Construction vibration risk assessment of LLE nonlinear characteristics based on ANFIS

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Abstract. The risk analysis related to construction projects is a decision-making tool, which can provide auxiliary decision-making information to the managers when they make decisions, thus improving the credibility of the decision. Project risk analysis tries to find all the abnormal events that may lead to the failure of the project to be carried out according to the scheduled plan. The risk management needs to identify all the risk factors that cause uncertainty, evaluate the probability and consequences of the occurrence of the event, and take reasonable measures to reduce the possibility and loss of the risk. The developed countries have taken the risk analysis as an important part of the feasibility analysis of the project planning stage. The variability of the project makes the managers unwilling to invest too much time and cost to take advanced risk management measures. Construction vibration risk assessment is based on high-dimensional and large data. LLE can effectively extract the nonlinear characteristics of high-dimensional data. ANFIS is an effective method of classification evaluation. Using LLE and ANFIS to classify and evaluate the high-dimensional feature vectors of construction vibration, it can effectively identify the risk of construction vibration.

1. Introduction
The relevant theoretical research [1–6] on the environmental impact of construction vibration is carried out to identify the risk of the construction vibration risk, as shown in figure 1. On the one hand, the vibration caused by the vibration source is transmitted through the soil, which may cause the densification of the soil and the foundation settlement of the buildings around the site. On the other hand, the interaction between the soil and the building foundation makes the building structure vibration response, which may cause damage to the building or the residence in the building. The interference of the person and the precision instrument. According to different risk objectives, the risk of construction vibration is divided into three parts: building settlement risk, building vibration risk and occupant risk.
Figure 1. The recognition of construction vibration risk transmission

Risk can be expressed as \( R (\text{risk}) = P \text{ (probability)} \times C \text{ (consequence)} \), namely the possibility of loss. According to the definition of risk, the environmental risk of construction vibration is defined as the possibility of the impact of construction vibration on the surrounding environment or the occurrence of damage. Among them, precision instruments are considered as occupants of special attributes and are classified into the risk of occupants. For the risk object (buildings and occupants) in the system, and the landslide risk model in the references, as shown in Formula 1.

\[
R(PD) = P(H) \times P(S) \times V(P) \times E
\]  

Among them, \( R(PD) \) refers to the risk of landslides; \( P(H) \) refers to the possibility of occurrence of landslides; it is a probability. \( V(P) \) refers to the possibility of damage to objects; \( E \) refers to the value of objects. Among them, Wong [7] thinks that it can be seen as a risk result. Leroueil [8] believes that it can be regarded as the risk of risk. Referring to Formula 1, a risk model for construction vibration is proposed, as shown in formula 2.
Among them, \( R(\nu) \) is the risk of construction vibration. \( H(\nu) \) refers to the possibility that the construction vibration is dangerous to the risk object, for short, \( V(\nu) \) refers to the possibility of the damage of the risk object, for short, the \( C(\nu) \) refers to the seriousness of the risk consequences or the possible risk loss, and \( H(\nu) \times V(\nu) \) can also be regarded as a risk occurrence. The possibility. The knowledge framework of expert system is also built based on the risk model of construction vibration environment.

\[
R(\nu) = H(\nu) \times V(\nu) \times C(\nu)
\]

(2)

Figure 2. Hierarchical index system of construction vibration evaluation

The knowledge system of construction vibration risk assessment is composed of the factors considered by experts in the risk assessment, and established on the basis of literature collection and expert investigation [9-12]. According to the spreading process of the risk of the construction vibration environment, the construction vibration risk is divided into two parts of the building risk and the resident risk, in which the building risk is divided into the building settlement risk and the building vibration risk. According to the construction vibration environment risk model, the risk module, the vulnerability module and the importance module are integrated into the risk, and the knowledge frame of the construction vibration risk assessment is shown in figure 2.

2. LLE nonlinear feature extraction method

The knowledge system of construction vibration risk assessment is composed of the factors considered by experts in the risk assessment. The vibration risk assessment high dimensional index eigenvector can be obtained according to the expert system index shown in figure 2. The eigenvector contains some characteristic information which is not related to the vibration risk assessment, and the feature set itself is a linear combination stack. How to get the nonlinear feature set that can reflect the vibration risk assessment is an urgent problem [12-16]. On this basis, the local line embedding algorithm is used
to extract two features of the linear data set. Next, we will first introduce the local linear feature embedding algorithm for subsequent applications.

Locally Linear Embedding (LLE) assumes that the data structure in the local sense is linear on the premise of the overall nonlinearity of the data, and it is a manifold algorithm that relies on local linearity to approximate the whole nonlinearity. Under the condition that the local geometric properties remain unchanged, the algorithm overlaps the local neighborhoods to provide the global characteristic information after dimensionality reduction of high-dimensional data.

LLE algorithm maps high dimensional data sets $A = \{a_1, a_2, \cdots, a_n\}$, $a_i \in \mathbb{R}^d$ to low dimensional data sets $B = \{b_1, b_2, \cdots, b_n\}$, $b_i \in \mathbb{R}^d$ ($D > d$). The algorithm is divided into 3 steps:

1. The distance between each sample point $a_i$ ($i = 1, 2, \cdots, n$) and the other sample $n-1$ points in the high dimensional data space is calculated. According to the distance between the sample points, the nearest $K$ and the nearest $a_j$ ($i = 1, 2, \cdots, n$) points are selected as their neighbourhood. The distance between two points is measured by Euclidean distance, that is $d_{ij} = \|a_i - a_j\|$, the distance between two points.

2. The weights between each sample point $a_i$ ($i = 1, 2, \cdots, n$) and its $K$ adjacent points in the high-dimensional data space are calculated respectively.

   $G(w) = \min \sum_{i=1}^{n} \left\| a_i - \sum_{j=1}^{K} w_{ij} a_j \right\|^2$  

In the form $\sum_{j=1}^{K} w_{ij}^{(j)} = 1$, if $a_i$ ($j = 1, 2, \cdots, n$) is not the nearest neighbor of $a_i$ ($i = 1, 2, \cdots, n$), then $w_{ij}^{(j)} = 0$;

3. The weights $w_{ij}^{(j)}$ between the high-dimensional sample points $a_i$ ($i = 1, 2, \cdots, n$) and the neighborhood sample points $a_j$ ($j = 1, 2, \cdots, n$) is used to calculate the sample points $b_i$ and $b_j$ in the low dimensional embedding space. In order to make the local linear characteristic of high dimensional space represented by the weight value $w_{ij}^{(j)}$ can be preserved to the maximum degree in the low dimensional space, the weight value $w_{ij}^{(j)}$ is fixed and then the loss function is minimized in the low dimensional space.

   $L(B) = \min \sum_{i=1}^{n} \left\| b_i - \sum_{j=1}^{K} w_{ij}^{(j)} b_j \right\|^2 = \text{tr} \left( B^T MB \right) \quad (4)$

In order to keep $L(B)$ the translation, rotation and stretching changes unchanged, the upper form should satisfy two constraints, namely: $\sum_{i=1}^{n} b_i = 0$, $\frac{1}{n} \sum_{i=1}^{n} b_i b_i^T = 1$. The eigenvector corresponding to the first $d+1$ minimum non zero eigenvalue of matrix $M$ is the solution to obtain the minimum value of $L(B)$. The eigenvectors of the corresponding minimum eigenvalues are extracted, and the matrix $B$ composed of the remaining $d$ eigenvectors is the eigenvectors in the low dimensional space.
3. Adaptive fuzzy neural inference system (ANFIS)

The adaptive fuzzy neural network inference system (Adaptive Neuro-Fuzzy Inference System abbr. ANFIS) is an integrated system of neural network and fuzzy theory proposed by the Chinese scholar Jyh-Skiing Roger Jang in 1993. The system uses the topology of neural network to express the fuzzy inference system through each of them. Each kind of fuzzy operation is realized by the neuron, and the hybrid algorithm combining the error back propagation and the least square estimation in the neural network theory adaptively adjusts the system parameters to approximate the implicit relationship between the input and output data. The fuzzy neural network system has the function of fuzzy inference and the ability of mapping and approximation. It has been tried and applied in system identification, time series prediction and fault diagnosis. The vibration characteristics of nonlinear high-dimensional construction extracted by LLE represent a risk state. We can input these nonlinear high-dimensional features into ANFIS neural network to identify their risk states.

3.1. The system structure of ANFIS

ANFIS is a multi input and single output system without loss of generality. It is illustrated with Sugen o-fuzzy system as an example. The system has two inputs and one output \( f \) for the first order Sugeno, and the typical fuzzy if-then rule is expressed as:

\[
\text{if } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ then } f_i = p_i x + q_i y + r_i. 
\]  
(5)

\[
\text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2 x + q_2 y + r_2. 
\]  
(6)

The corresponding ANFIS structure is shown in the figure. In figure 3, the connection between nodes only represents the transmission direction of the signal, and no weight is associated with it: the square node indicates that the parameters can be adjusted, and the circular node indicates that the parameters are fixed. The functions of each layer are as follows:

- **First layer**: each node is connected with a system input, and the input variables are fuzzed to output the membership degree of corresponding fuzzy sets of nodes.

\[
O_{1,i} = u_{A_i,1}(x), \quad i = 1, 2; \quad O_{1,3} = u_{B_i,1}(y), \quad i = 3, 4
\]  
(7)

(8)

According to the membership function corresponding to the node, the corresponding conditional parameter sets can be obtained. On the generalized bell shape membership function

\[
u_{A_i}(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i}\right)^{2b_i}}
\]  
(9)
The set of conditional parameters \( \{a_i, b_j, c_k\} \) is a set of all the parameters.

The second layer: each node represents a generation rule, which is connected to a node in the first layer that represents the corresponding rule condition. The input is calculated by a fuzzy product, and the applicability of each rule is output.

\[
O_{2i} = w_i = u_a(x) \times u_b(y)
\]  

(10)

The third level: each node corresponds to a rule and connects to all the nodes in the second tier, normalizing the applicability of the rules.

\[
O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}
\]  

(11)

The fourth layer: each node is connected with the corresponding nodes in the third tier and all the input of the system, and the output of corresponding rules is calculated.

\[
O_{4i} = \overline{w_i} f_i = \overline{w_i} (p_i x + q_i y + r_i)
\]  

(12)

The conclusion is that the set of parameters \( \{p_i, q_i, r_i\} \).

The fifth layer: only one node is connected to all the nodes in the fourth tier to calculate the output sum of all rules.

\[
O_5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} \overline{w_i} f_i}{\sum_{i=1}^{2} \overline{w_i}}
\]  

(13)

3.2. ANFIS learning algorithm

ANFIS uses the hybrid algorithm of error backpropagation and least squares estimation to adjust the variable parameters of the system. For the adaptive network with adjustable parameters, the linear parameter can be identified by the least square method, and the nonlinear parameter can be identified by the error back propagation algorithm. According to the network structure of ANFIS, when the conditional parameters are fixed, the output of the system can be expressed as a linear combination of the conclusion parameters.

\[
f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2
\]

\[
= \overline{w_1} f_1 + \overline{w_2} f_2
\]

\[
= (\overline{w_1} x) p_1 + (\overline{w_1} y) q_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2} y) q_2 + (\overline{w_2}) r_2
\]  

(14)

Therefore, the hybrid algorithm combining error back propagation and least squares estimation can be used to adjust the parameters of ANFIS. In each iteration, when the input of the system is forward, the parameter is fixed by the least square estimation method. When the output error is back propagating, the parameter is fixed by the gradient descent method. For the known conditional parameters, the global optimal conclusion can be obtained by this way, which can not only reduce the dimension of the search space in the gradient descent method, but also improve the convergence speed significantly.

4. A method of combining LLE nonlinear characteristics with ANFIS

The LLE method extracts the nonlinear characteristics of the multidimensional vector that characterizing the vibration risk characteristic index system, and uses the advantage of LLE to extract
the nonlinear characteristics. The eigenvector of the index system characterized by the high dimension nonlinear characteristics is reduced to get the nonlinear eigenvector of the vibration risk of the more bottom dimension. The vector input of ANFIS learning method is used to evaluate the risk of construction vibration at different sites. The concrete implementation steps of the method are as follows:

1. Taking a project as the research object, according to the index system shown in figure 2, the concrete indexes of the construction vibration risk are extracted, and a high dimensional eigenvector of the construction vibration risk is obtained.

2. Each component of the high-dimensional feature vector is normalized to form a normalized high-dimensional feature vector which represents the risk of the project construction.

3. According to the formula, the low dimensional nonlinear characteristics of the high-dimensional feature vectors are calculated as the input characteristics of the ANFIS method.

4. The ANFIS neural network is trained by the nonlinear characteristics of the known vibration risk grade of the engineering sample as the training sample. Then the characteristic values of the prepared samples are input to the neural network to obtain the construction vibration risk rating of the samples.

5. Practical engineering application
In order to verify the effectiveness of the method, the ANFIS method based on LLE nonlinear characteristics is applied to practical engineering to evaluate the vibration risk of the project.

The expansion and construction of the gateway office building (Gatesway project) of the Durham University library has been used for coal mining. Therefore, a number of concrete shaft wells were buried in the site, which produced great vibration during the demolition of the concrete shaft and the original ground structures, which had a great influence on the surrounding environment. In the stage of project risk assessment in the early stage of construction, it is necessary to evaluate the risks caused by construction vibration during construction. The location of the project is close to the road on both sides and the other side is only about 6m distance from the original project office building. The project map of the Gatesway project, as shown in figure 4 below, is the red area of the proposed building. The project map of the Gatesway project, as shown in figure 4 below, is the red area of the proposed building. Therefore, the huge vibration response generated by the building threatens the safety of the building structure, and has a disturbance to the work and life of the workers working in the building. In view of this, taking the engineering office building as a risk target, the ANFIS risk assessment method based on LLE nonlinear characteristic is proposed.
According to the expert system shown in figure 2, we get the vibration risk index of the project, as shown in table 1.

| Sample number | Feature 1   | Feature 2   | Feature 3   | …… | Feature n | Categories |
|---------------|-------------|-------------|-------------|-----|-----------|------------|
| 1             | -2.9162     | -1.9355     | -2.0444     | …… | -1.8470   | 1          |
| 2             | -2.8829     | -2.0310     | -2.0001     | …… | -1.9017   | 1          |
| 3             | -2.5277     | -2.0333     | -1.9573     | …… | -1.7425   | 1          |
| 4             | -2.9033     | -2.1010     | -1.9999     | …… | -1.8700   | 1          |
| 5             | -5.8000     | -5.3440     | -5.3440     | …… | -4.8126   | 2          |
| 6             | -5.8553     | -5.2851     | -5.2475     | …… | -4.8006   | 2          |
| 7             | -5.9013     | -5.3272     | -5.0881     | …… | -4.8999   | 2          |
| 8             | -6.0231     | -5.5462     | -4.9965     | …… | -4.8553   | 2          |
| 9             | -8.3260     | -7.9957     | -7.6545     | …… | -7.7851   | 3          |
| 10            | -8.7454     | -8.5252     | -8.0332     | …… | -7.5949   | 3          |
| 11            | -8.5466     | -8.0325     | -8.0027     | …… | -7.4227   | 3          |
| 12            | -8.7901     | -8.3527     | -8.1147     | …… | -7.5532   | 3          |
| 13            | -1.7142     | -1.2721     | -1.0357     | …… | -0.6999   | 4          |
| 14            | -2.0352     | -1.95487    | -1.5426     | …… | -1.2395   | 4          |

Among them, categories 1, 2, 3, 4 denote slight or no vibration risk, general vibration risk, serious vibration risk, and very serious vibration risk.

Using the ANFIS neural network, the actual engineering test sample vibration risk index vector is extracted by LLE characteristics, and the actual engineering vibration risk index characteristic vector is tested (method 1). The test results, as shown in table 2, are extracted directly into the ANFIS for classification without LLE feature extraction (method 2). The result of the table is shown in table 3.

| Category      | Category 1 | Category 2 | Category 3 | Category 4 |
|---------------|------------|------------|------------|------------|
| Category 1    | 10         | 0          | 0          | 0          |
| Category 2    | 0          | 10         | 0          | 0          |
| Category 3    | 1          | 0          | 9          | 0          |
| Category 4    | 0          | 0          | 1          | 9          |
| Actual project in this article | 1 | 0 | 0 | 0 |

| Category      | Category 1 | Category 2 | Category 3 | Category 4 |
|---------------|------------|------------|------------|------------|
| Category 1    | 10         | 0          | 0          | 0          |
| Category 2    | 1          | 7          | 2          | 0          |
| Category 3    | 0          | 3          | 7          | 0          |
| Category 4    | 2          | 0          | 0          | 8          |
From the above analysis, we can see that the method 1 is divided into two groups and the rest are classified correctly, while 2 methods are misclassified into 8 groups. It can be seen that the ANFIS method based on LLE nonlinear feature extraction improves the accuracy of construction vibration risk identification compared with the method 2. And from table 1, it can be seen that the risk level of construction risk of this project is slight risk.

6. Conclusions
A vibration risk assessment of ANFIS construction based on nonlinear characteristics of LLE is presented. Based on the characteristic quantities of conventional vibration risk indicators, the method extracts the LLE nonlinear characteristics of the original high-dimensional index feature vectors. In this way, the dimensionality of the eigenvector is reduced and the efficiency of the calculation is improved, and the accuracy of the construction vibration risk identification is improved. The method combines the larger amount of information, which not only makes the information contained in the original vibration risk index fully reflected by the nonlinear low dimension characteristic components, but also simplifies the dry of the characteristic information between the systems. Involving or coupling. In the end, the traditional ANFIS neural network is used to compare the traditional feature extraction method of vibration risk characteristic parameters. It is proved that this method improves the accuracy of feature extraction and vibration risk assessment, and can be used as a method of vibration risk assessment in actual engineering vibration risk assessment. Compared with other traditional methods, this method can effectively improve the recognition accuracy, avoid misjudgments and improve the recognition accuracy.

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