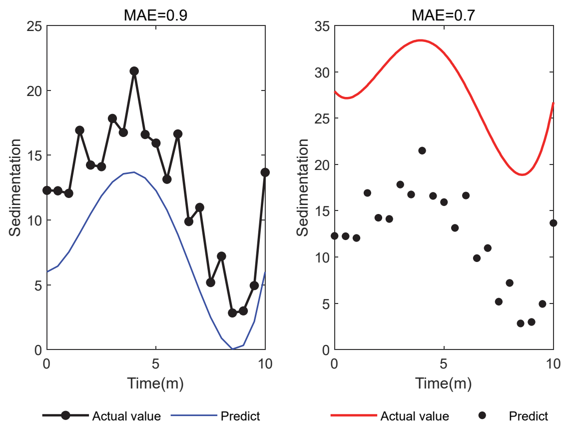


Figure 13 Comparison between predicted and measured damage values of civil engineering based on machine learning

The comparison between the predicted value and the measured value of the machine learning civil engineering damage prediction model is shown in Fig. 13. The blue lines and black dots represent the predicted values of the model, and the black and red lines represent the measured values of the model. Comparing the two figures, it can be seen that the machine learning civil engineering damage prediction model is more suitable for soil settlement prediction of civil structures.

6 CONCLUSION

The structural damage identification based on frequency variation parameters is simple and easy to judge without measuring other modal parameters such as vibration mode. The identification process is divided into three sub-processes: damage identification, localization and damage degree identification. With fewer parameters, the method also has strong robustness, which is not only less affected by model errors, but also does not affect the damage detection accuracy due to incomplete measurement information. The damage identification method based on the modification of machine learning damage detection model for civil structures has intuitive calculation process, clear physical significance, and can identify the location and degree of structural damage simultaneously. It is a direct and effective damage identification technology for civil engineering. However, the scale of civil engineering is huge, and the damage usually occurs in the local area. The time-consuming optimization calculation, uncertainty analysis and nonlinear calculation are limited to the local substructure, which effectively improves the accuracy and efficiency of damage identification, and opens up a new way for the damage identification technology modified by the traditional damage detection model of civil structure based on machine learning. In this paper, only rainfall, temperature and drought index are considered as influencing factors limiting vegetation change, and all important variables closely related to vegetation growth are not included. Therefore, in the following studies, the factors affecting vegetation growth should be comprehensively studied to the maximum extent, and the quantitative characterization of vegetation vulnerability under multi-factor conditions should be improved.

Acknowledgments

The research was supported by the Key scientific research project plan of Henan Higher Education Institutions (24B580003). The authors also would like to thank the Dr. Sun Hanzheng's studio, School of Civil Engineering and Transportation Engineering, Yellow River Conservancy Technical Institute.

7 REFERENCES

[1] Liao, W., Zhang, S., & Wu, Y. (2021). Research on intelligent damage detection of far-sea cage based on machine vision and deep learning. *Aquacultural Engineering: An International Journal*, *96*, 102219. https://doi.org/10.1016/j.aquaeng.2021.102219

[2] Shimada, M., Kurahashi, T., & Murakami, Y. (2021). Research on three-dimensional cavity shape identification in concrete structures based on machine learning using hammering response data. *The Proceedings of Conference of Hokuriku-Shinetsu Branch*, *182*(3), 3207-3214. https://doi.org/10.1299/jsmehs.2021.58.e025

[3] Hou, R. & Xia, Y. (2020). Review on the new development of vibration-based damage identification for civil engineering structures: 2010-2019. *Journal of Sound and Vibration*, *491*(9), 78-92. https://doi.org/10.1016/j.jsv.2020.115741

[4] Choe, D. E., Kim, H. C., & Kim, M. H. (2021). Sequence-based modeling of deep learning with LSTM and GRU networks for structural damage detection of floating offshore wind turbine blades. *Renewable Energy*, *174*, 218-235. https://doi.org/10.1016/j.renene.2021.04.025

[5] Zhao, Y., Hu, H., & Song, C. (2022). Predicting compressive strength of manufactured-sand concrete using conventional and metaheuristic-tuned artificial neural network. *Measurement*, *2022*(4), 194-207. https://doi.org/10.1016/j.measurement.2022.110993

[6] Avija, B. (2021). On the Use of Machine Learning Models for Prediction of Compressive Strength of Concrete: Influence of Dimensionality Reduction on the Model Performance. *Materials*, *14*, 713-726. https://doi.org/10.3390/ma14040713

[7] Islam, M. M. M. & Kim, J. M. (2019). Vision-Based Autonomous Crack Detection of Concrete Structures Using a Fully Convolutional Encoder-Decoder Network. *Sensors*, *19*(19), 4251-4263. https://doi.org//10.3390/s19194251

[8] Dung, C. V. & Anh, L. D. (2018). Autonomous concrete crack detection using deep fully convolutional neural network. *Automation in Construction*, *99*, 52-58. https://doi.org/10.1016/j.autcon.2018.11.028

[9] Shamsabadi, E. A., Xu, C., & Rao, A. S. (2022). Vision transformer-based autonomous crack detection on asphalt and concrete surfaces. *Automation in construction*, *2022*(Aug.), 140-147. https://doi.org/10.1016/j.autcon.2022.104316

[10] Qin, H. (2022). Autonomous Concrete Crack Semantic Segmentation Using Deep Fully Convolutional Encoder-Decoder Network in Concrete Structures Inspection. *Buildings*, *12*(11), 2019-2028. https://doi.org/10.3390/buildings12112019

[11] Shimada, M., Yamamoto, K., & Kurahashi, T. (2023). Identification of non-dimensional density distribution of concrete structures based on self-attention using hammering response data. *Engineering Optimization*, *55*(7), 1083-1099. https://doi.org/10.1080/0305215X.2022.2141731

[12] Zhu, Y., Wang, J., & Fu, C. (2023). Temporally and spatially resolved molecular profiling in fingerprint analysis using indium vanadate nanosheets-assisted laser desorption ionization mass spectrometry. *Journal of Nanobiotechnology*, *21*(1), 12951-12968. https://doi.org/10.1186/s12951-023-02239-w

[13] Fa-Ming, Z., Ya-Jun, G., & Ping-Tao, Y. I. (2019). A Method of Group Evaluation Information Aggregation Based on Two-dimensional Density Operator. *Journal of Systems & Management*, *18*(4), 397-401. https://doi.org//10.1016/S1874-8651(10)60074-9

[14] Sakhakarmi, S., Arteaga, C., & Park, J. W. (2019). Automated Scaffolding Safety Analysis: Strain Feature Investigation using Support Vector Machines. *Canadian Journal of Civil Engineering*, *47*(8), 89-103. https://doi.org/10.1139/cjce-2019-0150

[15] Liu, J. J., Bharati, M. H., & Dunn, K. G. (2019). Automatic masking in multivariate image analysis using support vector machines. *Chemometrics & Intelligent Laboratory Systems*, *79*(1-2), 42-54. https://doi.org/10.1016/j.chemolab.2005.03.004

[16] Luo, Y., Dong, Z., Liu, Y. et al. (2021). Research on stage-divided water level prediction technology of rivers-connected lake based on machine learning: a case study of

Hongze Lake, China. *Stochastic Environmental Research and Risk Assessment*, *2021*(7). https://doi.org/10.1007/s00477-021-01974-6

[17] Sabahi, S. & Parast, M. M. (2020). The Impact of Entrepreneurship Orientation on Project Performance: A Machine Learning Approach. *International Journal of Production Economics*, *2020*, 107621-107635. https://doi.org/10.1016/j.ijpe.2020.107621

[18] Xin, Y., Wang, C., & Dong, Y. (2020). Management and Entrepreneurship Management Mechanism of College Students Based on Support Vector Machine Algorithm. *Computational Intelligence*, *12*(25), 842-854. https://doi.org/10.1111/coin.12430

[19] Nie, X. (2020). Research on economic function data and entrepreneurship analysis based on machine learning and computer interaction platform. *Journal of Intelligent and Fuzzy Systems*, *39*(4), 5635-5647. https://doi.org/10.3233/JIFS-189043

[20] Chung, D. (2023). Machine learning for predictive model in entrepreneurship research: predicting entrepreneurial action. *Small Enterprise Research*, *30*(1), 89-106. https://doi.org/10.1080/13215906.2022.2164606

[21] Zonzini, F., Aguzzi, C., & Gigli, L. (2020). Structural Health Monitoring and Prognostic of Industrial Plants and Civil Structures: A Sensor to Cloud Architecture. *IEEE Instrumentation and Measurement Magazine*, *23*(9), 21-27. https://doi.org/10.1109/MIM.2020.9289069

[22] Chen, Z., Wang, Y., & Wu, J. (2021). Sensor data-driven structural damage detection based on deep convolutional neural networks and continuous wavelet transform. *Applied Intelligence*, *11*(2), 2092-2098. https://doi.org/10.1007/s10489-020-02092-6

[23] Dinh-Cong, D., Dang-Trung, H., & Nguyen-Thoi, T. (2018). An efficient approach for optimal sensor placement and damage identification in laminated composite structures. *Advances in Engineering Software*, *119*(MAY), 48-59. https://doi.org/10.1016/j.advengsoft.2018.02.005

[24] Nguyen, A., Chan, T. H., & Zhu, X. (2019). A novel deep learning-based method for damage identification of smart building structures. *Structural Health Monitoring*, *18*(1), 143-163. https://doi.org/10.1177/1475921718804132

[25] Zare Hosseinzadeh, A., Bagheri, A., & Ghodrati Amiri, G. (2021). A flexibility-based method via the iterated improved reduction system and the cuckoooptimization algorithm for damage quantification with limited sensors. *Smart Material Structures*, *23*(4), 45019-45028. https://doi.org/10.1088/0964-1726/23/4/045019

[26] Luleci, F., Catbas, F. N., & Avci, O. (2022). Generative adversarial networks for labeled acceleration data augmentation for structural damage detection. *Journal of Civil Structural Health Monitoring*, *13*(1), 181-198. https://doi.org/10.1007/s13349-022-00627-8

[27] Li, H., Spencer, B. F., & Mao, J. (2021). Toward data anomaly detection for automated structural health monitoring: Exploiting generative adversarial nets and autoencoders. *Structural Health Monitoring*, *20*(4), 1609-1626. https://doi.org/10.1177/1475921720924601

[28] Kopan, J., Kvarek, O., & Klimo, M. (2021). Anomaly detection using Autoencoders and Deep Convolution Generative Adversarial Networks. *Transportation Research Procedia*, *55*, 1296-1303. https://doi.org/10.1016/j.trpro.2021.07.113

[29] Daneshvar, M. H. & Sarmadi, H. (2022). Unsupervised learning-based damage assessment of full-scale civil structures under long-term and short-term monitoring. *Engineering Structures*, *256*, 114059-114087. https://doi.org/10.1016/j.engstruct.2022.114059

[30] Flah, M., Nunez, I., & Ben Chaabene, W. (2021). Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review. *Archives of Computational Methods in Engineering*, *28*(4), 2621-2643. https://doi.org/10.1007/s11831-020-09471-9

Contact information:

Jianling TAN
(Corresponding author)
School of Water Conservancy Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China
E-mail: htanjl_2023@163.com

Xuejing ZHANG
School of Water Conservancy Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China

Dan LI
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute, Kaifeng, 475004, China
E-mail: 986394895@qq.com

Hanzheng SUN
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China
E-mail: Dorsun0326@163.com